An overview
About me

• Past:
  • Research Intern at IIIT- Hyderabad.
    • Supervisor: Jayanthi Sivaswamy
  • MS by Research at IIIT-Hyderabad.
    • Supervisor: Jayanthi Sivaswamy
About me

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  • Research Intern at IIIT- Hyderabad.
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  • MS by Research at IIIT-Hyderabad.
    • Supervisor: Jayanthi Sivaswamy

• Present
  • Started PhD in Fall 2017 at ETS Montreal
    • Supervisors: Hervé Lombaert and Christian Desrosiers
A design for an automated Optical Coherence Tomography analysis system

Karthik Gopinath
Advisor : Prof. Jayanthi Sivaswamy
CVIT, IIIT Hyderabad
Anatomy of eye

Projection imaging

Cross sectional imaging
Why Optical Coherence Tomography?

- 3D representation of retina.
- Non-invasive in nature.
- Shorter image acquisition time.
Retinal diseases

Age related macular degeneration (AMD)
Vision of a normal person and a person with AMD

Cystoidal macular edema (CME)
Vision of a normal person and a person with CME

Glaucoma
Vision of a normal person and a person with Glaucoma
Proposed OCT analysis system

OCT Data

Retinal layer segmentation

Volume level disease diagnosis

Slice level disease diagnosis

Pixel level Abnormality segmentation

Anatomy analysis

Retinal layers

Normal vs Glaucoma

Normal vs AMD / CME

Cyst regions

Disease analysis
Motivation and Challenges in retinal layer segmentation

• Motivation
  – Quantifying retinal layer thickness
  – Understanding progressive health of the retina.

• Challenges
  - Presence of speckle noise.
  - Vessel shadows.
  - Various layer orientation.
  - Pathologies affecting layer morphology.
Comparison of retinal layer segmentation algorithms

Previous works

- Included pre-processing steps:
  - Denoising.
  - Vessel shadow removal.
  - Flattening.
- Sequential segmentation of layers[1].
- Pathology dependent methods[3].

Proposed work

- No requirement for any pre-processing.
- One-shot solution multi-layer segmentation.
- Robustness to presence of pathologies.
- Robustness to imaging systems and image quality.
Visualization of different retinal layers

Retinal layer boundaries in OCT B-scans of a) Healthy retina, listed from top to bottom: ILM(Red), NFL/GCL(Green), IPL/INL(blue), INL/OPL(yellow), OPL/ONL(cyan), IS/OS(magenta), RPEin(pink) and RPEout(purple); b) Retina with AMD: ILM(Red), RPEin(Green) and RPEout(Blue).
Proposed Architecture
Data and Training Method

• Dataset description (Public datasets)

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chiu_norm [1] (Normal cases)</td>
<td>110 B-scans from 10 healthy subjects (11 B-scans per subject).</td>
</tr>
<tr>
<td>OCTRIMA3D [2] (Normal cases)</td>
<td>100 B-scans from 10 healthy subjects (10 B-scans per subject).</td>
</tr>
<tr>
<td>Chiu_path[3] (Pathology cases)</td>
<td>220 B-scans from 20 subjects (11 B-scans per subject).</td>
</tr>
</tbody>
</table>

• Training
  - Two copies:
    • Only normal cases $M_{\text{norm}}$.
    • Both normal and pathological cases $M_{\text{mixed}}$.
  - Training and testing set split: 8:2.
  - Online data augmentation.
  - Entire network trained in an end-to-end fashion.
Intermediate results
Qualitative results

\[ M_{\text{norm}} \]

Comparison with manual (green) segmentation and obtained results.

\[ M_{\text{mixed}} \]

Comparison with manual (green) segmentation and obtained results.
## Quantitative results

- **Pixel-wise mean absolute error/standard deviation:**
  - $M_{\text{norm}}$:

<table>
<thead>
<tr>
<th></th>
<th>Chiu_norm</th>
<th>OPTIMA 3D</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>MAE</td>
<td>2.25/1.08</td>
<td>1.34/0.44</td>
<td>1.44/0.47</td>
</tr>
</tbody>
</table>

- $M_{\text{mixed}}$:

<table>
<thead>
<tr>
<th></th>
<th>Chiu_norm</th>
<th>OPTIMA 3D</th>
<th>Chiu_path</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>MAE</td>
<td>2.14/1.19</td>
<td>1.16/0.46</td>
<td>1.34/0.45</td>
<td>0.89/0.348</td>
</tr>
</tbody>
</table>
Proposed OCT analysis system

- Retinal layer segmentation
- Volume level disease diagnosis
- Slice level disease diagnosis
- Pixel level abnormality segmentation

OCT Data

Retinal layers

Anatomy analysis

Normal vs Glaucoma
Normal vs AMD / CME
Cyst regions

Disease analysis
Glaucoma diagnosis at volume level

- **Glaucoma**
  - Second leading cause of blindness in the world.
  - Cause of irreversible blindness.

- **Multiple Indicators.**
  - From projection imaging.
  - From structural image.

- We attempt glaucoma diagnosis from functional imaging.

- **Our proposal:** Detect glaucoma via **vascular health** assessment.

- To get information about **functioning** of the vessel network
  - New modality - OCT Angiography (3D)
    - non-invasive technique
    - vasculature information available at various retinal layers
Data visualization from OCT Angiography

The different enface images in relation to a cross-sectional OCT Angiography slice.
Proposed Method

- Choroid Disc Angioflow Image
- Region of Interest Extraction
- Four Angioflow images
- Capillary Density Estimation
- RNFL thickness Estimation
- OCTA volume
- Feature Extraction
- Labels
- Classifier
- Model
- Labels
Region of interest extraction

*Choroid Disc Angioflow image*

*Eight sectors in ROI*
Feature extraction

Four Angioflow images

Capillary Density Estimation

RNFL thickness Estimation

OCTA volume

Capillaries at different layers

Capillaries at different layers in ROI

OCTA image

Intensity profile
Training and Testing

Features → Linear SVM Classifier → Labels

Features → Model → Labels
Experiments and results

- OCTA images from an Optovue scanner collected from a Anand Eye hospital.
- Dataset

<table>
<thead>
<tr>
<th></th>
<th>Normal</th>
<th>Glaucomatous</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of eyes</td>
<td>49</td>
<td>18</td>
</tr>
</tbody>
</table>

- Data per eye/volume
  - A OCTA volume
  - Four angioflow images at different layers (choroidal disc, nerve head, RPC and the vitreous layers).
  - Ground truth from one expert
**Experiments and results**

RNFL thickness for a Glaucomatous and a Normal case across sectors (left). Capillary density (CD) variation for a Glaucomatous and a Normal case across sectors. The average CD across 4 layers is shown for each sector.

<table>
<thead>
<tr>
<th></th>
<th>RNFL alone</th>
<th>CD alone</th>
<th>RNFL + CD for all layers</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean (Std. Dev.)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sensitivity</td>
<td>0.44 (0.17)</td>
<td>0.83 (0.18)</td>
<td>0.94 (0.13)</td>
</tr>
<tr>
<td>Specificity</td>
<td>0.87 (0.13)</td>
<td>0.79 (0.14)</td>
<td>0.91 (0.10)</td>
</tr>
<tr>
<td>Accuracy</td>
<td>0.76 (0.12)</td>
<td>0.80 (0.09)</td>
<td>0.92 (0.08)</td>
</tr>
</tbody>
</table>
Proposed OCT analysis system

OCT Data

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Volume level disease diagnosis

Normal vs Glaucoma

Normal vs AMD / CME

Slice level disease diagnosis

Pixel level Abnormality segmentation

Disease analysis

Retinal layers

Cyst regions
Slice level disease diagnosis

- Different disease indicators:
  - AMD case - drusen (aberration in bright layer).
  - CME case - retinal cyst/fluid filled regions (dark regions).

Normal case  AMD case  CME case
Comparison of disease classification algorithms

Previous works

- Statistical analysis of layer thickness. [4]
- Morphological and textural features with decision tree. [5]
- Histogram of Oriented Gradients (HOG) descriptors + SVM. [6]

Proposed work

- An automated CNN based solution
- Disease classification using extremal representations.
Motion blur in natural setting

Motion blur due to moving object

Motion blur due to moving source
Synthesizing motion blur from Generalised motion pattern (GMP) [8][9]
Proposed Architecture for disease diagnosis
Experiments and Results

• Datasets:
  – Train set: 3500 OCT slices
  – Test set: 1995 OCT slices

• Performance of the proposed system

<table>
<thead>
<tr>
<th></th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal vs Abnormal</td>
<td>0.98</td>
<td>0.98</td>
<td>0.98</td>
</tr>
<tr>
<td>DME vs Rest</td>
<td>0.86</td>
<td>0.98</td>
<td>0.95</td>
</tr>
<tr>
<td>AMD vs Rest</td>
<td>0.96</td>
<td>0.96</td>
<td>0.95</td>
</tr>
<tr>
<td>Mean Result</td>
<td>0.93</td>
<td>0.97</td>
<td>0.96</td>
</tr>
</tbody>
</table>
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Cyst regions
Motivation and Challenges in abnormality segmentation

• Motivation
  – Treatment planning for the patients.
  – Localizing and quantifying them will aid in accurate surgical interventions.

• Challenges

Inter-scanner variability in images

Variable shape, size, appearance and arbitrary locations
Comparison of abnormality segmentation algorithms

Previous works

- Semi-automatic. [9]
- Thresholding and boundary tracing. [10]
- Graph-search/graph-cut based algorithm. [11]
- Voxel classification approaches. [12]

Proposed work

- Unique representation for the OCT data, based on motion patterns. [7][8]
- Selective enhancement of cysts with CNN.
- Combining both 2D and 3D information in CNN.
- Vendor independent and robust system for detecting and localizing cysts.
The proposed pipeline for abnormality segmentation

OCT Data

Pre-processing

ROI extraction

Denoising

LOI extraction

Generalized motion patterns

Convolutional Neural Network

K-means Clustering

Segmentation results

Stack of GMP

Probability map
Pre-Processing for abnormality segmentation

The original image

The ROI image

The denoised image

The LOI image
Selective enhancement from Generalised motion pattern

Translation motion

Original Image $f$

Stack $S$

$f_{15}$

$f_{10}$

$f_5$

$f_2$

$f_1$

Translation motion

Image $f_0$

Generalised motion pattern
Proposed Architecture
Evolution of the mapping function over epochs

(a) ROI input, (b) Ground truth: Grader1 ∩ Grader2, the output of CNN is shown as a probability (heat) map at (c). 10th, (d) 50th, (e) 100th, (f) 200th, (g) 300th, (h) 500th, (i) 900th, (j) 1420th epochs.
Segmentation

- The output of the trained is thresholded to obtain a binary map.
- Multiplied ROI image with binary map.
- K-means clustering is applied on this product image.
  - Cysts
  - False positives region
  - Background.
### Experiments and Results

#### Datasets

<table>
<thead>
<tr>
<th>OCSC dataset (Public)</th>
<th>DME dataset (Public)</th>
<th>Anand Eye Institute dataset (Private)</th>
</tr>
</thead>
<tbody>
<tr>
<td>15 training and 15 testing volumes with varying number of (5-200) B-scans from 4 different scanners.</td>
<td>10 volumes with 61 B-scans.</td>
<td>10 volumes with varying number of (30-51) B-scans</td>
</tr>
<tr>
<td>GT from two experts</td>
<td>GT markings for 11 B-scans per volume (not continuous).</td>
<td>GT for every 5(^{th}) slice from one expert.</td>
</tr>
</tbody>
</table>

*Note:* Training is done only on OCSC train set.
Qualitative results

- (a) ROI of a slice
- (b) Ground truth
- (c) Probability
- (d) Segmentation results by thresholding probability map
- (e) Segmentation results using K-means clustering
Qualitative results

(a) ROI of a slice
(b) Ground truth Grader1 ∩ Grader2
(c) Probability map
(d) Segmentation results by thresholding probability map
(e) Segmentation results using K-means clustering
Effect of the number of GMPs

Segmentation performance as a function of the number (K) of GMPs.
Effect of the number of translation in each GMP

Segmentation performance as a function of the extent (N) of translation in each GMP.
Pixel level abnormality segmentation

- System performance is assessed by computing the Dice Coefficient.

\[ \text{Dice Coefficient} = 2 \frac{|\text{Detected} \cap \text{GT}|}{|\text{Detected}| + |\text{GT}|} \]

- Mean DC values for different variants of the proposed CNN model on the OCSC test set

<table>
<thead>
<tr>
<th>Input</th>
<th>2D</th>
<th>Proposed architecture</th>
<th>Proposed architecture + K-means clustering</th>
</tr>
</thead>
<tbody>
<tr>
<td>DC</td>
<td>0.56</td>
<td>0.64</td>
<td>0.69</td>
</tr>
</tbody>
</table>

- Mean DC values for different inputs and variants for selective enhancement

<table>
<thead>
<tr>
<th>Method</th>
<th>OCSC Test set</th>
<th>DME dataset</th>
<th>AEI dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td>U-net [15] with ROI as input</td>
<td>0.58</td>
<td>0.51</td>
<td>0.69</td>
</tr>
<tr>
<td>U-net with GMP as input</td>
<td>0.61</td>
<td>0.55</td>
<td>0.71</td>
</tr>
<tr>
<td>Proposed architecture + K-means clustering</td>
<td>0.69</td>
<td>0.67</td>
<td>0.79</td>
</tr>
</tbody>
</table>
Summary

• We developed an anatomy segmentation module
  – Parameter independent.
  – can handle both normal and AMD affected retina.
• We explored the use of additional angio information for glaucoma classification.
• We proposed a slice level multiple disease classification using extremal representation and CNN.
• We presented an algorithm for localizing/segmenting retinal.
  – Generic approach independent of scanners.
  – Use of CNN to learn a mapping function for selective enhancement of cysts.
Future work

• Anatomy extraction:
  – Segmentation of retinal layers in presence of pathologies like cysts.
  – Segmentation of retinal layer around optic disc (OD).

• Classification of diseases at volume level:
  – Investigate the new imaging modality OCTA for the effect of vasculature on other retinal disease.

• Classification of diseases at volume level:
  – Multiple disease diagnosis.
  – Grading of the diseases according to its stages.

• Abnormality extraction:
  – Enhance the existing segmentation scheme by developing an end to end CNN based module.
Related Publications

• Domain knowledge assisted cyst segmentation in OCT retinal images.
  
  **Karthik Gopinath** and Jayanthi Sivaswamy.
  

• Automatic glaucoma assessment from angio-OCT images.
  
  **Karthik Gopinath**, Jayanthi Sivaswamy and Tarannum Mansoori.
  
  IEEE 13th International Symposium on Biomedical Imaging (ISBI) 2016, Prague, Czech Republic.

• A deep learning framework for segmentation of retinal layers from OCT images.
  
  **Karthik Gopinath**, Samrudhdhi B*, and Jayanthi Sivaswamy.
  
  The 4th Asian Conference on Pattern Recognition (ACPR), November 2017, Nanjing, China.

• Under Review in Journal of Biomedical and Health Informatics
  
  Automated segmentation of retinal cysts from Optical Coherence Tomography volumes.
  
  **Karthik Gopinath** and Jayanthi Sivaswamy.
References


We thank

Anand Eye Institute, Hyderabad
(for data and ground truth)
Thank you