One single model for GA segmentation with multiple scan patterns and OCT instruments

Qinqin Zhang, PhD[1]; Luis de Sisternes, PhD[1]; Gissel Herrera, MD[2]; Giovanni Gregori, PhD[2]; Philip J Rosenfeld, PhD, MD[2]; Niranchana Manivannan, PhD[1]

[1]Carl Zeiss Meditec, Inc., Dublin, CA, USA; [2]Department of Ophthalmology, Bascom Palmer Eye Institute, University of Miami Miller School of Medicine, Miami, FL, USA

Poster #1109 – C0203

PURPOSE

Geographic atrophy (GA) is a condition present at the advanced stages of non-exudative macular degeneration and can grow over time worsening patient's vision (especially once it reaches the fovea). Automated GA segmentation has been proposed based on deep learning approaches on OCT images. However, it has only been utilized on specific scan patterns or instruments, which may constrain its ability to monitor the progression of GA across various instruments and scan patterns. We have developed a single deep learning model capable of segmentation of GA on OCT data obtained from different instruments and using various scan patterns.

METHODS

- A 2D U-net was utilized with Adam optimizer and the loss function was initialized as the mean squared error and changed to 1-Dice index after the first 300 steps.
- A 5-fold cross-validation model with data augmentation techniques was trained with 126 Angio 6x6 mm scan images from PLEX® Elite 9000 SS-OCT (ZEISS, Dublin, CA), 80 Angio 12x12 mm PLEX Elite images, and 188 Macular Cube 512x128 or 200x200 scan images from CIRRUS^{TM} HD-OCT 5000 SD-OCT (ZEISS, Dublin, CA) (Figure 1).
- Pseudo-color images characterizing the main OCT features of GA were generated from the volume data using an automated algorithm that includes hyper-transmission in sub-retinal pigment epithelium (RPE) slab, regions of RPE loss, and loss of retinal thickness as training inputs. (Figure 2).
- GA lesions were manually outlined by a human grader (GH) based on sub-RPE slabs as ground truth for training and evaluation.
- Each image was evaluated with each of the 5 training models to produce 5 different prediction maps and then averaged to generate a model ensemble prediction map. The binary predict GA mask was generated by thresholding the ensemble prediction map.
- Sensitivity was defined by the number of scans correctly predicted to have any sign of GA divided by the total number of scans with GA. Specificity was defined as the number of scans correctly predicted to have no signs of GA divided by the total number of scans without GA.
- Symmetric Dice coefficient (SDC) was used to evaluate the accuracy of the GA and was measured between the automated method and the manual grader in the training dataset and in the test dataset.

RESULTS

- A test dataset consisting of 15 GA eyes and 15 non-GA eyes with PLEX Elite Angio 6x6 mm, Angio 12x12 mm and CIRRUS Angio 6x6 mm, Macular cube 512x128 and 200x200 scans was evaluated (Figure 4).
- A sensitivity of 0.95, a specificity of 0.83 and a SDC of 0.91 in the training dataset and a sensitivity of 0.996, a specificity of 0.940 and the SDC of 0.922 in the validation/test dataset were achieved.
- A high correlation (r^2=0.97) of GA area was observed between manual measurements and automated measurements. Bland-Altman plot showed a slight larger measurement (mean value=0.19mm^2) with automated algorithm.

CONCLUSIONS

The single deep learning model that incorporates various scan patterns and different OCT instruments was able to accurately delineate GA lesions with a high sensitivity and specificity. This model could serve as a new management tool for GA detection across multiple scan patterns and OCT devices.

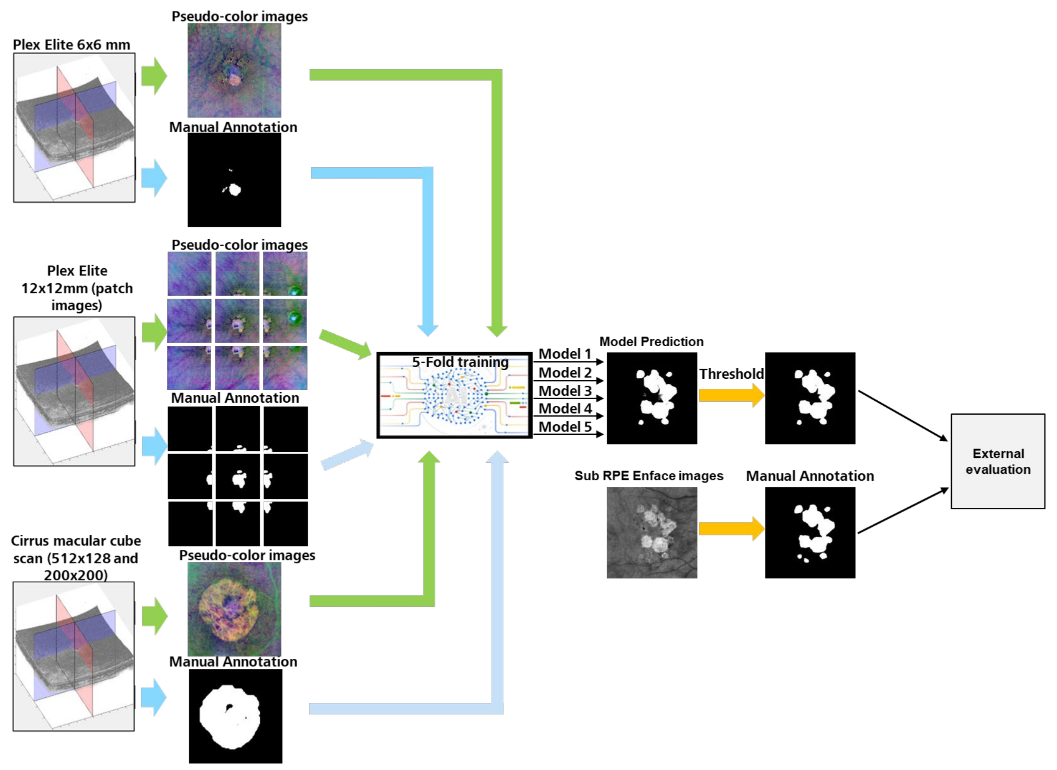

Figure 1: Diagram for the en face generation, annotation, training and evaluation process of the 5-fold model.

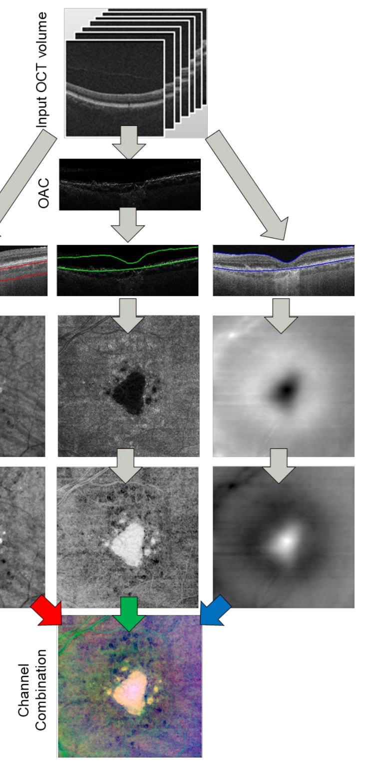

Figure 2: Generation of pseudo-color input images. OAC: Optical Attenuation Coefficient.

Evaluation Set	Sensitivity				Specificity				Sym. Dice Index: Avg.			
	PlexElite Angio 6mm	PlexElite Angio 12mm	Cirrus 200x200	Cirrus 512x128	PlexElite Angio 6mm	PlexElite Angio 12mm	Cirrus 200x200	Cirrus 512x128	PlexElite Angio 6mm	PlexElite Angio 12mm	Cirrus 200x200	Cirrus 512x128
Training Fold1	1.00	0.92	1.00	0.94	0.83	0.83	0.75	0.88	0.94	0.91	0.93	0.88
	0.93				**0.82**				**0.91**			
Training Fold2	1.00	0.97	1.00	1.00	0.86	1.00	0.67	1.00	0.93	0.93	0.89	0.91
	0.97				**0.87**				**0.92**			
Training Fold3	1.00	0.89	1.00	1.00	0.83	1.00	0.88	0.88	0.95	0.89	0.90	0.90
	0.91				**0.88**				**0.89**			
Training Fold4	1.00	0.95	1.00	1.00	1.00	0.92	0.71	0.88	0.96	0.92	0.92	0.88
	0.96				**0.88**				**0.92**			
Training Fold5	1.00	0.96	1.00	1.00	0.86	0.57	0.67	0.89	0.94	0.90	0.89	0.90
	0.97				**0.72**				**0.90**			
Training Average	**1.00**	**0.94**	**1.00**	**0.99**	**0.88**	**0.86**	**0.74**	**0.91**	**0.94**	**0.91**	**0.91**	**0.89**
	0.95				**0.83**				**0.91**			

Evaluation Set	Sensitivity					Specificity					Sym. Dice Index: Avg.(std.)				
	PlexElite Angio 6mm	PlexElite Angio 12mm	Cirrus Angio 6mm	Cirrus 200x200	Cirrus 512x128	PlexElite Angio 6mm	PlexElite Angio 12mm	Cirrus Angio 6mm	Cirrus 200x200	Cirrus 512x128	PlexElite Angio 6mm	PlexElite Angio 12mm	Cirrus Angio 6mm	Cirrus 200x200	Cirrus 512x128
New Test	1.000	1.000	1.000	1.000	0.967	0.933	0.90	1.000	0.867	1.000	0.936 (0.068)	0.912 (0.089)	0.923 (0.045)	0.910 (0.056)	0.889 (0.101)
	0.996					0.940					0.922 (0.074)				

Table 1: Sensitivity, Specificity and measured SDC on training dataset and new test dataset

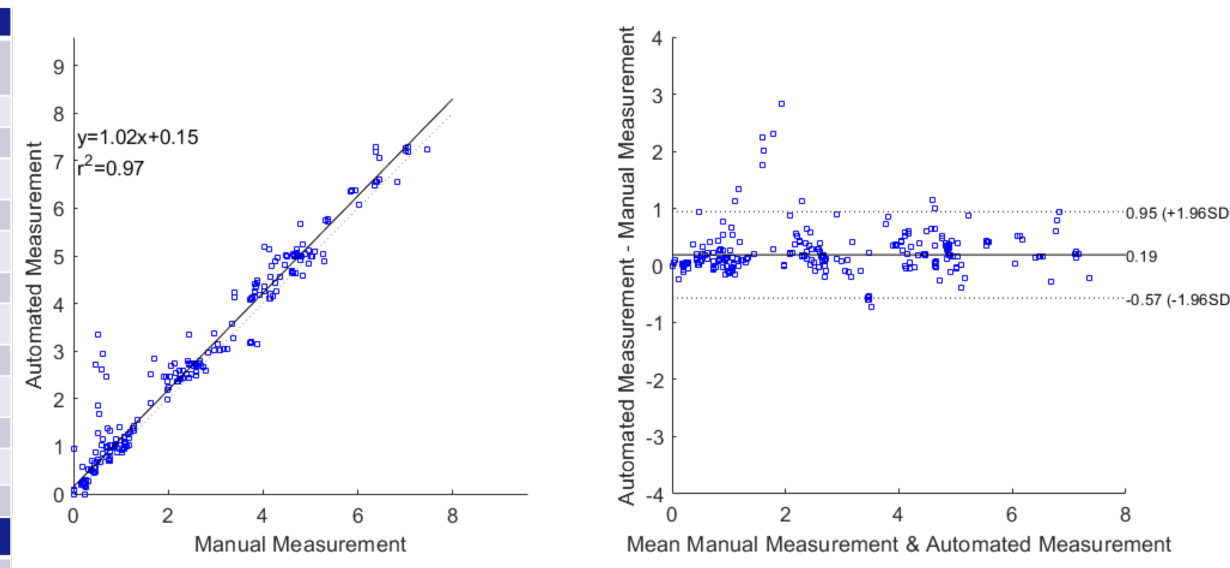

Figure 3: Bland-Altman plot comparing manual GA area measurements from manual measurement to the algorithm results (automated measurement).

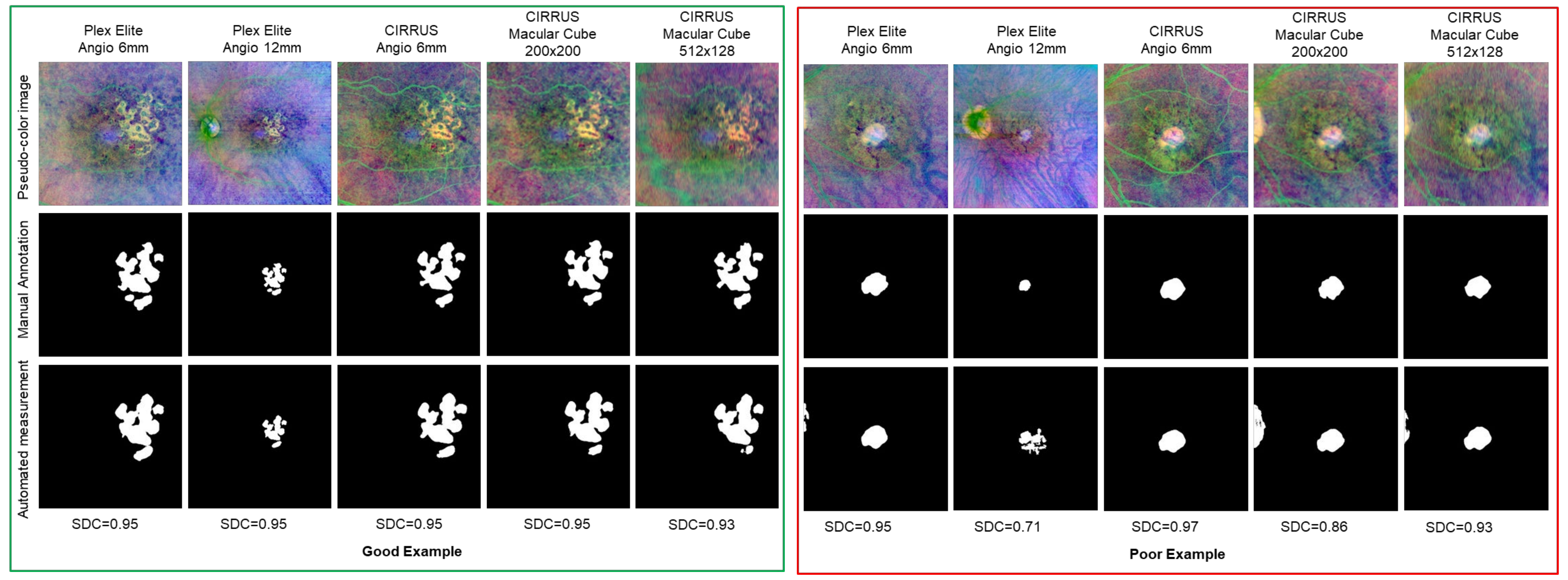

Figure 4: Evaluation results of good (high SDC) and poor (low SDC) examples with various scan patterns and different instruments.

Email: qinqin.zhang@zeiss.com

Disclosures: QZ (E), LdS (E), NM (E): Carl Zeiss Meditec, Inc.;

GG (F): Carl Zeiss Meditec, Inc.;

PJR (F): Carl Zeiss Meditec, Inc., Alexion, Gyroscope Therapeutics, Stealth Bio Therapeutics; PJR (C): Annexon, Apellis, Bayer, Boehringer-Ingelheim, Carl Zeiss Meditec, Inc., Chengdu Kanghong Biotech, InflammX, Ocudyne, Regeneron, Unity Biotechnology; PJR (I): Apellis, Ocudyne, Valitor, Verana Health.