Macular GCIPL Thickness Map Prediction Via Time-Aware Convolutional LSTM

Zhiqi Chen[1,2], Yao Wang[2], Gadi Wollstein[1], Maria de los Angeles Ramos-Cadena[1], Joel Schuman[1], Hiroshi Ishikawa[1]

[1] Department of Ophthalmology, NYU Langone Health, New York, NY, USA. [2] Department of Electrical and Computer Engineering, New York University, NY, USA.

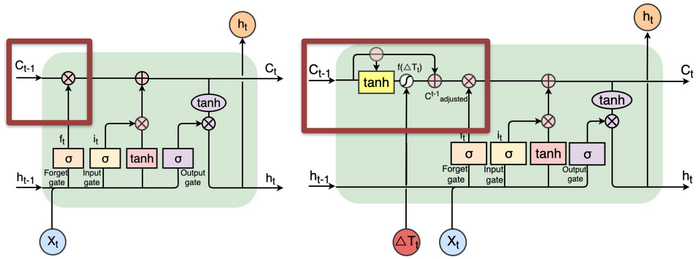
IEEE ISBI 2020 International Symposium on Biomedical Imaging

BACKGROUND

- Longitudinal progression monitoring of glaucoma is essential.
- Biomarker for diagnosis and monitoring of glaucoma: macular ganglion cell inner plexiform layer (GCIPL) thickness measured on optical coherence tomography (OCT) scans.
- Prior clinical progression analysis on GCIPL uses only summarized numbers (e. g. global measurements).
- 2D GCIPL thickness maps often reveal subtle abnormalities.
- Spatial patterns of GCIPL is also useful to understand the extent and magnitude of localized damages.
- Therefore, projection of 2D GCIPL maps may allow clinicians to fine tune their treatment strategy case by case.
- In this study, we aim to predict the next-visit 2D GCIPL thickness map based on the current and past maps (Figure 1).

METHODS

- Time-aware convolutional LSTM (TC-LSTM, Figure 2):
- Time penalty function (Eq. (12) - (14)):



$$i_t = \sigma(W_{xi} * X_t + W_{hi} * H_{t-1} + b_i) \quad (1)$$

$$f_t = \sigma(W_{xf} * X_t + W_{hf} * H_{t-1} + b_f) \quad (2)$$

$$C_t = f_t \circ C_{t-1} + i_t \circ tanh(W_{xc} * X_t + W_{hc} * H_{t-1} + b_c) \quad (3)$$

$$H_t = \sigma(W_{xo} * X_t + W_{ho} * H_{t-1} + W_{co} \circ C_t + b_o) \quad (4)$$

$$C^{t-1}_{short} = tanh(W_{cs} \circ C^{t-1} + b_s) \quad (5)$$

$$C^{t-1}_{long} = C^{t-1} - C^{t-1}_{short} \quad (6)$$

$$C^{t-1}_{adjusted} = f(\Delta T_t) C^{t-1}_{short} + C^{t-1}_{long} \quad (7)$$

$$i^t = \sigma(W_{xi} * X^t + W_{hi} * H^{t-1} + b_i) \quad (8)$$

$$f^t = \sigma(W_{xf} * X^t + W_{hf} * H^{t-1} + b_f) \quad (9)$$

$$C^t = f^t \circ C^{t-1}_{adjusted} + i^t \circ tanh(W_{xc} * X^t + W_{hc} * H^{t-1} + b_c) \quad (10)$$

$$H^t = \sigma(W_{xo} * X^t + W_{ho} * H^{t-1} + W_{co} \circ C^t + b_o) \quad (11)$$

Figure 2. Architecture of (left) Standard convolutional LSTM (cLSTM) cell (Eq. (1) - (4)) and (right) TC-LSTM cell (Eq. (5) - (11)).

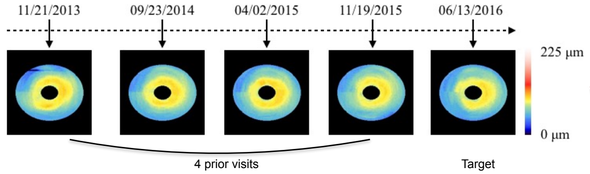


Figure 1. Example of a GCIPL thickness map sequence with **irregular sampling interval.**

$$f(\Delta T_t) = \frac{1}{log(e + \Delta T_t)} \quad (12)$$

$$f(\Delta T_t) = \frac{1}{a\Delta T_t + b} \quad (13)$$

$$f(\Delta T_t) = \frac{1}{e^{a\Delta T_t + b}} \quad (14)$$

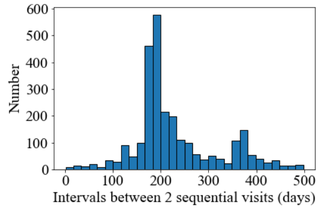


Figure 3. Histogram of intervals between 2 sequential visits.

EXPERIMENTS

- **Dataset**: 346 eyes from 191 patients (avg. number of visits: 9.5 ± 3.4, avg. follow-up period: 5.9 ± 2.0 years, avg. GCIPL thinning: 0.8 μm/year, sampling intervals: Figure 3).
- **Data Augmentation**: 576 progressing sequences were simulated according to GCIPL thinning patterns of glaucoma (Figure 4) because 83.2% of patients are under stable states (avg. GCIPL thinning < 2 μm/year).
- **Compared methods**: Linear regression (LR) and standard cLSTM.
- **Quantitative evaluation metrics**: Peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM).

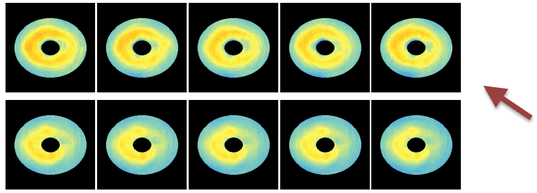


Figure 4. Examples of GCIPL thinning patterns. *Top:* hemifield damage. *Bottom:* diffuse damage.

RESULTS

- **Quantitative results** (Table 1)**:**

Method	PSNR	SSIM
Copy last	30.27	0.947
LR	32.52	0.967
cLSTM (L2)	33.93	0.939
TC-LSTM (L2 & Eq(13))	34.08	0.966
TC-LSTM (L1 & Eq(13))	34.18	**0.973**
TC-LSTM (L1+L2 & Eq(13))	**34.45**	0.972
TC-LSTM (L2 & Eq(12))	33.83	0.972
TC-LSTM (L2 & Eq(14))	34.10	0.965

Table 1. Method comparison.

Rater	TC-LSTM	LR
Rater 1	**92.8%**	7.2%
Rater 2	**93.4%**	6.6%
Rater 3	**94.8%**	5.2%

Table 2. Subjective Rating Results. Numbers in columns indicates percentages of maps predicted by a particular method is rated the best.

- **Subjective evaluation** (Table 2, Figure 5)**:**

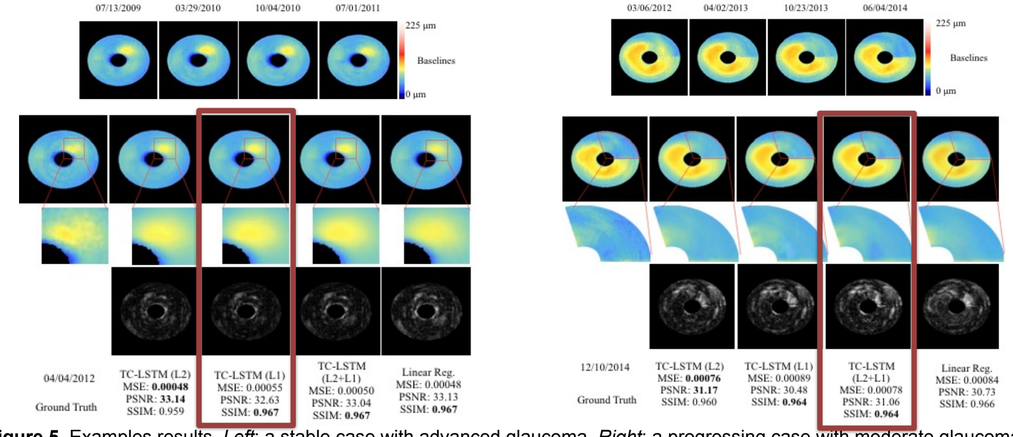


Figure 5. Examples results. *Left*: a stable case with advanced glaucoma. *Right*: a progressing case with moderate glaucoma.

CONCLUSIONS

- Our model was able to handle irregularly sampled spatiotemporal sequence modeling.
- The next-visit GCIPL thickness maps were successfully generated using TC-LSTM with higher accuracy compared to LR and cLSTM both quantitatively and subjectively.
- This prediction model may help clinicians in fine tuning individual treatment plans with projections not only for the global summarized number but also for potential spatial GCIPL thinning pattern.