RITnet: Real-time Semantic Segmentation of the Eye for Gaze Tracking

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facebook research OpenEDS Challenge

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Overview

- Accurate eye segmentation improves **eye-gaze estimation**
- Current segmentation models suffer from **person-dependent accuracy**, lack of **robustness** and inability to run in **real-time**.
- We present ***RITnet***, a deep neural network architecture, which obtains **state-of-the-art** results on the 2019 OpenEDS[1] Semantic Segmentation Challenge.
- Model Size: **<1 MB** to allow **real-time** gaze tracking

Architecture

- ***RITnet*** (248,900 trainable parameters) is based on DenseUNet-K[2] architecture which combines U-Net[3] and DenseNet[4] architectures.
- Direct '**skip**' connections with simplified **dense** connected feature maps
- Constant channel size of 32 to reduce model complexity
- The back-propagated loss is:

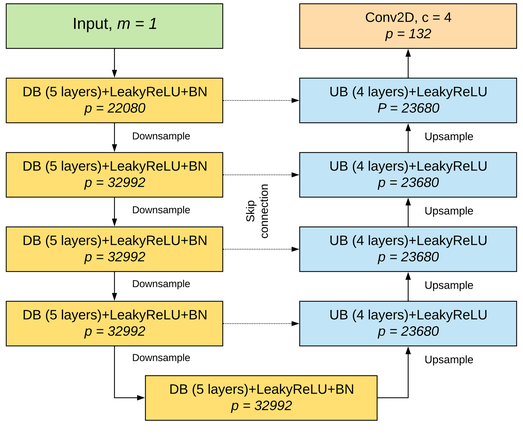
$$L = L_{CEL}(\lambda_1 + \lambda_2 L_{BAL}) + \lambda_3 L_{GDL} + \lambda_4 L_{SL}$$

Cross Entropy Loss (L_{CEL})

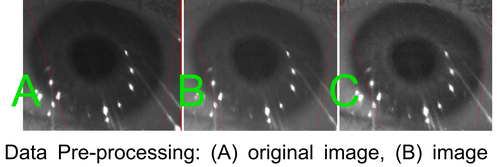
Generalized Dice Loss (L_{GDL})

Boundary Aware Loss (L_{BAL})

Surface Loss (L_{SL})



Architecture details of RITnet



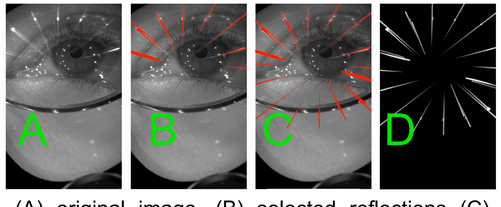
Data Pre-processing: (A) original image, (B) image after Gamma correction with a factor of 0.8, and (C) image after local Contrast Limited Adaptive Histogram Equalization

Experimental Details

- OpenEDS Semantic Segmentation dataset consists of *train (8916)*, *validation (2403)* and *test (1440)* images.
- Each image contains four semantic labels: *pupil, iris, sclera*, & *background*.
- Adam optimizer with learning rate 0.001 and batch size of 8 images for 175 epochs.
- **Loss scheduling scheme** to prioritize production of **crisp boundary pixels**, handle **class imbalance** and penalize **stray patches**.

Augmented the training images by

- Horizontal flip
- Translation (0-20 pixels)
- Gaussian Blur ((7,7), $2 \leq \sigma \leq 7$)
- Thin lines around random center
- *Starburst* pattern from train image



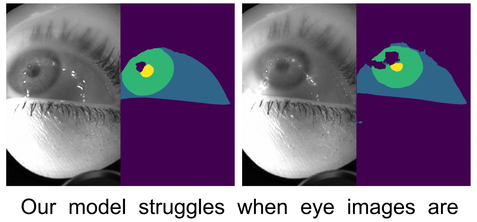
(A) original image, (B) selected reflections (C) concatenating with 180° rotation (D) final mask which is appended with training image.

Results

- Evaluation is based on mean Intersection over Union (mIoU) and the number of model parameters (s) as

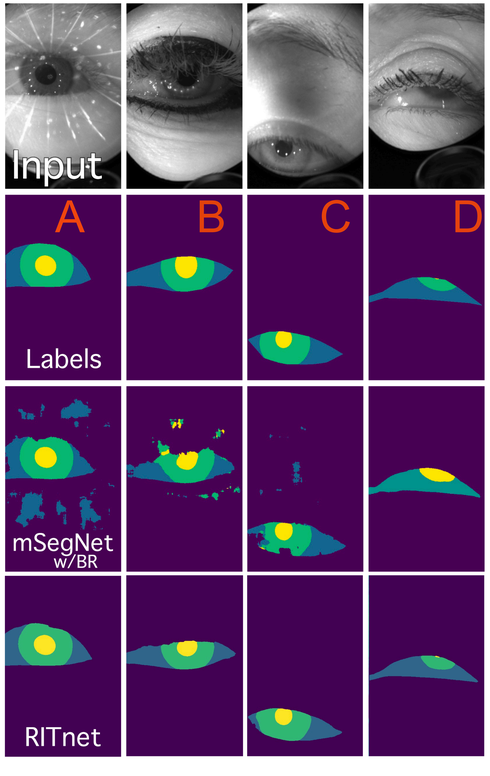
$$(mIoU + min(1/s, 1))/2$$

- Our model achieves a ~**6%** improvement in mIoU score while the complexity is reduced by ~**38%** compared to the baseline model modified SegNet with Separable convolutions (SC)[1]



Our model struggles when eye images are **heavily blurred** or **defocused.**

Model	Mean F1	mIoU	Model Size (S)	No. of parameters (million)	Overall Score
mSegNet*	97.9	90.7	13.3	3.5	0.491
mSegNet* w/BR	98.3	91.4	13.3	3.5	0.495
mSegNet* w/SC	97.4	89.5	1.6	0.4	0.762
Ours	**99.3**	**95.3**	**0.98**	**0.25**	**0.976**



Comparison of results in the challenging conditions (A) multiple reflections due to prescription glasses, (B) heavy mascara (C) dim light (D) partial eyelid closure.

Contributions

- State-of-the-art results of 95.3% with model size of <1 MB
- Real-time segmentation at >300 Hz for 640x400 images on an NVIDIA 1080Ti GPU
- Domain-specific augmentation schemes
- Boundary aware loss functions with a loss scheduling strategy

References

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