IterNet: Retinal Image Segmentation Utilizing Structural Redundancy in Vessel Networks (Supplementary Material)

Liangzhi Li
Osaka University
li@ids.osaka-u.ac.jp

Manisha Verma
Osaka University
mverma@ids.osaka-u.ac.jp

Yuta Nakashima
Osaka University
n-yuta@ids.osaka-u.ac.jp

Hajime Nagahara
Osaka University
nagahara@ids.osaka-u.ac.jp

Ryo Kawasaki
Osaka University
ryo.kawasaki@ophthal.med.osaka-u.ac.jp

Figure A shows the connectivity value under different threshold for several methods on three popular datasets, *i.e.*, DRIVE [1], CHASE-DB1 [2], and STARE [3]. The area under the curve is used as the measurement in the paper. We can see that IterNet almost always outperforms the other three methods.

Tables A, B, and C give the results on various criteria for two variants of IterNet. The first one is the IterNet model without skip connections among the first layer of the base UNet and the first layers of the mini-UNets, while the second one is to replace mini-UNets in IterNet with full-size UNets. Results show that they both suffer from a performance drop on all three datasets.

Table D shows the detailed time cost in the inference process. We used 128×128 image patches and tested different strides (the image patches are extracted every 3 or 8 pixels in both horizontal and vertical directions). We can see that a smaller stride may lead to a better refinement, while it also brings much bigger time cost.

Figures B, C, and D present the visualization results of the segments in the prediction results. We can see that IterNet almost consistently produces a smaller number of segments.

References

[1] J. Staal, M. Abramoff, M. Niemeijer, M. Viergever, and B. van Ginneken, "Ridge based vessel segmentation in color images of the retina," *IEEE Transactions on Medical Imaging*, vol. 23, no. 4, pp. 501–509, 2004.

[2] C. G. Owen, A. R. Rudnicka, R. Mullen, S. A. Barman, D. Monekosso, P. H. Whincup, J. Ng, and C. Paterson, "Measuring retinal vessel tortuosity in 10-year-old children: validation of the computer-assisted image analysis of the retina (CAIAR) program," *Investigative Ophthalmology & Visual Science*, vol. 50, no. 5, pp. 2004–2010, 2009.

[3] A. D. Hoover, V. Kouznetsova, and M. Goldbaum, "Locating blood vessels in retinal images by piecewise threshold probing of a matched filter response," *IEEE Transactions on Medical Imaging*, vol. 19, no. 3, pp. 203–210, 2000.

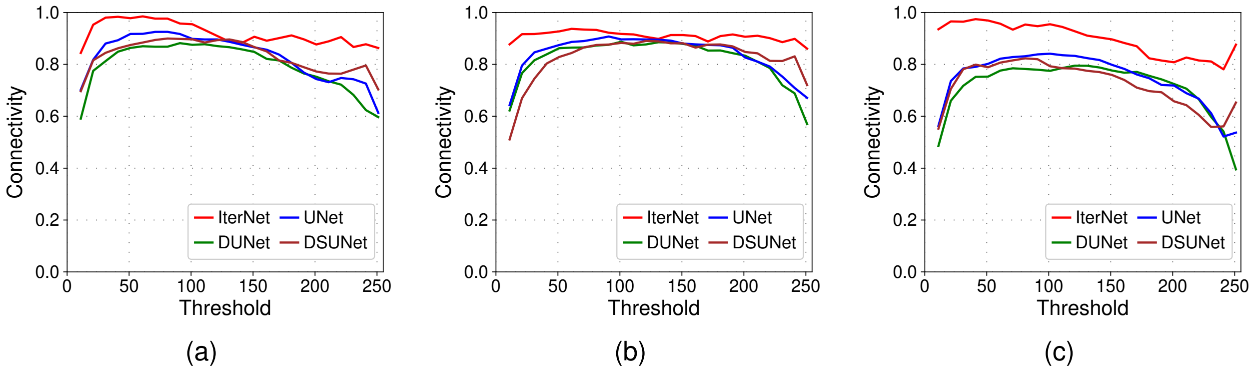


Figure A. Connectivity versus threshold on the three datasets: (a) DRIVE. (b) CHASE-DB1. (c) STARE.

Table A. Performance comparison on the DRIVE dataset (with mask).

Method	Conn.	F1 Score	Sensitivity	Specificity	Accuracy	AUC
IterNet	**0.9193**	**0.8205**	**0.7735**	0.9838	**0.9573**	**0.9816**
w/o Skip Connection	0.9106	0.8160	0.7659	0.9839	0.9565	0.9799
Iterated UNets	0.8893	0.8123	0.7575	**0.9845**	0.9559	0.9794

Table B. Performance comparison on the CHASEDB1 dataset (with mask).

Method	Conn.	F1 Score	Sensitivity	Specificity	Accuracy	AUC
IterNet	**0.9091**	**0.8073**	**0.7970**	0.9823	**0.9655**	**0.9851**
w/o Skip Connection	0.8920	0.7647	0.7001	**0.9870**	0.9610	0.9770
Iterated UNets	0.8773	0.7997	0.7670	0.9849	0.9652	0.9845

Table C. Performance comparison on the STARE dataset (with mask).

Method	Conn.	F1 Score	Sensitivity	Specificity	Accuracy	AUC
IterNet	**0.8977**	**0.8146**	**0.7715**	0.9886	**0.9701**	**0.9881**
w/o Skip Connection	0.8967	0.7482	0.6494	**0.9920**	0.9628	0.9808
Iterated UNets	**0.8977**	0.7641	0.6764	0.9913	0.9645	0.9830

Table D. Time costs for prediction of one image using IterNet with and without cropping.

Method	Read	Load Model	Crop	Pred (Patches)	Combine	Write	SUM	AUC
w. Image Patch (Stride 3)	8.55s	2.51s	2.94s	58.45s (22801)	1.03s	0.01s	73.49s	**0.9816**
w. Image Patch (Stride 8)	8.56s	2.50s	0.43s	10.49s (3249)	0.16s	0.01s	22.15s	0.9815
w. Whole Image. Crop	8.56s	2.50s	-	0.01 (1)	-	0.01s	**11.08s**	0.9813

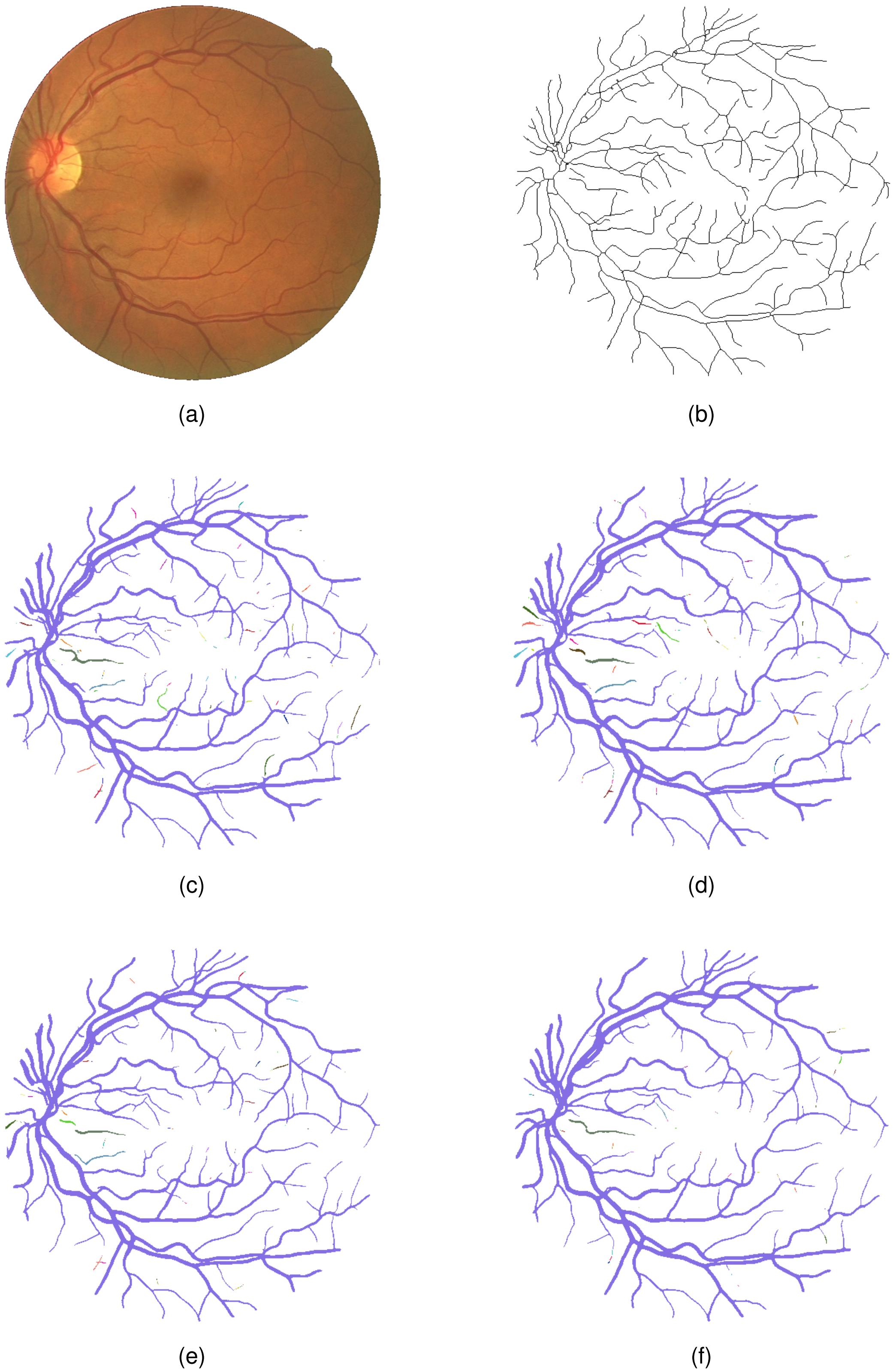


Figure B. Vessel segments visualization of a retina image from DRIVE (when threshold $= 110$ and the connectivity values are provided for each method in the parentheses). (a) Raw image. (b) Extracted center-line from the ground-truth. (c) UNet (0.7905). (d) DenseNet (0.8282). (e) DUNet (0.8290). (f) IterNet (0.9049). Different colors means different segments. IterNet produces the fewest segments among all these methods.

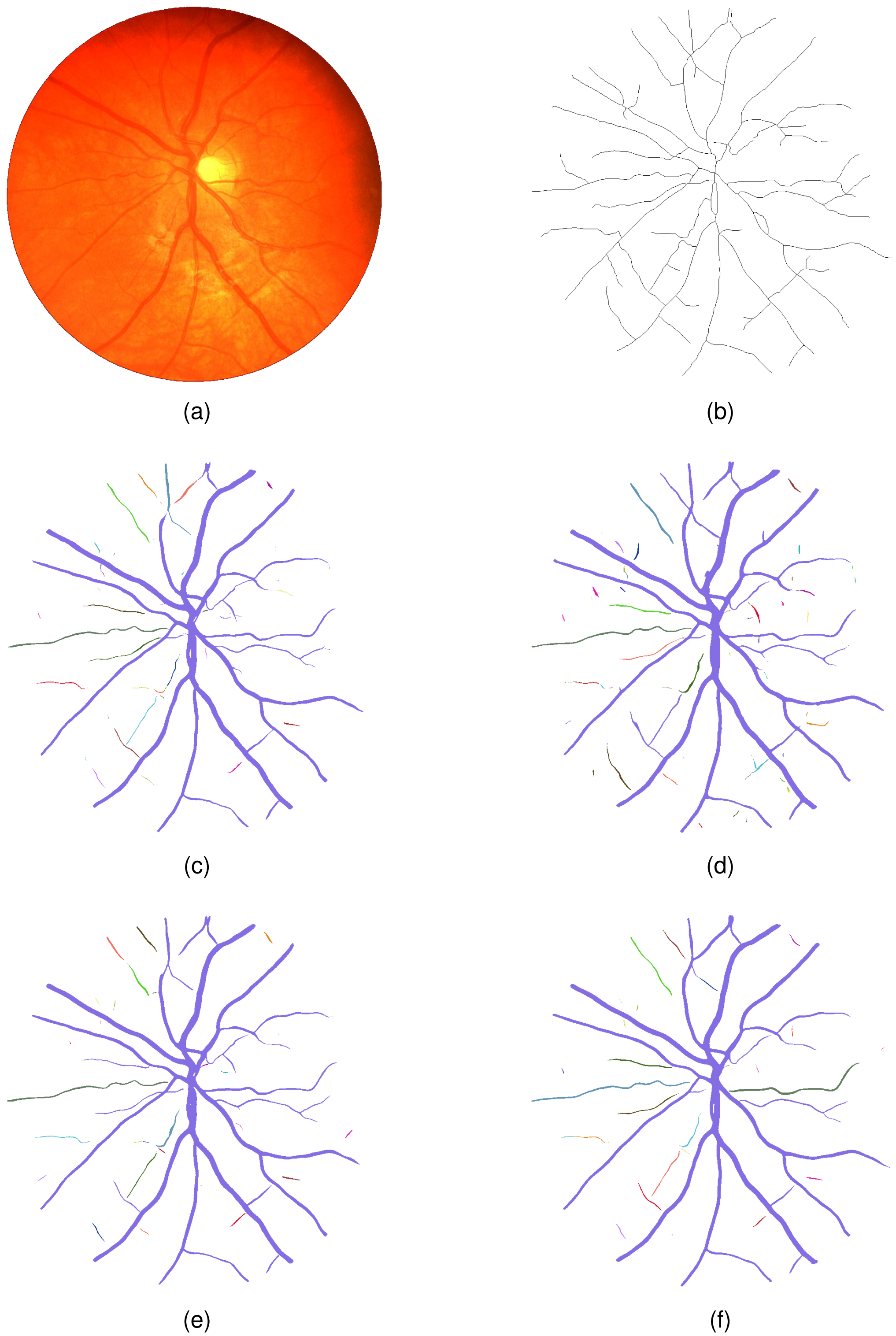
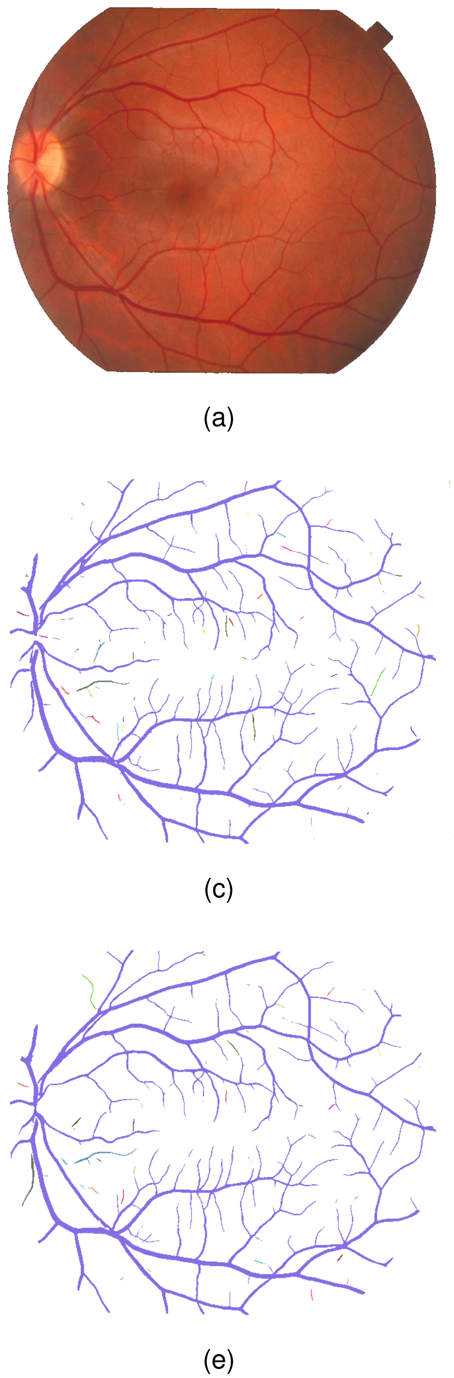


Figure C. Vessel segments visualization of a retina image from CHASE-DB1 (when threshold $= 110$ and the connectivity values are provided for each method in the parentheses). (a) Raw image. (b) Extracted center-line from the ground-truth. (c) UNet (0.8085). (d) DenseNet (0.8019). (e) DUNet (0.8423). (f) IterNet (0.9034). IterNet also gives the smallest number of segments.



(a) (b) (c) (d) (e) (f)

Figure D. Vessel segments visualization of a retina image from STARE (when threshold $= 110$ and the connectivity values are provided for each method in the parentheses). (a) Raw image. (b) Extracted center-line from the ground-truth. (c) UNet (0.7128). (d) DenseNet (0.7260). (e) DUNet (0.7095). (f) IterNet (0.9035). Different colors mean different segments. Again, IterNet is the best in connectivity.