Joint Learning of Blind Super-Resolution and Crack Segmentation for Realistic Degraded Images

Technical Report of Additional Experiments

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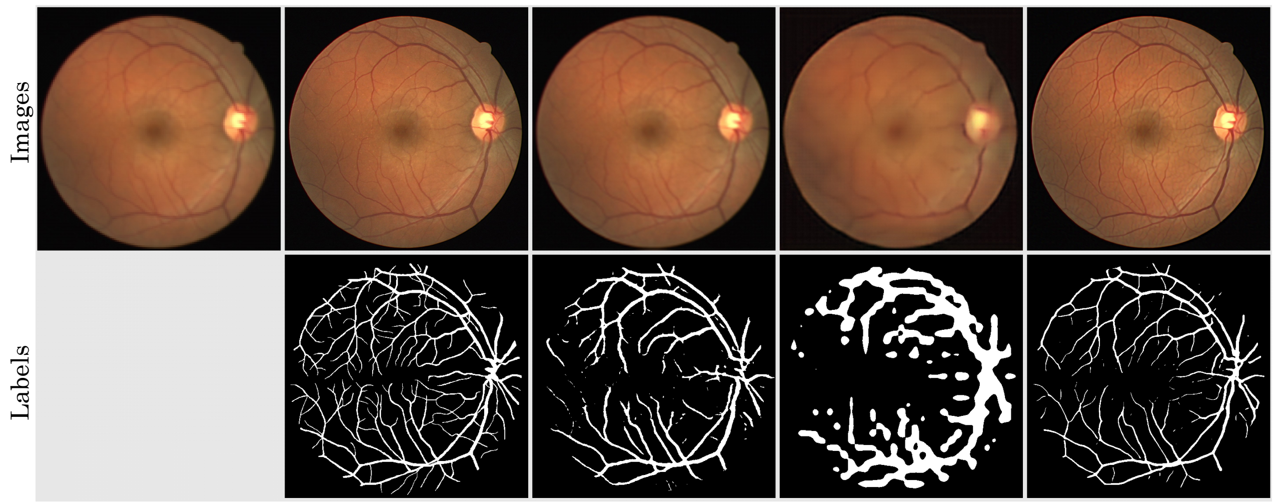

Fig. 1. Visual results of comparative experiments on the DRIVE dataset.

While CSBSR is proposed for crack segmentation, it is applicable to other similar problems. Here, CSBSR is applied to vessel detection in retinal images[1]. For this task, the DRIVE dataset [4] was used. From the DRIVE dataset, we selected 20 retinal images with their ground-truth segmentation images. The 20 images are split into 12, 3, and 5 training, validation, and test images. The training images were used for finetuning the SR and segmentation networks. The size of each image is 565×584 pixels, which is regarded as a HR image.

Table I shows the results of quantitative evaluation. For comparison, the results of SrcNet [1] and DSRL [2] are also shown. CSBSR outperforms these two SOTA crack segmentation methods on this dataset, as on the Khanhha dataset. Visual results are shown in Fig. 1. We can see that our CSBSR can detect capillary vessels in contrast to SrcNet and DSRL.

Additional visual results on the DRIVE dataset [4] are shown in Fig. 2. In the DRIVE dataset, a number of significantly-fine blood vessels are annotated as segmentation targets. On the other hand, the annotations given to the DRIVE dataset are consistent among all images, while images and their annotations are diverse in the Khanhha dataset. These differences make it meaningful to conduct experiments on the DRIVE dataset as well as on the Khanhha dataset.

It can be seen that the segmentation images obtained by CSBSR are closer to those of their ground-truths than other SOTA methods, SrcNet and DSRL. While it is obvious that DSRL has difficulty in detecting thin crack pixels, it seems that SrcNet can detect these thin crack pixels. However, the thin cracks are more fragmented in (c) than (e). This advantage of (e) CSBSR is useful in the double-check process for careful visual inspection in medical intervention.

It seems that CSBSR can detect finer lines on the DRIVE dataset than on the Khanhha dataset. This might be because the annotations given to the DRIVE dataset are more consistent, accurate, and fine than those in the Khanhha dataset. As expected, this fact clarifies that the annotation quality is important for improving the performance of CSBSR.

TABLE I
QUANTITATIVE RESULTS OF THE DRIVE DATASET [4].

Model	$\mathrm{IoU}_{max}\uparrow$	AIU↑	$\mathrm{HD95}_{min}\downarrow$	AHD95↓	PSNR↑	SSIM↑
SrcNet [1]	0.513	0.505	1.45	1.84	37.75	0.9171
DSRL [2]	0.238	0.129	15.96	75.35	20.73	0.3475
CSBSR	**0.580**	**0.577**	**1.00**	**1.00**	**38.88**	**0.930**

[1] This experiment is a technical report showing the results of an additional experiment performed after our paper [3] was accepted by IEEE TIM and was not published in the original paper.

References

[1] H. Bae, K. Jang, and Y.-K. An, "Deep super resolution crack network (srcnet) for improving computer vision–based automated crack detectability in in situ bridges," *Structural Health Monitoring*, vol. 20, no. 4, pp. 1428–1442, 2021.

[2] L. Wang, D. Li, Y. Zhu, L. Tian, and Y. Shan, "Dual super-resolution learning for semantic segmentation," in *CVPR*, 2020.

[3] Y. Kondo and N. Ukita, "Joint learning of blind super-resolution and crack segmentation for realistic degraded images," *IEEE Transactions on Instrumentation and Measurement*, vol. 73, pp. 1–16, 2024.

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

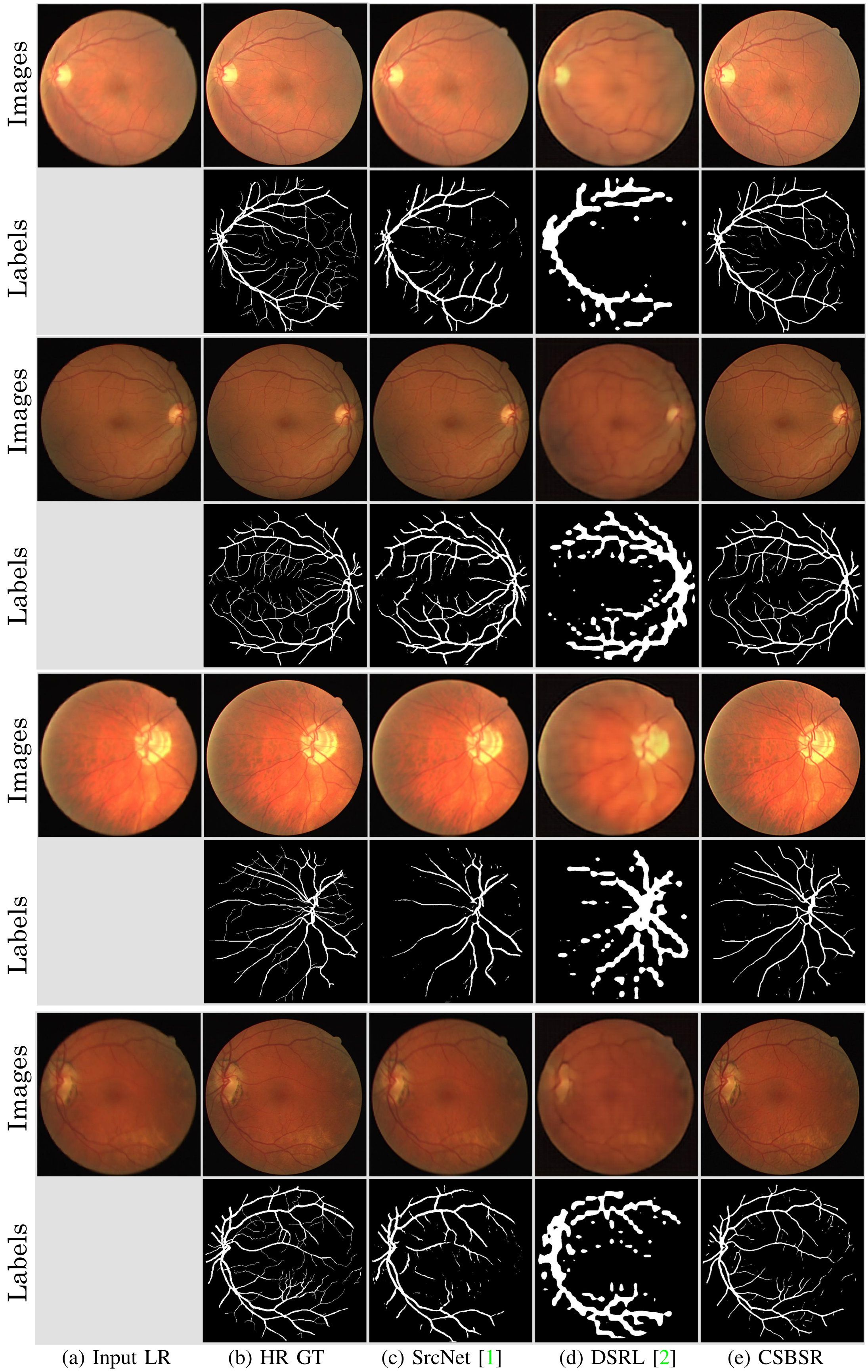

Fig. 2. Visual comparison on the DRIVE dataset [4]. In the upper row of each example: (a) Input LR image. (b) Ground-truth HR image. SR images shown in (c), (d), and (e) are obtained by SrcNet, DSRL, and CSBSR. In the lower row: (a) No image. (b) Ground-truth segmentation image in HR. SR segmentation images (c), (d), and (e) are obtained by SrcNet, DSRL, and CSBSR.