High-resolution luminescence imaging of solar cells using deep learning

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To mitigate climate change, the Intergovernmental Panel on Climate Change (IPCC) has set a clear goal to achieve one-third of the world's energy demand through renewable resources [1]. Due to the abundance of solar resources [2], low cost, and high bankability [3] of photovoltaic (PV) installation, PV has a key role to play in reducing global carbon emissions. The high reliability and durability of PV modules will enable harnessing the full potential of PV as the major energy source of the future.

Luminescence imaging is a powerful characterization method that provides spatial information about defects in solar cells and modules [4, 5]. Luminescence images with the high spatial resolution are desirable to reliably identify even small defects; however, high spatial resolution images are typically achieved at the expense of costly imaging systems. This study investigates algorithmic-based approaches to increase the spatial resolution of luminescence images and thereby enhance the capabilities of existing luminescence imaging systems with no additional cost.

Deep learning techniques for enhancing image spatial resolution have achieved promising results [10]. The super-resolution convolutional neural network (SRCNN) approach is the first method to use a convolutional neural network for super-resolution (SR) imaging and achieved superior results compared to the then state-of-the-art techniques [6]. Not long after, fast super-resolution convolutional neural network (FSRCNN) was suggested as an upgrade of SRCNN and found to be 40 times faster [7]. With the advancement in convolutional neural networks, SR techniques have been improved as well [11, 12]. Recently, generative adversarial network (GAN)-based super-resolution methods have achieved promising results due to the additional adversarial loss used in their networks [8, 9]. In this study, we propose to use the enhanced super-resolution GAN (ESRGAN) algorithm [9] to generate high-resolution luminescence images from low-resolution images. To our knowledge, this is the first use of deep learning to enhance image resolution for PV applications.

For network training, electroluminescence (EL) images of nine-busbar (16,500 images) and five-busbar (10,000 images) mono-crystalline industrial solar cells with a resolution of 520×520 pixels were used. These images were used as the high-resolution (HR) images in the training. Low-resolution (LR) images of 130×130 pixels were generated by down sampling the HR images by a factor of four. The paired dataset of LR and HR images was then used to train the network. A test dataset of 438 EL images unseen by the algorithm was used for validation purposes.

We evaluate the results obtained by our ESRGAN-based method using the peak signal-to-noise ratio (PSNR) and structure similarity (SSIM) image metrics which represent pixel-wise difference and structural similarity with ground truth images, respectively. We also compare the results obtained by the proposed method with a traditional baseline technique called Bicubic interpolation [13] on the test dataset. The comparison is done based on PSNR, SSIM, and visual inspection.

Figure 1 shows a representative low-resolution image as well as the generated Bicubic and ESRGAN images. The generated images are compared with the ground truth (the high-resolution) image using the PSNR (infinite PSNR is desired) and SSIM (SSIM of unity is preferred) metrics. To aid visual inspection, zoomed regions of each image is presented in Fig.1. The qualitative visual comparison shows the superior image quality of the image that was reconstructed using ESGRAN [Fig.1(c)]. Even the smallest features, including the pin-like defects along the busbars, are clearly reconstructed using ESRGAN, whereas they appear extremely blurred in the image reconstructed via Bicubic interpolation. In fact, the image reconstructed via ESGRAN is virtually indistinguishable from the ground truth image shown in Fig.1(d). The results demonstrate the substantial potential of the proposed method to provide super-resolution luminescence imaging.

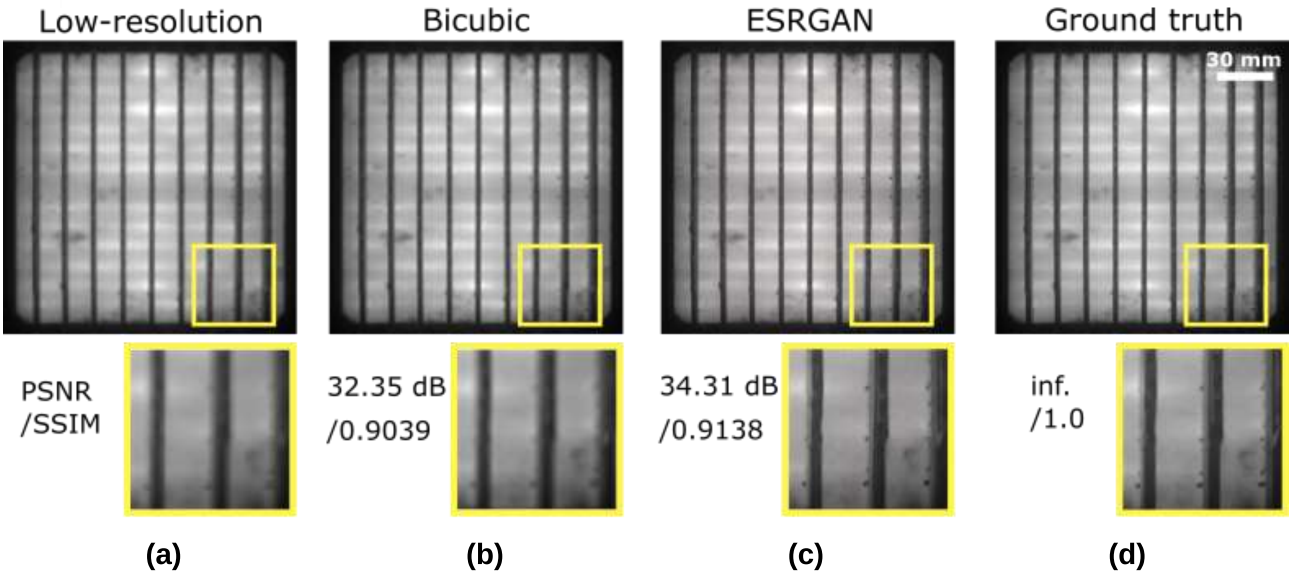

Figure 1: Representative low-resolution (a), Bicubic up-sampled (b), ESRGAN up-sampled (c), and ground truth (d) images. Zoomed in regions (marked with yellow rectangles) are shown as well as the calculated PSNR and SSIM metrics.

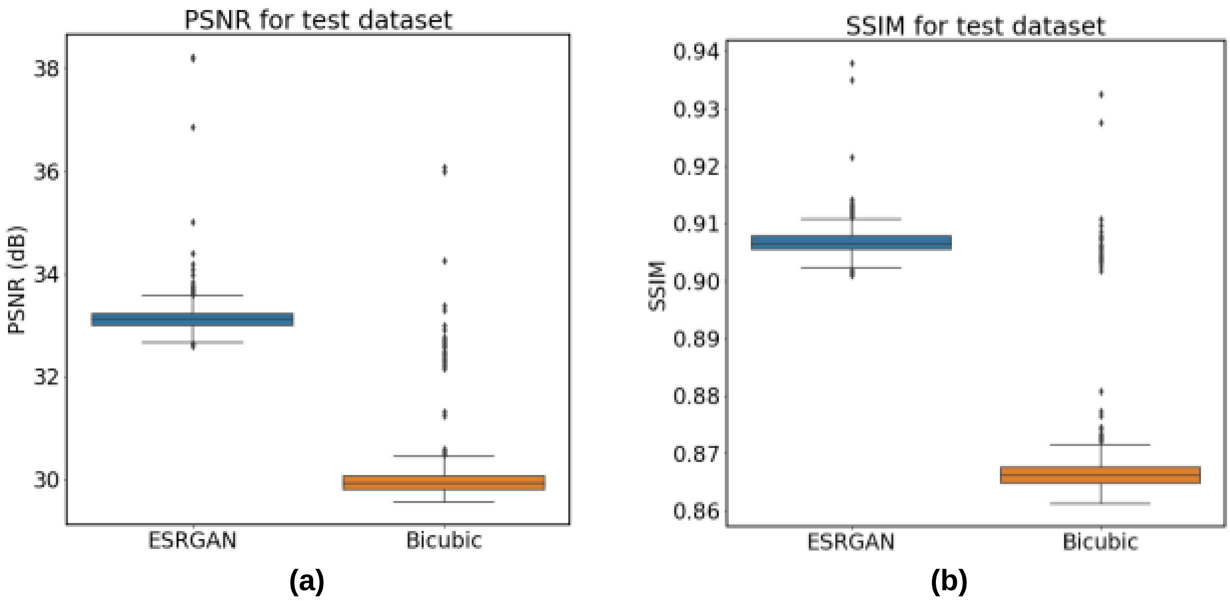

Figure 2: Distribution of image metrics of the test dataset: PSNR (a), and SSIM (b).

In Figure 2, the distributions of PSNR (a) and SSIM (b) of the generated high-resolution images using ESRGAN and the Bicubic interpolation are shown for the test dataset. Our deep learning-based approach outperforms the baseline technique.

To summarise, in this study, we demonstrate the use of the enhanced super-resolution generative adversarial network (ESRGAN) to enhance the spatial resolution of luminescence images which could be captured using a low-cost camera, or to enhance the capability of a current luminescence imaging system by increasing the spatial resolution to detect even smallest defects. The image quality generated by the deep learning method is better than the traditional baseline method in image processing. This approach can be applied to other PV-related imaging techniques, such as thermal imaging, visible imaging, and fluorescence imaging.

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References

[1] ITRPV, "International Technology Roadmap for Photovoltaics, 2018 results," 2019.

[2] Moriarty, P. and Honnery, D., 2012, 'What is the global potential for renewable energy?', *Renewable Sustainable Energy Rev.*, 16, 244-252.

[3] Hoffmann W, 2006, 'PV solar electricity industry, market growth and perspective', Sol. Energy Mater. Sol. Cells, 90, 3285–3311.

[4] Fuyuki, T., Kondo, H., Yamazaki, T., Takahashi, Y., and Uraoka, Y., 2005, 'Photographic surveying of minority carrier diffusion length in polycrystalline silicon solar cells by electroluminescence.' *Applied Physics Letters*, 86, 26, p62108.

[5] Trupke, T., Bardos, R. A., Schubert, M. C., and Warta, W., 2006, 'Photoluminescence imaging of silicon wafers', *Applied Physics Letters*, 89, 4, p044107.

[6] Dong, C., Loy, C. C., He, K. and Tang, X., 2016, 'Image super-resolution using deep convolutional networks' *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 38, 2, 295–307.

[7] Dong, C., Loy, C. C., and Tang, X., 2016, 'Accelerating the super-resolution convolutional neural network', *In Computer Vision – ECCV*, 391–407.

[8] Ledig, C. et al., 2017, 'Photo-realistic single image super-resolution using a generative adversarial network' *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 105–14.

[9] Wang, X., Yu, K., Wu, S., Gu, J., Liu, Y., Dong, C., Qiao, Y. and Loy, C. C., 2018, 'ESRGAN: Enhanced super-resolution generative adversarial networks,' *European Conference on Computer Vision (ECCV) Workshops*.

[10] Wang, Z., Chen, J., and Hoi, S. C. H., 2020, 'Deep learning for image super-resolution: A survey,' *IEEE Transactions on Pattern Analysis and Machine Intelligence*.

[11] Lim, B., Son, S., Kim, H., Nah, S., and Lee, K. M., 2017, 'Enhanced deep residual networks for single image super-resolution,' *IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, 136-144.

[12] Zhang, Y., Li, K., Li, K., Wang, L., Zhong, B., and Fu Y., 2018, 'Image super-resolution using very deep residual channel attention networks,' *The European Conference on Computer Vision (ECCV)*, 286-301.

[13] Keys, R., 1981, 'Cubic convolution interpolation for digital image processing,' *IEEE Transactions on Acoustics, Speech, and Signal Processing*, 29, 6, 1153-1160.