Root-SRGAN:SRGAN-based super resolution reconstruction of root image with limited samples

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1. Introduction

Roots are vital organs of plants, and accurate measurements of root morphological parameters assist researchers in identifying root traits and assessing plant growth and development. However, directly observing roots presents challenges due to their underground nature and intricate structures like lateral and adventitious roots. Non-invasive acquisition of root image data is a prevailing approach to obtain comprehensive root configuration information. Nevertheless, root imaging is constrained by experimental techniques and imaging devices, leading to issues like limited sample size and image blurriness, which hinder the extraction of crucial root phenotypic parameters (such as branching and surface area). Super-resolution (SR) imaging technology[1, 2, 6, 7] aims to reconstruct low-resolution (LR) images, which are blurry and contain limited information, into high-resolution (HR) images that are clearer and contain more information. In recent years, with the improvement of hardware capabilities, deep learning-based SR techniques[4, 8] have achieved better reconstruction quality. However, existing deep learning-based SR methods struggle to effectively distinguish high-frequency artifacts and real edge details in root imagess[3, 5], resulting in suboptimal reconstruction quality and poor visual perception, especially when dealing with limited sample datasets. Therefore, this paper introduces a novel approach called Root-SRGAN, specifically designed for super-resolving root images with limited samples.

2. Proposed Method

Due to the inclusion of numerous lateral and adventitious root structures, root system images necessitate a higher demand for edge detail quality. To address the challenge of distinguishing between details and artifacts in root system image super-resolution reconstruction tasks, this study introduces a method tailored for root system image super-resolution reconstruction, termed as Root-SRGAN. The Root-SRGAN incorporates a distinct feature extraction backbone structure to acquire multiscale contextual information and introduces a pseudo-artifact loss factor to preserve the edge details of the reconstructed images. Through training and testing on a dataset of Arabidopsis root system images, the R-SRGAN yields high-resolution root system images with exceptional visual effects and image quality.

We employed a method of cultivating Arabidopsis plants in transparent gel and directly capturing Arabidopsis root system images using a camera. The original images had dimensions of 800 by 800 pixels, resulting in a total of 50 images. Image augmentation was performed through random cropping, resulting in a final collection of 2500 images with dimensions of 256 by 256 pixels, referred to as HR images. Each HR image was subjected to a 4x downsampling process to produce 2500 low-resolution images with dimensions of 64 by 64 pixels, termed as LR images. The obtained dataset of Arabidopsis root system images was divided, with 2000 randomly selected HR-LR image pairs forming the training set, while the remaining 500 pairs constituted the test set.

3. Results

Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are fundamental metrics for evaluating the quality of reconstructed compressed images in the context of super-resolution tasks. Generally, a higher PSNR value indicates better image quality. A larger SSIM value suggests a smaller degree of image distortion and better image quality. In this section, we compare the proposed R-SRGAN with the classical super-resolution reconstruction methods SRCNN, SRGAN, and bicubic interpolation in terms of both subjective visual effects and objective evaluation metrics. We assess their respective performance in root system image reconstruction.

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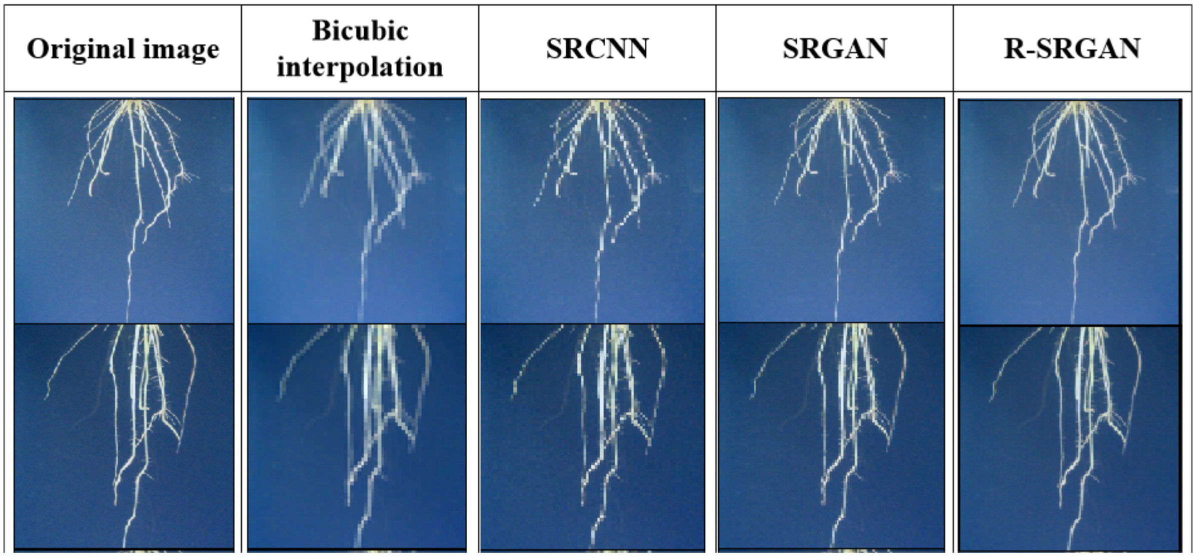

Figure 1. Results of Different Super-Resolution Methods.

Method	R-SRGAN	Interpolation	SRCNN	SRGAN
PSNR	23.43dB	20.64dB	21.33dB	19.85dB
SSIM	0.7720	0.6987	0.7102	0.7223

Table 1. Performance Comparison of R-SRGAN with SRCNN, SRGAN, and Others.

3.1. Subjective Visual Effects

Figure 1 demonstrates the reconstruction results of various super-resolution methods on the Arabidopsis root system image dataset. When compared to deep learning algorithms, the bicubic interpolation method yields results that are notably more blurred, lacking in high-frequency details, particularly evident at the root system's edges. In contrast to SRCNN, which relies solely on Mean Squared Error (MSE) as its loss function, both SRGAN and R-SRGAN exhibit exceptional performance in restoring image textures. This observation underscores the significance of the high-dimensional feature perceptual loss in safeguarding high-frequency information. Remarkably, the proposed R-SRGAN approach achieves the most favorable visual outcomes, displaying the clearest edge details and effectively mitigating artifacts. This underscores the efficacy of the introduced artifact loss factor.

3.2. Objective Evaluation Metrics

Table 1 presents the quantitative outcomes of PSNR and SSIM metrics for various methods in the Arabidopsis root system image super-resolution reconstruction task. From a PSNR perspective, R-SRGAN and SRCNN achieve the optimal and second-best results, respectively. This stems from the fact that PSNR is a pixel-based evaluation metric, and SRCNN utilizes MSE as its loss function, specifically constraining pixel-level differences, which consequently yields higher PSNR values. Considering the SSIM index, which incorporates perceptual loss with high-dimensional feature-level constraints, both SRGAN and R-SRGAN exhibit advantages. The proposed R-SRGAN, tailored to the characteristics of the root system image dataset, stands out as a deep learning model. Unlike SRGAN, it circumvents the necessity for extensive training on other large datasets, thus saving time costs. Ultimately, R-SRGAN outperforms in both PSNR and SSIM metrics. In comparison to SRGAN, PSNR has been enhanced by 3.58 dB, and SSIM has increased by 0.0497. Experimental results underscore the effectiveness of the proposed R-SRGAN approach for the challenging task of super-resolving root system images with limited samples.

4. Conclusion

This study introduces a Root-SRGAN model specifically tailored for the task of super-resolving root system images, aiming to preserve the image's root edge details and perceptual authenticity during the reconstruction process. The proposed approach is compared against various classical methods on a limited-sample Arabidopsis root system image dataset. Not only does the proposed method achieve the clearest edge details subjectively, but it also attains the best performance in terms of PSNR and SSIM metrics. Compared to SRGAN, PSNR has been enhanced by 3.58 dB, and SSIM has increased by 0.0497. Consequently, Root-SRGAN emerges as an effective approach for the super-resolution reconstruction task of plant root system images.

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