Postprint: Multi-Focus Green Plant Image Fusion Algorithm Based on PADC-PCNN and Stationary Wavelet Transform

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Abstract

[Purpose/Significance] Constructing 3D point cloud models of green plants requires a large number of clear images. Limited by the depth of field of lenses, when capturing images of plants with large depth, the images become partially out of focus, leading to problems such as blurred edges and loss of texture details. Existing processing algorithms struggle to balance processing quality and speed. The objective of this study is to propose a novel algorithm that improves fused image quality while also considering processing speed. [Method] A plant image fusion method based on Non-Subsampled Shearlet Transform (NSST) Parameter-Adaptive Dual-Channel Pulse Coupled Neural Network (Parameter Adaptation Dual Channel Pulse Coupled Neural Network, PADC-PCNN) and Stationary Wavelet Transform (SWT) is proposed. First, channel separation is performed on the RGB images of plants. For the G channel, which contains more features such as texture details, NSST decomposition is applied, with the low-frequency subband using gradient energy fusion rules and the high-frequency subband using PADC-PCNN fusion rules. For the R and B channels, which contain more contour and background information, the fast and shift-invariant Stationary Wavelet Transform is adopted to suppress pseudo-Gibbs effects. A dataset of 480 images across 8 groups was self-constructed, with lighting environment, distance, and plant color as variables, and images at different focal lengths were simultaneously captured to verify algorithm performance. [Results and Discussion] Compared with five commonly used algorithms including Fast Guided Filter (FGF), Random Walk (RW), Nonsubsampled Shearlet Transform based Pulse-Coupled Neural Network (NSST-PCNN), Stationary Wavelet Transform (SWT), and Nonsubsampled Shearlet Transform based Parameter-Adaptive Dual-Channel Pulse-Coupled Neural Network (NSST-PADC), the PADCPCNN-SWT algorithm improves sharpness by 5.6%, 8.1%, 6.1%, and 17.6% respectively compared to the first four algorithms, and improves spatial frequency by 2.9%, 4.8%, 7.1%, and 15.9% respectively.

Moreover, compared with the NSSTPADC algorithm which has the best fusion performance, the processing speed is improved by an average of 200.0%, with a focal adjustment range of approximately 6 mm. [Conclusion] The multi-focus image fusion algorithm based on PADC-PCNNSWT proposed in this study achieves improved efficiency of fused images while ensuring fusion quality, providing high-quality data for constructing 3D point cloud models of green plants while saving time.

Full Text

A Multi-Focal Green Plant Image Fusion Method Based on Stationary Wavelet Transform and Parameter-Adaptive Dual-Channel Pulse-Coupled Neural Network

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Abstract

[**Objective/Significance**] Constructing 3D point cloud models of green plants requires a large number of clear images. However, due to lens depth-of-field limitations, images of large-depth-of-field plants often suffer from partial defocusing, leading to edge blurring and loss of texture details. Existing algorithms struggle to balance processing quality and speed. This study proposes a novel algorithm to improve fused image quality while maintaining processing efficiency.

[**Methods**] We present a plant image fusion method combining Non-Subsampled Shearlet Transform (NSST) based Parameter-Adaptive Dual-Channel Pulse-Coupled Neural Network (PADC-PCNN) with Stationary Wavelet Transform (SWT). First, plant RGB images are separated into channels. The G channel, rich in texture details, undergoes NSST decomposition (4 layers, 16 directions), yielding one low-frequency and 64 high-frequency subband groups. Low-frequency subbands use gradient energy fusion rules, while high-frequency subbands employ PADC-PCNN fusion rules. For R and B channels containing more contour and background information, we use fast, translation-invariant SWT to suppress pseudo-Gibbs effects. A custom dataset was built with 480 multi-focal images of potted plants, varying illumination, distance, and plant color to validate algorithm performance.

[**Results and Discussion**] Compared with five algorithms—Fast Guided Filter (FGF), Random Walk (RW), NSST-PCNN, SWT, and NSST-PADC—the proposed PADC-PCNN-SWT algorithm achieved clarity improvements of 5.6%, 8.1%, 6.1%, and 17.6% over the first four algorithms respectively, and spatial frequency improvements of 2.9%, 4.8%, 7.1%, and 15.9%. While slightly lower than NSST-PADC in these metrics (by 7.2% and 7.0% respectively), it achieved a 200% average speed improvement over NSST-PADC. The effective focal adjustment range is approximately 6 mm.

[**Conclusion**] The proposed PADC-PCNN-SWT multi-focal image fusion algorithm achieves high-quality fusion while significantly improving efficiency, providing high-quality data for 3D point cloud modeling of green plants while saving substantial time.

Keywords: multi-focal length; image fusion; stationary wavelet transform; parameter-adaptive; pulse-coupled; neural network

1. Introduction

Three-dimensional point cloud reconstruction of green plants is an important application of virtual reality technology in agriculture. Studying crop morphology and growth processes through plant 3D point clouds is significant for breeding optimization, growth monitoring, and condition assessment [1, 2]. Common 3D reconstruction methods such as motion recovery and multi-view stereo vision require large quantities of precise, undistorted plant images [3-5]. However, due to lens depth-of-field limitations, large-depth-of-field green plant images often suffer from partial defocusing and edge blurring, making it difficult to obtain fully clear images and severely affecting 3D point cloud model accuracy [6, 7].

To address this challenge, researchers have employed multi-focal image fusion to obtain relatively clearer images [8], which can be primarily categorized into spatial domain fusion and transform domain fusion [9]. Spatial domain methods construct fused images by directly selecting pixels from source images, but this creates artifacts and color differences in multi-channel images, reducing fusion quality [10]. Transform domain algorithms avoid these issues. For instance, wavelet transform can remove artifact noise while preserving edge details, offering good time-frequency characteristics and translation invariance, but is limited to extracting information in finite directions, yielding suboptimal results [11].

Consequently, curvelet, contourlet, and shearlet transforms were developed, addressing directional decomposition limitations while maintaining translation invariance. Currently, the most widely used is Non-Subsampled Shearlet Transform (NSST), which is fast and typically designs fusion rules based on local feature information. However, these local features focus on single image characteristics, failing to simultaneously preserve overall structural information and extract detail information [12].

To solve this problem, researchers proposed NSST combined with Pulse-Coupled Neural Network (PCNN) algorithms [13]. Due to their pulse synchronization and global coupling characteristics, these algorithms effectively address NSST' s limitation of not simultaneously considering structural and detail information, playing an important role in image fusion. However, NSST-PCNN algorithm fusion quality is generally proportional to decomposition layers—more layers yield better quality but longer processing times. Additionally, multiple high-frequency subbands require PCNN optimization, making the algorithm complex. Constructing plant 3D point cloud models requires large amounts of image data, ranging from hundreds to thousands of images. Balancing image quality with fusion efficiency to reduce modeling time has become a critical challenge.

Many scholars have investigated this issue. Gong et al. [14] used an improved Laplacian energy fusion strategy for low-frequency subbands, achieving 6.8% precision improvement but minimal speed enhancement due to limited low-frequency subband count. Di et al. [15] reconstructed RGB images in Lab color space before NSST decomposition, adaptively adjusting PCNN parameters based on human visual characteristics to enhance brightness, contrast, and processing speed. However, spatial transformation introduced high-frequency noise interference, leaving fusion quality to be improved. Ullah et al. [16] proposed a parameter-adaptive PCNN with local Laplacian filtering, featuring fast convergence but requiring multiple color space conversions that increased data complexity and distortion risk. Liu et al. [17] presented an adaptive dual-channel PCNN heterogeneous image fusion model that fused depth and visible light information across different light fields, achieving 100% recognition fusion rate but poor color reproduction due to depth image influence.

This study improves the algorithm by employing targeted processing for different RGB channels based on green plant structural characteristics and texture distribution, effectively improving processing speed while ensuring fusion quality.

2.1 Multi-Focal Image Fusion Model Construction

This study combines NSST transform with stationary wavelet transform. NSST uses image gradient energy fusion rules in its low-frequency band and parameter-adaptive dual-channel PCNN fusion rules in its high-frequency band. After multi-scale reconstruction, the fused image is obtained. Stationary wavelet transform uses energy gradient function as a focus measure index to decompose into low and high-frequency subbands. The PADC-PCNN and SWT algorithm effectively compensates for the deficiencies of both NSST and SWT, achieving higher precision than SWT and faster processing speed than NSST-based PCNN.

2.1.1 NSST Model The NSST transform first employs Non-Subsampled Pyramid (NSP) algorithm for initial decomposition, obtaining high-frequency and low-frequency subband coefficients. The low-frequency subband is then decomposed repeatedly for K iterations. Second, multi-layer shearlet directional localization decomposition is performed on each layer' s high-frequency subband, ultimately yielding one low-frequency subband and $\sum_{i=1}^{K} 2^i$ high-frequency subbands. The NSST transformation process is shown in Figure 1 [Figure 1: see original paper].

2.1.2 PCNN Model Each PCNN neuron consists of a receptive field, coupling modulation domain, and pulse generator. Adjacent neurons can transmit superimposed energy, enabling synchronous pulse emission due to neuronal cluster conduction [18]. The mathematical expressions are given by equations (1)-(5):

$$F_{ij}(n) = S_{ij} \tag{1}$$

$$L_{ij}(n) = e^{-\alpha_L} L_{ij}(n-1) + V_L \sum_{kl} W_{ijkl} Y_{kl}(n-1) \tag{2}$$

$$U_{ij}(n) = F_{ij}(n)(1 + \beta_{ij} L_{ij}(n)) \tag{3}$$

$$Y_{ij}(n) = \begin{cases} 1, & \text{if } U_{ij}(n) > \theta_{ij}(n-1) \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

$$\theta_{ij}(n) = e^{-\alpha_\theta} \theta_{ij}(n-1) + V_\theta Y_{ij}(n) \tag{5}$$

where n represents iteration number; i, j represent neuron location; $S_{ij}(n)$, $F_{ij}(n)$, $L_{ij}(n)$, $U_{ij}(n)$, $Y_{ij}(n)$, and $\theta_{ij}(n)$ are external input, feedback input, linking input, internal activity item, coupling output, and threshold function respectively; α_L, α_θ are time constants; β_{ij} is linking strength; V_L, V_θ are amplitude constants. The final PCNN mathematical model is shown in Figure 2 [Figure 2: see original paper].

2.1.3 Stationary Wavelet Transform Model Stationary wavelet transform is a multi-scale redundant wavelet transform with multi-resolution characteristics and translation invariance. Compared with NSST, it sacrifices detail extraction capability but effectively reduces noise interference during image reconstruction [19, 20], making it suitable for fusing image channels with less detail and more contour information. According to literature [21], its decomposition formulas and energy gradient function are given by equations (6)-(10):

$$A_j(m,n) = \sum_k \sum_l h_j(k) h_j(l) A_{j-1}(k+m, l+n) \tag{6}$$

$$H_j(m,n) = \sum_k \sum_l g_j(k) h_j(l) A_{j-1}(k+m, l+n) \tag{7}$$

$$V_j(m,n) = \sum_k \sum_l h_j(k) g_j(l) A_{j-1}(k+m, l+n) \tag{8}$$

$$D_j(m,n) = \sum_k \sum_l g_j(k) g_j(l) A_{j-1}(k+m, l+n) \tag{9}$$

$$F(i,j) = \sqrt{x(i,j)^2 + y(i,j)^2} \tag{10}$$

where $h_j(n)$ and $g_j(n)$ represent low-pass and high-pass filters for 2D stationary wavelet decomposition. The original image is decomposed to obtain horizontal, vertical, and diagonal high-frequency detail information $H_j(m,n)$, $V_j(m,n)$, $D_j(m,n)$ and low-frequency approximation $A_j(m,n)$ at scale 2^j. F represents the energy gradient function.

2.2 Improved Multi-Focal Image Fusion Algorithm

Given that green plants contain abundant texture details in the G channel while R and B channels have more contour information, this study processes both algorithms in parallel, incorporating attention mechanisms and multi-source image dual-channel parallel methods into PCNN high-frequency fusion rules. The attention mechanism is designed for high-frequency subbands containing substantial detail and structural information. Following literature [14], we adopt eight-neighborhood modified Laplacian operator weighting as PCNN high-frequency fusion link strength, which is sensitive to detail and edge information. When processing detailed texture features, link strength increases accordingly. The link strength and modified Laplacian operator are given by equations (11)-(12):

$$\beta_{ij} = \sum_{m=-r}^{r} \sum_{n=-r}^{r} W(m,n) \cdot EML(i+m, j+n) \tag{11}$$

$$EML(i,j) = |2I(i,j) - I(i-1,j) - I(i+1,j)| + |2I(i,j) - I(i,j-1) - I(i,j+1)| \tag{12}$$

where $I(i,j)$ represents pixel value at location (i,j); W is a $(2r+1) \times (2r+1)$ weighting matrix. Referring to equation (11), when $r = 1$, $EML(i,j)$ represents a 3×3 weighted fusion matrix, i.e., the modified Laplacian operator at (i,j). Parallel processing with both algorithms enhances pixel correlation while shortening computation time, as shown in Figure 3 [Figure 3: see original paper].

Algorithm Flow: 1. Separate two source images into RGB channels 2. For the G channel (rich in texture details), perform NSST decomposition (4 layers, 16 directions), yielding 1 low-frequency and 64 high-frequency subband groups. Low-frequency subbands use image gradient energy method; high-frequency subbands use PADC-PCNN adaptive parameter adjustment. NSST reconstruction produces the fused G channel image. 3. For R and B channels (rich in contour/background information), use faster, translation-invariant SWT to suppress pseudo-Gibbs effects [22, 23]. Multi-scale coefficient method obtains fusion matrices, and inverse SWT reconstructs R and B channel fused images. 4. Recombine three color channels to obtain final RGB fused image.

2.3 Multi-Focal Image Acquisition System

2.3.1 System Design The system consists of an HIK camera, stepper motors, ultrasonic motor, temperature sensor, limit sensor, and multi-channel power supply circuits. Camera model: MV-CA016-10UC (1.6 megapixels, IMX273 CMOS sensor). Lens model: MVL-MF2518M-5MPE zoom lens (25 mm focal length, F1.8-F16). Plants are placed on a rotating base controlled by stepper motors for rotation angle and distance adjustment. The camera is fixed on a slide rail for vertical height and shooting angle control. The host computer obtains plant position information through motor feedback, controls the ultrasonic motor to adjust focus, rotates the base to collect omnidirectional multi-focal images, and performs image fusion to obtain fully clear plant images. System 3D schematic and physical diagram are shown in Figure 4 [Figure 4: see original paper].

2.3.2 Image Acquisition To accurately capture front-focused and back-focused images, a lookup table maps plant distance to ultrasonic motor rotation angle. Before each shot, position information from motor feedback controls the ultrasonic motor to adjust to near-focus angles, capturing two images focused on foreground and background respectively.

To validate performance across environments and viewpoints, we built a dataset using the plant phenotype acquisition system. Three viewing angles were set: panoramic, close-up, and overhead. After capturing front images, the base motor rotated the plant 36° for subsequent captures until completing 360° image collection, then adjusted viewing angles. Three lighting environments were established: natural light (1900-2100 lux outdoor sunlight), indoor light (50-150 lux LED tubes), and artificial lighting (400-600 lux LED fill light). After capturing front images under each light source, the base rotated to collect 10 directional images. The dataset comprises 8 groups of common potted plants. The first 3 groups (pothos and bird's nest fern with large leaves and obvious texture details) were used to study fusion performance under different light intensities. The middle 3 groups (spider plant with slender leaves for panoramic/close-up groups; small, appropriately deep-sized Malabar chestnut for overhead group) studied viewpoint performance and pseudo-Gibbs suppression. The final 2 groups (poinsettia with red flowers; croton with yellow leaves) studied non-green plant fusion effects, using blue backgrounds to avoid equipment interference. The first 3 groups collect front/back-focused images in 3 lighting conditions × 10 directions;

the middle 3 groups collect images in 3 viewpoints × 10 directions; the final 2 groups collect front/back-focused images of non-green plants. The complete dataset contains 480 plant images.

3. Results and Analysis

We compared PADC-PCNN-SWT with five algorithms: SWT [24], FGF [25], RW [26], NSST-PCNN [27], and NSST-PADC [28] using 480 multi-focal plant images. All NSST algorithms used 4 decomposition layers and 16 directional subbands. The computing environment was MATLAB R2021a, 64-bit Windows 10, 8 GB RAM, i5-7300HQ 2.50GHz CPU.

3.1 Subjective Evaluation Multi-focal source images are shown in Figure 5 [Figure 5: see original paper]. Figure 5(a) shows the front-focused image with blurred leaves; Figure 5(b) shows the back-focused image with lost texture details. Both images suffer from varying degrees of defocusing due to depth-of-field limitations.

PADC-PCNN-SWT fusion results (Figure 6 [Figure 6: see original paper]) restore both defocused areas to focused states with clear leaf contours and obvious texture features. Compared with non-NSST algorithms, PADC-PCNN-SWT essentially eliminates pseudo-Gibbs phenomena, demonstrating good overall clarity, color reproduction, and texture preservation.

3.2 Objective Evaluation Four objective metrics evaluate fusion performance: Average Gradient (AG), Spatial Frequency (SF), Entropy (EN), and Standard Deviation (SD) [29].

- **AG** sensitively reflects image expression of minute detail contrast and texture feature quantity (Equation 13). Larger AG values indicate more details and higher clarity—the most important quality metric.
- **SF** represents spatial variation rate, reflecting overall image activity (Equation 14).
- **EN** evaluates information content based on gray value distribution probability (Equation 15).
- **SD** measures information richness through gray value distribution density (Equation 16).

Partial fusion images from the six algorithms are shown in Figure 7 [Figure 7: see original paper]. Local leaf magnifications appear in Figure 8 [Figure 8: see original paper]. PADC-PCNN-SWT shows more obvious texture details and clearer edges than FGF, RW, NSST-PCNN, and SWT, with better visual effects.

Performance Comparison (Table 1):
AG and SF show large variations among algorithms due to different detail fusion effects. EN values remain essentially unchanged across algorithms, indicating similar color reproduction (stable around 6.5 for first 6 groups, ~7.7 for color

groups due to different color compositions). SD values are similar within groups but vary across groups due to different plant contours.

PADC-PCNN-SWT improves clarity by 5.6%, 8.1%, 6.1%, and 17.6% over FGF, RW, NSST-PCNN, and SWT respectively, and spatial frequency by 2.9%, 4.8%, 7.1%, and 15.9%. Compared with NSST-PADC, it scores 7.2% and 7.0% lower on these metrics but achieves 200% faster processing (Table 2)—averaging 500s vs. NSST-PADC' s 1500s.

Color Group Analysis: For non-green plants (red/yellow groups), PADC-PCNN-SWT performance degrades significantly (1.1% clarity decrease, 5.1% SF decrease), though green parts maintain good fusion. Thus, the algorithm is primarily suitable for green plants.

Focal Length Range Study (Table 3 , Figure 9 [Figure 9: see original paper]):
With indoor light group as example (reference focal length 18 mm, 1.5 mm steps, \$±\$4 adjustments), EN and SD remain stable across focal lengths, indicating good contour/color restoration even with severe defocusing. However, AG and SF are optimal only in the 15-21 mm range, demonstrating an effective focal adjustment range of approximately 6 mm.

4. Conclusion

Addressing the challenge of balancing quality and speed in green plant image fusion, this study proposes the PADC-PCNN-SWT multi-focal image fusion method. Using a 480-image dataset, comparisons with five common algorithms show PADC-PCNN-SWT excels in AG and SF metrics while maintaining comparable EN and SD values, indicating superior detail fusion with similar contour/color reproduction. Processing speed is 200% faster than the quality-optimal NSST-PADC algorithm. However, fusion quality degrades seriously for non-green plant parts, limiting the algorithm' s effectiveness primarily to green plants. The effective focal adjustment range is approximately 6 mm. In summary, the proposed method effectively balances green plant image fusion quality and speed, demonstrating stronger detail fusion performance to provide high-quality data for 3D point cloud modeling while saving substantial time. Future research will enrich non-green plant data and further improve the algorithm for multi-color plant multi-focal image fusion.

Conflict of Interest Statement: The authors declare no conflicts of interest.

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