

Vectorized Grid Detection and Color Rectification for 3D Point Clouds of Photovoltaic Panels

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Abstract

UAV-borne PV point clouds often suffer from severe shadow artifacts and color dropouts, limiting their use for reliable inspection and digital twin construction. We introduce a fully vectorized color rectification framework that exploits panel symmetry and 1D signal processing to restore a consistent radiometric appearance. Starting from a segmented solar-panel point cloud, the method first normalizes panel geometry via RANSAC-based plane segmentation and rotation to a canonical xy-plane, then extracts base colors by clustering RGB values to identify “panel blue” and “grid white” regions. It subsequently detects grid parameters by projecting filtered grid and panel points into 1D spatial density histograms along the x- and y-axes to estimate spacing, offset, and grid-line thickness, and finally performs vectorized recoloring and color remapping of grid and panel points using the recovered parameters. By decoupling periodic grid structure from illumination noise, our approach achieves visually near-perfect color restoration while eliminating intra-semantic variance across modules. The resulting high-fidelity, shadow-free point clouds provide a mathematically consistent foundation for PV digital twins and automated asset evaluation.

1. Introduction

In recent years, driven by the accelerating global transition toward renewable energy, the scale of the photovoltaic (PV) power generation industry has expanded exponentially. To efficiently ensure the operation and maintenance (O&M) of PV arrays, unmanned aerial vehicle (UAV)-borne 3D Light Detection and Ranging (LiDAR) and photogrammetry technologies have been widely employed (Chen et al., 2023). These technologies are critical for PV panel shape inspection, condition assessment, and the construction of Building Information Modeling (BIM) (Olayiwola and Camara, 2024; Casirano and Claridades, 2026). For instance, researchers have combined UAV photogrammetry and geographic information systems (GIS) to configure PV layouts and estimate energy potential. Other studies have developed automated methods using digital surface models to determine optimal rooftop solar panel layouts or utilized point clouds directly as shading geometry to simulate solar irradiance. Furthermore, automated UAV-based monitoring pipelines integrating RGB-thermal dual imaging have been developed to map thermal values onto oriented surfaces and assess panel conditions (Lysy et al., 2025). In these complex digital workflows, the 3D geometric coordinates of point clouds provide a highly precise spatial foundation, while the accompanying color (RGB) information is crucial for preserving the visual fidelity of both the point clouds and their derived models (e.g., Chan et al., 2021). This color data enables essential tasks such as defect visualization, semantic labeling, and high-quality digital twin creation (Teofilo et al., 2025).

However, acquiring PV panel point clouds with perfect color consistency during actual UAV data collection faces severe physical and environmental challenges. To maximize land utilization, PV arrays are typically installed in tightly packed configurations. As the solar incidence angle varies over time, inter-panel occlusions generate extensive shadows on the panel surfaces. Secondly, the glass coating on PV panels exhibits strong specular reflective characteristics and complex bidirectional reflectance distribution function (BRDF)

properties. This specular effect easily causes camera sensors to overexpose, leading to severe color dropout or appearance inconsistencies (Almukhtar and Kurnaz, 2026; Vourkos et al., 2025). Together, these factors result in final 3D point clouds that exhibit severe color fragmentation, shadow artifacts, and visual discontinuities across the PV panel surfaces. This not only severely degrades the aesthetics of the 3D point cloud models but also significantly hinders their interpretability and downstream usability in automated recognition, feature extraction, and other machine vision tasks.

Addressing these pain points using existing point cloud color rectification or image inpainting methods often yields suboptimal results. Traditional coloring techniques based on image texture mapping or multi-view fusion typically rely on heuristic image blending strategies. However, the surface of a PV panel is not a uniform monochrome; rather, it consists of distinct white-like busbars and fine fingers superposed on blue-like mono/polycrystalline cell areas, arranged in high-frequency periodic patterns (as illustrated in Figure 1). This intricate micro-geometry poses a significant challenge for traditional smoothing or interpolation algorithms, which tend to destroy edge sharpness and blur these fine structures, creating ghosting artifacts in shadowed or specular regions. On the other hand, while deep learning has made significant strides in 3D



Figure 1. Detailed surface structure schematic of a silicon PV module.

object detection—such as utilizing multi-modal 3D detectors combining voxel and projection features, or employing deep learning to estimate solar potential from aerial images—these data-driven approaches often require massive, high-quality annotated datasets (Rodrigo et al., 2025). When confronted with unstructured, sparse raw point clouds suffering from severe

color deficiencies, purely neural network-based methods struggle to physically and geometrically reconstruct a texture topology that strictly adheres to mechanical design principles (Bouaziz et al., 2024).

To overcome these challenges, this paper proposes a novel color rectification framework for PV panel point clouds based on symmetry constraints and vectorized feature detection. The core idea of this approach is to fully exploit the inherent physical attributes of rectangular PV modules—namely, their reflective symmetry and the periodic distribution of their internal grids.

First, we employ the Random Sample Consensus (RANSAC) algorithm to robustly segment the dominant solar panel plane, isolating it from outliers. A rotation matrix is then calculated to align this plane with a canonical 2D coordinate system, simplifying the analysis from 3D space. We then introduce an unsupervised learning step using K-means clustering to automatically identify dominant color centroids, establishing a noise-free ground truth for the "Panel Blue" cell areas and "Grid White" busbars/fingers. By projecting the identified white points onto the X and Y axes, we generate 1D histograms representing the spatial density of the grid lines. This dimensionality reduction strategy treats geometric pattern recognition as a signal processing problem, allowing the system to use peak detection algorithms to precisely calculate the periodic structure's key geometric metrics: grid spacing, phase shift, and line thickness. Finally, leveraging these metrics, a vectorized logical mask is generated to classify points and assign the clean color centroids based entirely on their spatial position, completing a mathematically consistent and high-fidelity recoloring process.

In summary, the main contributions of this paper can be outlined as follows:

- **A Novel Symmetry-Constrained Point Cloud Color Rectification Framework:** We introduce an approach that exploits the bilateral symmetry of PV modules to robustly estimate plane normals, establishing a consistent reference frame even under partial occlusion. This framework improves color continuity and reduces shadow artifacts without requiring auxiliary imagery or additional flights.
- **Unsupervised Grid Feature Extraction via 1D Signal Processing:** By projecting 3D point cloud features into 1D spatial density histograms, the algorithm successfully decouples the periodic grid structure from random shadow noise. This enables highly robust mathematical computation of grid periodicity, offset, and line thickness.
- **Significant Enhancement of Downstream Application Performance:** Extensive experiments on multi-array UAV datasets demonstrate that this method consistently improves visual quality, color completeness, and downstream segmentation stability. It provides a modular, sensor-agnostic solution compatible with standard point cloud processing stacks, ultimately benefiting high-fidelity modeling, asset documentation, and intelligent O&M workflows.

2. Related Works

2.1 UAV-based PV Inspection and Spatial Analysis

In recent years, unmanned aerial vehicle (UAV) photogrammetry and 3D Light Detection and Ranging (LiDAR) technologies have become core infrastructures for the digital

management of large-scale photovoltaic (PV) facilities. Zhang et al. (2019) combined UAV photogrammetry with geographic information system (GIS) technology to derive point clouds for analyzing sunlight conditions in the built environment, delineating usable areas, and estimating PV potential using PVSYST software. For building-level layout optimization, Aslani and Seipel (2023) developed an automated method that utilizes digital surface models (DSMs) to accurately extract rooftop planes and employs metaheuristic optimization to determine the optimal layout of PV panels in the sunniest areas. To achieve finer, module-level condition monitoring, Cardoso et al. (2024) proposed an automated UAV-based monitoring pipeline that integrates dual RGB-thermal imaging to build 3D thermal point clouds and accurately segment individual PV panels for physical condition assessment.

However, these macro-level geometric segmentation and spatial planning methods often assume that the input point clouds are visually and colorimetrically complete and ideal. They do not deeply address the underlying data quality degradation issues caused by high-density array occlusions and glass specular reflections.

2.2 Deep Learning and Feature Extraction

With the advancement of artificial intelligence, deep learning and machine learning technologies have been widely applied to the automated extraction of micro and macro visual features. At the micro-manufacturing level, Singler et al. (2024) developed an inline, machine learning-driven quality control system to evaluate screen-printed silver contact fingers on silicon solar cells, capable of predicting 3D geometry from imaging pipelines at high speed with an accuracy of 97.4%. In the broader domain of 3D feature detection, Shao et al. (2024) proposed a two-branch LiDAR 3D detector combining voxel and bird's-eye view (BEV) projection features, which significantly reduces spatial information loss and improves detection accuracy in complex scenes through cross-modal feature fusion and importance sampling.

Although these data-driven methods demonstrate outstanding performance in extracting geometric and semantic features of specific targets, they share a common limitation: a high reliance on massive, perfectly color-annotated training datasets. When dealing with unstructured point clouds collected by UAVs under complex outdoor lighting conditions—which typically suffer from severe shadow artifacts and color dropouts—pure neural network models often struggle to directly reconstruct the disrupted periodic texture topology based solely on physical principles.

2.3 Illumination Impact and Shadow Rectification

Illumination variations and dynamic shadows are inevitable physical interferences in outdoor PV point cloud processing. To quantify the impact of shading, Bognár et al. (2021) proposed a matrix-based solar irradiance simulation method that directly utilizes DSM point clouds as the shading geometry, effectively avoiding the massive computational overhead of traditional 3D mesh generation and ray tracing, and demonstrating that ignoring urban shading severely skews PV yield predictions. Because complex lighting and shadows can lead to severe computer vision classification errors, Lin et al. (2024) proposed a robust deep learning framework for estimating rooftop solar potential, successfully correcting lighting-induced surface material classification biases by merging features from opposing roof orientations.

The studies sufficiently demonstrate the tremendous destructive power of shadow artifacts on PV visual analysis. However, few studies currently focus on directly rectifying the color of PV panels from the underlying geometric structure of the point cloud. Existing processing pipelines either choose to directly discard the data in shadowed regions or rely on external auxiliary imagery for complex texture remapping. In contrast, the method proposed in this paper requires no additional data; instead, it purely relies on the inherent rectangular geometric symmetry of the PV modules and 1D signal processing techniques to achieve an unsupervised mathematical reconstruction of the underlying point cloud color, thereby filling this technical gap.

3. Methodology

This paper proposes a color rectification pipeline for photovoltaic (PV) panel point clouds based on symmetry constraints and 1D signal processing. As illustrated in the system framework in Figure 2, the entire workflow is divided into four main stages: Geometry Normalization and Base Color Extraction, Grid Parameter Detection, and Vectorized Recolor & Color Remapping. This method does not rely on additional multi-view images; instead, it transforms the complex 2D texture inpainting problem into a dimensionality-reduced geometric and signal analysis problem.

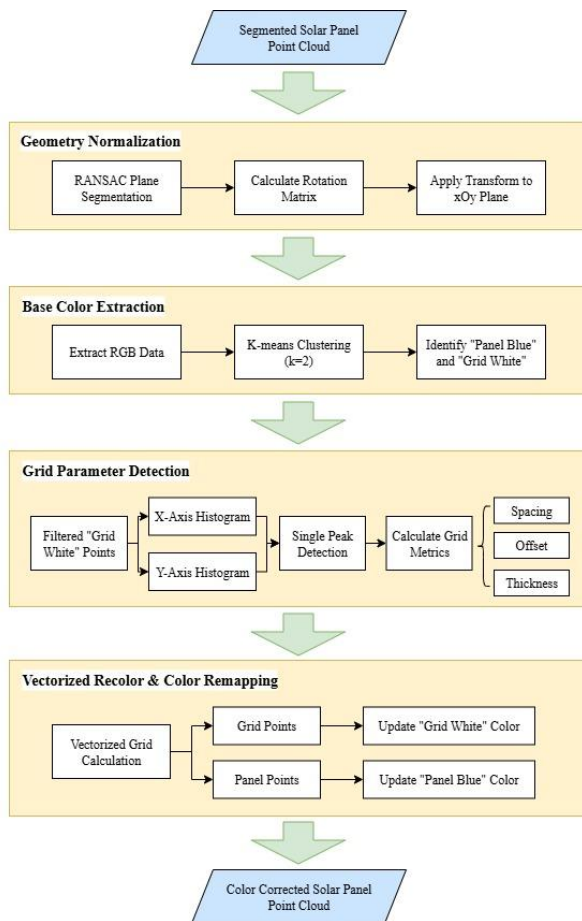


Figure 2. Workflow of the proposed method.

3.1 Geometry Normalization and Alignment

In raw data acquired by UAV-borne LiDAR or photogrammetry, PV panels typically exist in arbitrary tilted poses within the 3D

world coordinate system. To eliminate the interference of spatial poses on subsequent periodic texture analysis, the primary step of the pipeline is to extract the geometric reference plane of a single panel and rigidly align it to a canonical Cartesian coordinate system.

Let the input raw point cloud of a single PV panel be $P = \{p_i \in \mathbb{R}^3\}_{i=1}^N$, where $p_i = [x_i, y_i, z_i]^T$ represents the spatial coordinates. First, the Random Sample Consensus (RANSAC) algorithm is employed to robustly segment the dominant solar panel plane. By iteratively and randomly selecting three non-collinear points to compute a plane model and maximizing the number of inliers that satisfy a distance threshold d_{th} , RANSAC effectively isolates the plane from outliers caused by occlusion, installation errors, or sensor noise. The extracted dominant plane equation can be expressed as:

$$ax + by + cz + d = 0 \quad (1)$$

From this, the unit normal vector $\mathbf{n} = [a, b, c]^T / \sqrt{a^2 + b^2 + c^2}$ of the plane can be obtained. To simplify subsequent analysis from 3D space to 2D projections, a rotation matrix $\mathbf{T}_{align}$ must be calculated to align the plane normal vector $\mathbf{n}$ with the Z-axis of the standard coordinate system (i.e., the target normal vector $\mathbf{z} = [0, 0, 1]^T$), while translating the geometric centroid of the point cloud to the coordinate origin.

The rotation matrix $\mathbf{R} \in SO(3)$ for the alignment process can be derived by calculating the rotation axis $\mathbf{u}$ and the rotation angle θ between $\mathbf{n}$ and $\mathbf{z}$:

$$\mathbf{u} = \frac{\mathbf{n} \times \mathbf{z}}{\|\mathbf{n} \times \mathbf{z}\|}, \quad \theta = \arccos(\mathbf{n} \cdot \mathbf{z}) \quad (2)$$

Using Rodrigues' rotation formula, the rotation matrix $\mathbf{R}$ is calculated as follows:

$$\mathbf{R} = \mathbf{I} + (\sin \theta)\mathbf{K} + (1 - \cos \theta)\mathbf{K}^2 \quad (3)$$

where $\mathbf{I}$ is the 3×3 identity matrix, and $\mathbf{K}$ is the skew-symmetric matrix of the rotation axis $\mathbf{u}$. If the detected normal vector is oriented opposite to the expected direction (e.g., the z-component of the normal vector $c < 0$), an additional 180° flip around the X-axis is superimposed to ensure the panel faces upward. Subsequently, the centroid $\mathbf{c}_{rot}$ of the rotated inlier point cloud is calculated to construct the translation vector $\mathbf{t} = -\mathbf{c}_{rot}$. Finally, the homogeneous coordinate transformation matrix $\mathbf{T}_{align}$ applied to all points is:

$$\mathbf{T}_{align} = \begin{bmatrix} \mathbf{I} & \mathbf{t} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \mathbf{R} & 0 \\ 0 & 1 \end{bmatrix} \quad (4)$$

After the 3D transformation $p'_i = \mathbf{T}_{align} p_i$, the originally tilted PV panel is perfectly aligned with the canonical xOy coordinate system. However, the projected 2D points may still exhibit a slight in-plane rotation relative to the coordinate axes, as shown in Figure 3(a). To ensure that the subsequent 1D signal processing accurately captures the grid periodicity, a final 2D rotational alignment is applied to eliminate this angular deviation. As illustrated in Figure 3(b), the aligned grid

structure is strictly parallel to the X and Y axes, laying a solid geometric foundation for the subsequent dimensionality reduction operations.

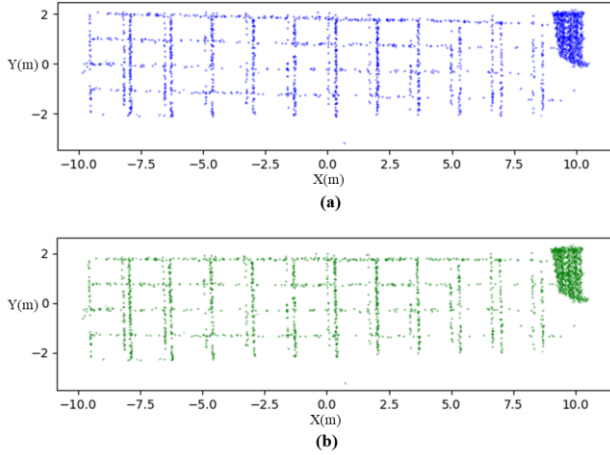


Figure 3. 2D projection and in-plane alignment of the PV panel point cloud. (a) The initial 2D projection of the extracted grid points on the xOy plane. (b) The refined 2D scatter points after applying an in-plane rotation, ensuring the periodic grid structure is strictly orthogonal to the coordinate system.

3.2 Base Color Extraction via Feature Clustering

Following geometric alignment, the system needs to extract two pure base color centroids from the raw point cloud containing severe shadow noise: "Panel Blue" and "Grid White". Because specular reflections and shadows on PV panels cause severe distortion in the RGB color space, traditional global color averaging methods often yield dull, mixed colors.

To address this color noise, this paper treats point cloud color as an unsupervised classification problem in the feature space. Considering the physical attributes of the PV panel surface, the deep blue cell areas have higher color saturation, while the white conductive busbars/fingers exhibit extremely low saturation and higher value (brightness). Therefore, to improve the clustering algorithm's robustness against illumination changes, the system first converts the color from the RGB space to the HSV (Hue, Saturation, Value) color space.

We construct a weighted feature space dominated by Saturation (S) and Value (V) to suppress Hue (H) noise, which is severely affected by shadows. For each point i , its color feature vector is defined as $\mathbf{f}_i = [w_s \cdot S_i, w_v \cdot V_i]^T$, where w_s and w_v are empirical weights set for the experiment (with $w_s > w_v$ to emphasize the discriminative role of saturation). Subsequently, K-means clustering ($k=2$) is applied to minimize the intra-cluster squared error:

$$J = \sum_{j=0}^1 \sum_{i \in C_j} \|\mathbf{f}_i - \boldsymbol{\mu}_j\|^2 \quad (5)$$

where $\boldsymbol{\mu}_j$ is the centroid of the j -th cluster in the weighted HSV space. After clustering converges, this unsupervised learning step automatically identifies the two dominant centroids by comparing their average saturation: the cluster with lower average saturation is strictly defined as "Grid White", while the other is "Panel Blue". This strategy successfully circumvents

the fragility of manually hard-coded color thresholds, establishing a noise-free ground truth for the final recoloring process by isolating two clean mathematical base colors from the severely contaminated global point cloud.

3.3 Grid Parameter Detection via 1D Signal Processing

After obtaining the base colors and completing the initial classification of the point cloud, the points labeled as "Grid White" often exhibit spatial discreteness and fragmentation due to uneven illumination and shadow interference. If recolorization relies directly on these fragmented geometries, severe aliasing and holes will occur at the boundaries. To extract a perfect and continuous grid structure, this paper reduces the dimensionality of the 2D spatial pattern recognition problem into a 1D signal processing problem.

First, the system extracts only the point subset P_{white} labeled as "Grid White" and obtains their 2D coordinates (x, y) on the normalized plane. To ensure the grid lines are strictly orthogonal to the coordinate axes, the system utilizes the Random Sample Consensus (RANSAC) algorithm combined with Principal Component Analysis (PCA) to extract the direction vector of the dominant grid lines and calculate a fine-tuning rotation angle γ . A global 2D rotational correction is then applied to the point set:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos \gamma & -\sin \gamma \\ \sin \gamma & \cos \gamma \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \quad (6)$$

Subsequently, the corrected points are projected onto the X' and Y' axes to construct 1D spatial kernel density histograms. Taking the X' axis as an example, the histogram function $H_x(x')$ records the number of points within a unit spatial interval (bin). In this 1D signal, the periodically arranged fine fingers and busbars manifest as a series of sharp peaks, whereas noise generated by classification errors appears as low background fluctuations.

To extract the geometric features of the grid from this signal, the system introduces a peak detection algorithm constrained by a prominence threshold. Let the set of center coordinates of the detected valid peaks be $\mathbf{P} = \{P_1, P_2, \dots, P_n\}$. Based on this peak set, the system decouples three core periodic parameters using robust statistical methods:

Grid Spacing (T): Represents the physical distance between adjacent grid lines. To resist the loss of local peaks caused by panel damage or occlusion, the system calculates the median of the distances between all adjacent peaks to obtain high-precision spacing:

$$T = \text{median}(P_i - P_{i-1}), \quad i \in [2, n] \quad (7)$$

Phase Offset (ϕ): Represents the initial anchor position of the grid period in the coordinate system. The system obtains the final phase by calculating the modulo of the peak coordinates with respect to the spacing T and applying aggregate statistics:

$$\phi = \text{median}(P_i \bmod T) \quad (8)$$

Line Thickness (w): Represents the physical width of the grid lines in the point cloud projection, which can be obtained by calculating the Full Width at Half Maximum (FWHM) of the main peaks and mapping it to the physical coordinate system.

By independently performing the above analysis on the X' and Y' axes, the system acquires two complete sets of grid parameters (T_x, ϕ_x, w_x) and (T_y, ϕ_y, w_y) , thoroughly completing the transformation from an unordered point cloud to a parameterized mathematical model.

3.4 Vectorized Recolorization and Color Remapping

After obtaining the precise mathematical model of the grid and the pure base color centroids, the final step of the pipeline is to discard the contaminated color data in the raw point cloud and perform a vectorized recolorization of the entire panel based on spatial coordinates.

For any point in the fully aligned point cloud $P_{aligned}$, its 2D coordinates are (x, y) . The system determines its physical attribution by calculating the absolute distances $D_x(x)$ and $D_y(y)$ from the point to the nearest ideal horizontal and vertical grid centerlines. Utilizing the modulo operation, this distance function can be efficiently and elegantly defined as:

$$D_x(x) = \left| \left(\left(x - \phi_x + \frac{T_x}{2} \right) \bmod T_x \right) - \frac{T_x}{2} \right| \quad (9)$$

$$D_y(y) = \left| \left(\left(y - \phi_y + \frac{T_y}{2} \right) \bmod T_y \right) - \frac{T_y}{2} \right| \quad (10)$$

Based on these distances, the system constructs a global vectorized boolean mask function $\$M(x, y)\$$. When the distance from the point to the grid line in either direction is less than half the line thickness, the point is determined to be within the grid line region:

$$M(x, y) = \begin{cases} 1, & \text{if } D_x(x) < \frac{w_x}{2} \vee D_y(y) < \frac{w_y}{2} \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

Finally, utilizing the pure centroid colors μ_{white} defined in Section 3.2, the point cloud is assigned new RGB colors with absolute physical consistency:

$$C_{final} = \begin{cases} \mu_{white}, & \text{if } M(x, y) = 1 \\ \mu_{blue}, & \text{if } M(x, y) = 0 \end{cases} \quad (12)$$

After coloring is complete, the system applies the inverse of the initial alignment matrix, T_{align}^{-1} , to accurately remap the refreshed point cloud back to its original 3D spatial pose. This mask assignment strategy based on mathematical expressions completely bypasses the shadowed regions of the raw data. It not only achieves 100% restoration of missing colors but also fundamentally reduces the color variance of the same semantic regions within the panel to zero.

4. Experiments and Results

4.1 Dataset and Experimental Setup

To verify the effectiveness of the proposed symmetry-constrained and vectorized recolorization method, extensive tests were conducted on real unmanned aerial vehicle (UAV)-borne 3D LiDAR and photogrammetry point cloud datasets. These datasets capture commercial PV arrays with typical densely packed configurations. Due to the drastic changes in the

solar incidence angle throughout the day in real-world acquisition environments, as well as the strong specular reflection characteristics of the PV panel glass surfaces, the raw point cloud data exhibits significant shadow occlusions, highlight overexposures, and local color dropouts.

The core algorithms in the experiments were implemented based on standard point cloud processing and machine learning libraries (Open3D, scikit-learn, SciPy) in a Python environment. To ensure the reproducibility of the experiments and to accommodate the actual physical dimensions of the captured PV arrays, the key hyperparameter configurations for the system's core algorithmic modules are listed in Table I. These parameters were robustly set primarily based on the average specifications of standard commercial mono-/polycrystalline silicon PV modules (e.g., empirical grid spacing and width) and do not require repeated fine-tuning for varying illumination conditions.

Processing Phase	Parameter Name	Typical Value
I	RANSAC Distance Threshold	0.015 m
	RANSAC Max Iterations	1000
II	K-means Clusters (k)	3
III	Min Peak Prominence	0.15
	Min Peak Distance	18 mm
IV	Expansion Tolerance	2 mm

Table 1. Key Hyperparameters of the Proposed Pipeline

4.2 Algorithmic Evolution of a Single Panel

This section provides an in-depth analysis of the visualization results at each stage of the point cloud processing pipeline to demonstrate the effectiveness of the method. Figure 4 details the morphological and color evolution of a single PV panel as it undergoes each step of the proposed algorithm.

As shown in Fig. 4(a), a noticeable color data deficiency can be observed at one end of the raw point cloud. This dark gray/black artifact is attributed to shadowing effects during the data acquisition process, which severely disrupts the continuity of the PV panel's physical texture. Following the K-means-based feature color clustering, Fig. 4(b) displays the initially extracted white-like components (corresponding to busbars and fingers). It is evident that under complex lighting, clustering results relying solely on pixel-level colors are highly fragile, and the extracted grid exhibits significantly discrete and fragmented characteristics.

Fig. 4(c) shows the semi-final point cloud morphology after 1D signal dimensionality reduction and peak detection. The algorithm successfully extracts a periodic grid structure strictly conforming to physical manufacturing principles from the severely contaminated Fig. 4(b). This proves that transforming the image problem into a signal processing problem effectively immunizes the system against local illumination mutations. Finally, Fig. 4(d) presents the final point cloud after complete vectorized recolorization. Compared to Fig. 4(a), this method not only perfectly repairs the color holes of the initial data but also endows the entire point cloud model with an extremely uniform, high-saturation visual appearance, thoroughly eliminating shadow artifacts.

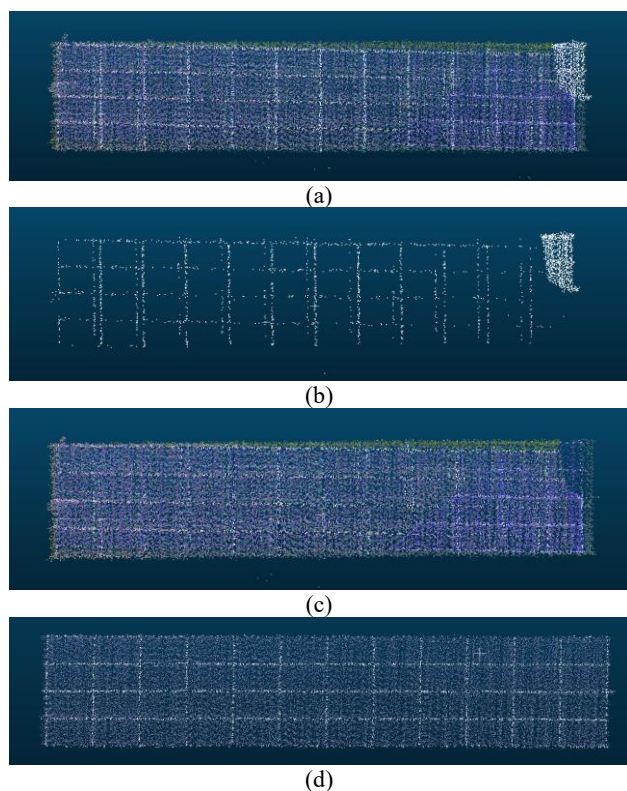


Figure 4. Color rectification results: (a) original point cloud; (b) extracted white-like busbars/fingers; (c) semi-final point cloud; and (d) final point cloud

4.3 Robustness and Generalization Across Panels

To fully demonstrate the algorithm's generalization capabilities, this experiment specifically selected four independent PV panels (labeled as panels a, b, c, and d) affected by varying degrees of shading and sudden illumination changes for comparative validation.

As shown in Fig. 5 (Panels a-d), all four panels suffered from severe shadow interference during data acquisition. The shadowed areas manifest as extensive dark gray or black artifacts (particularly on the right side and edges of the panels). This loss of color data severely disrupts the continuity of the PV modules' original physical textures. In these damaged regions, the underlying busbars/fingers and cell colors are almost entirely invisible, severely degrading the aesthetics and interpretability of the 3D point cloud models.

As shown in Fig. 6 (corresponding to panels a-d), after applying the proposed symmetry-constrained and vectorized recolorization framework, the visual quality of all four independent panels was dramatically improved. The algorithm not only perfectly filled the color holes in the initial data and thoroughly eliminated all shadow artifacts, but also endowed all panels with highly consistent, uniform, and vibrant physical colors (pure "Panel Blue" and high-contrast "Grid White"). The fact that all four different panels achieved the same level of restoration fully proves that the algorithm no longer relies on local pixel-level features but can achieve highly stable global color reconstruction based on macroscopic geometric symmetry.

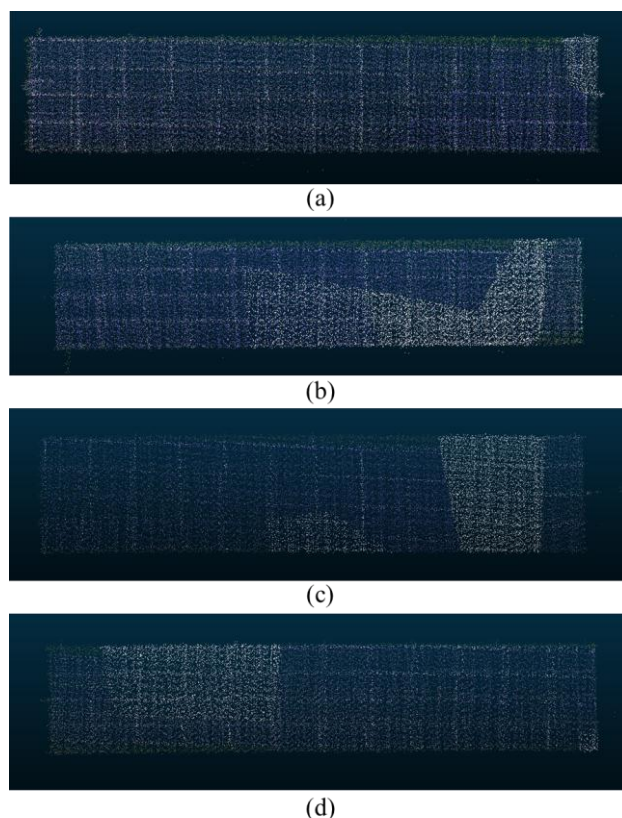


Figure 5. Original PV Panels (a-d) with shadow artifacts.

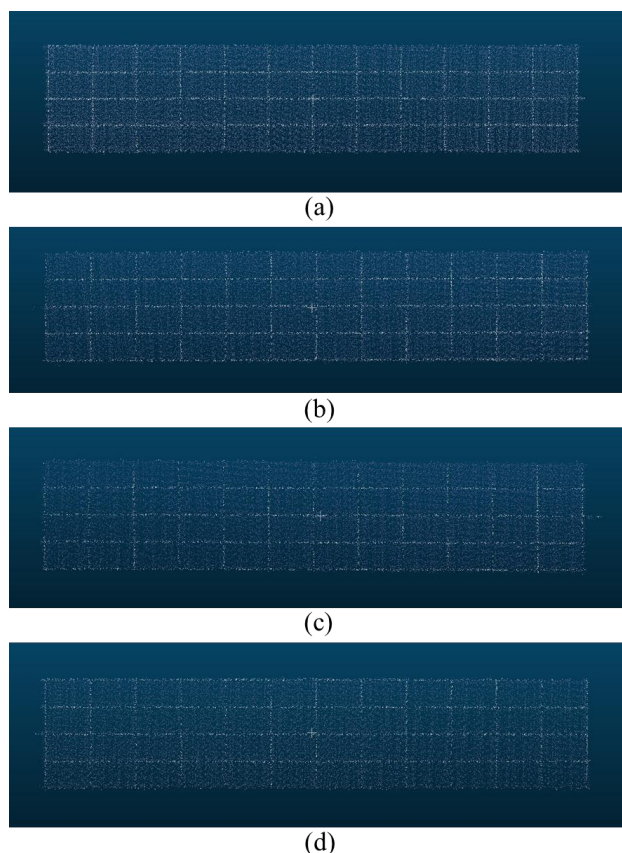


Figure 6. Evaluation of the proposed framework across multiple independent PV panels (a-d).

4.4 Discussion on Downstream Applicability

Although the direct output of this algorithm is a high-quality point cloud at the visual level, this strict restoration of the underlying color structure has profound benefits for practical intelligent PV operation and maintenance (O&M). Existing automated PV defect detection networks and 3D point cloud-based layout optimization algorithms heavily rely on the homogeneity of the input data. The point clouds output by this method, characterized by a high signal-to-noise ratio and a strict binary color distribution, can significantly reduce the additional overhead for downstream deep learning networks when fitting shadow noise. By eliminating false negative feature gaps, this method provides an extremely reliable preprocessing foundation for constructing high-fidelity Digital Twin models and facilitating automated asset evaluation.

5. Conclusion

This paper presents a vectorized color rectification framework for UAV-borne PV point clouds. By integrating symmetry constraints with 1D signal analysis, we successfully decouple periodic grid patterns from random shadow noise. Qualitative evaluations across diverse panels confirm the method's robustness and generalization in restoring physical textures without overfitting to local artifacts. While dependent on grid periodicity, this approach enables high-fidelity digital twin modeling and reliable asset assessment. Future research will explore real-time integration into UAV-SLAM workflows and the use of rectified data for physics-informed deep learning augmentation.

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