Comparative Evaluation for Tracking the Capability of Solar Cell Malfunction Caused by Soil Debris between UAV Video versus Photo-Mosaic

Young-Seok Hwang 1, Stephan Schlüter 2, Seong-Il Park 3 and Jung-Sup Um 4,*

1 Kyungpook Institute of Oceanography, Kyungpook National University, Daegu 41566, Korea; youngseokhwang@knu.ac.kr
2 Department of Mathematics, Natural and Economic Sciences, Ulm University of Applied Sciences, 89075 Ulm, Germany; stephan.schlueter@thu.de
3 Innovation Growth Research Division, Ulsan Bigdata Center, Ulsan Research Institute, Ulsan 44720, Korea; sipark227@uri.re.kr
4 Department of Geography, Kyungpook National University, Daegu 41566, Korea
* Correspondence: jsaeom@knu.ac.kr

Abstract: Monitoring the malfunction of the solar cells (for instance, 156 mm by 156 mm) caused by the soil debris requires a very low flight altitude when taking aerial photos, utilizing the autopilot function of unmanned aerial vehicle (UAV). The autopilot flight can only operate at a certain level of altitude that can guarantee collision avoidance for flight obstacles (for instance, power lines, trees, buildings) adjacent to the place where the solar panel is installed. For this reason, aerial photos taken by autopilot flight capture unnecessary objects (surrounding buildings and roads) around the solar panel at a tremendous level. Therefore, the autopilot-based thermal imaging causes severe data redundancy with very few matched key-points around the malfunctioned solar cells. This study aims to explore the tracking capability on soil debris defects in solar cell scale between UAV video versus photo-mosaic. This study experimentally validated that the video-based thermal imaging can track the thermal deficiency caused by the malfunction of the solar cell at the level of the photo-mosaic in terms of correlation of thermal signatures (0.98–0.99), detection on spatial patterns (81–100%), and distributional property (90–95%) with 2.5–3.4 times more matched key-points on solar cells. The results of this study could serve as a valuable reference for employing video stream in the process of investigating soil debris defects in solar cell scale.

Keywords: unmanned aerial vehicle (UAV); video; solar cell; photo-mosaic; soil debris; thermal deficiency; hot spots

1. Introduction

The typical solar module is the aggregation of solar cells [1]. The solar module is made up of smaller individual solar photovoltaic (PV) cells. PV cells always come in the same standard size: 156 mm by 156 mm. The busbars and the fingers are the main components of the solar cell. The fingers of the solar cell collect the generated direct current (DC) current and deliver it to the busbars [2]. The generated electric voltage is transmitted through busbars to the inverter. Hence, as the busbar or fingers of solar cells are short-circuited or malfunctioning, it causes abnormal heat generation in solar cells owing to overloads on fingers or busbar. As the number of malfunctioned solar cells increases, the decreasing solar panel efficiency is followed. Therefore, the solar cell is the minimum survey unit in the process of investigating a solar power plant.

A defect of a solar cell can be defined as everything different from the expected in a solar cell [3]. It specifies a part of a solar cell that is different from an ideal one. Solar cells’ common defects are mismatch, cracks, discolorations, snail trails/tracks, and soiling [4]. Among the defects in solar cells, soiling is a frequent cause of the defect. Soiling is related
to the accumulation of dirt on the surface. This results from various soil agents such as dust, pollution, bird droppings, and soil debris. The accumulation of soil debris on solar cells can directly reduce the light transmission on busbars and fingers of solar cells. As a result, soiling on solar cells reduces output power from the single solar module in the range of 2–50\%\cite{6}. Since soiling is generated from many sources, including climatic factors (wind direction, velocity, rainfall, and snow), the amount of accumulated soil debris on single solar cells depends on its location, environment, and geometric status of solar cells (tilts angles and aspect). Thus, even within the same solar module, the single solar cells have a diverse thickness, spatial patterns, and accumulated soil debris. Therefore, the monitoring of soil debris defects should be carried out in units of the single solar cell.

The thermal aerial photos taken by UAV equipped with autopilot have been positioned to be applied as a standardized instrument to substitute in situ visual inspections and I-V curve tests for the defective solar module because of its time and cost efficiency. The autopilot is activated by executing pre-defined waypoints following a specific flight plan. The autopilot flight needs a certain flight altitude (30–50 m) at a level to guarantee collision avoidance from flight obstacles around the solar power plant. For this reason, the autopilot-based thermal imaging causes serious data redundancy that non-soil debris defect area takes up more than 99\% in imageries. It leads to a serious lack of key-points on malfunctioned solar cells caused by soil debris. Insufficient key-points produce the matching failure or mismatch on a soil debris defect during building thermal photo-mosaics. It results in errors in exterior orientation parameters such as direct measurements of distances, angles, positions, and areas of soil debris defect. Furthermore, the unnecessary targets possibly hinder tracking the thermal deficiency of soil debris defect by contaminating the thermal contrasts between defective and normal operating solar cells due to ambient light's influence from unnecessary targets.

Insufficient key-points and data redundancy on the solar cell can be solved by targeting exclusively single solar cells with a high overlapping rate while guaranteeing enough video frames. Video has a distinguished feature and offers several benefits in securing accurate and sufficient key-points to detect soil debris defects in a solar module. Unlike the aerial photo captured by autopilot flight, dynamic stereo coverage between individual frames can be achieved with very intensive and constant overlapping within a single solar cell. This video characteristic can complement the data redundancy and insufficient key-points caused by traditional UAV thermal inspection using autopilot flight. Concerning UAV video thermal imaging, most studies have assessed its capability in the perspective of real-time detection, classification, and tracking of objects, for instance, field phenotyping of water stress and fire monitoring.

Several studies have explored the development of real-time mosaicking for detecting defective solar panels in large-scale solar farms with UAV video thermal imaging. In addition, other studies have evaluated the suitability of UAV-borne video thermal imaging in terms of mapping accuracy and thermal signature compared to autopilot-based imaging of solar panels. Nonetheless, literature has not discussed the capability of UAV video-based inspection on malfunctioned solar cells caused by soil debris. Therefore, the study aims to explore the tracking capability of UAV video streams by comparing video versus photo-mosaics with respect to the spatial patterns and distributional similarity of thermal signatures in solar cell scales.

This article is divided into three main sections. The first section introduces the overall procedure for acquiring and analyzing data. The second section presents a comparative evaluation for spatial patterns and thermal signatures of solar cells malfunctioned by soil debris between the photo-mosaic and video-mosaic. The final section validates the distributional similarity between the photo-mosaic and video-mosaic.
2. Materials and Methods

2.1. Study Area

In this study, we set three testbeds of solar modules with a different soil debris-covered area of solar cells in Bokhyeon hall, Kyungpook National University (KNU), Daegu, southeastern South Korea (Figure 1). Testbeds made up of three solar modules are established with different soil debris-covered areas (Testbed 1: 50%; Testbed 2: 5%; Testbed 3: 0.1%) to evaluate the tracking capabilities of autopilot-based and video-based mosaics under the realistic circumstances of the urban area.

Figure 1. Mosaic of thermal imageries and an in situ photo of the study site. Black box is the location of experimental targets. The magnified picture (left side) is the in-situ photo of experimental targets.

KNU is located in the north administrative district in Daegu Metropolitan City, the third most populated city in South Korea. Daegu is called the “Solar City” due to its abundant solar radiation and little precipitation. Therefore, this city is the ideal place for solar power generation. University campuses are well known as the living lab of the urban area since they exhibit spatial variation similar to city-specific landscapes containing a variety of buildings, such as those for vehicle traffic areas, road, green space, libraries, parking lots, lectures, dormitories, and so on [24–26]. Furthermore, the city center’s typical land-use patterns and characteristics are shown at the KNU area, such as commercial and business centers, parks, high- and low-rise buildings, dormitories, road networks, playgrounds, green spaces, and other mixed uses [27]. Therefore, it is expected that the solar panels installed in KNU can serve as an ideal testbed for setting allowable errors or parameters for evaluating the tracking capability of solar panel malfunctioning caused by soil debris between the video stream and photo-mosaic at a city-wide scale.

2.2. Data Collection

The UAV video was recorded on 6 August 2021, when the highest solar zenith angle (13:00) to avoid shade and poor weather (for instance, rainfall) occurred. The UAV thermal video was recorded using a quadcopter DJI Matrice 200 V2, equipped with a Zenmuse XT2 camera (Table 1). The testbeds (Canadian Solar HiDM 400W, CS1U-400MS, 992 × 2078 mm) consist of three solar modules with 162 half solar cells (green dotted line). Shingled solar modules are assembled with an imbricated structure on cells, which are interconnected directly similar to roof tiles. No visible busbars are another characteristic of shingled-type solar modules [28]. Chaichan and Kazem (2020) address that the illumination intensity on the solar cell is reduced according to the amount of deposited soil [29].
radiance is reduced by over 2%, the average solar cell productivity (voltage, current and power) is decreased severely. Reduction in solar cell productivity is relatively stable at the 2–20% reduction of transmittance radiance on the solar cell. Solar cell productivity keeps decreasing as the transmittance reduction is over 20% reduction in transmittance radiance. Thereby, we set the three types of testbeds with the soil debris-covered area differently, distributed based on variations in solar cell productivity: (1) Testbed 1: over 80% of solar module area covered with soil debris; (2) Testbed 2: from 10–20% of solar module area covered with soil debris; (3) Testbed 3: under 1% of solar module area covered with soil debris.

### Table 1. Specifications of UAV and thermal camera.

| UAV (DJI Matrice 200 V2) | Camera (DJI Zenmuse XT2) |
|--------------------------|--------------------------|
| Weight                   | 4.69 kg                  | Pixel numbers |
|                          |                          | (width × height) |
| Maximum flight altitude  | 3000 m                   | 640 × 512      |
|                          | (flight altitude used in this experiment: 80 m) |                      |
| Hovering accuracy        |                          | Sensor size |
| z (height)               | Vertical, ±0.1 m         | (width × height) |
|                          | Horizontal, ±0.3 m       | 10.88 mm × 8.7 mm |
| x, y (location)          | Horizontal, ±1.5 m or ±0.3 m | Focal length * |
|                          | (Downward Vision System) | 19 mm          |
|                          |                          | FOV/IFOV      |
|                          |                          | 32° × 26°/0.895 mr |
|                          |                          | Spectral band |
|                          |                          | 7.5–13.5 µm   |
|                          |                          | ISO           |
|                          |                          | 128           |
|                          |                          | Full frame rates |
|                          |                          | 30 Hz         |
|                          |                          | Exposure value |
|                          |                          | 4.55          |
| Maximum flight speed     | 61.2 km/h (P-mode)       | Sensitivity [NEDT]/Aperture <0.05 °C, f/1.0 |

* Focal length of Zenmuse XT2 is fixed at 19 mm while capturing video and still imageries in autopilot mode.

NEDT: Noise equivalent differential temperature.

To detect the thermal deficiency of the solar cells in the testbeds, the ground sampling distances (GSD) of thermal still imageries and video frames should be less than 16 cm. Therefore, the GSD of a UAV video can be estimated with the sensor width of the camera (Sw), flight height (H), focal length of the camera (FR), and image width (imW), as follows (Equation (1)):

\[
GSD = \frac{Sw \times H \times 100}{FR \times imW}
\]  

Because the camera specifications are fixed, flight height is the main factor to determine the GSD. For this reason, we set the flight altitude to 30 m to attain the best GSD (2.68 cm) available for detecting individual thermal deficiency on solar cells in the study area while leaving sufficient space for the UAV to fly freely over the solar panels. As a result, thermal infrared (TIR) video in the form of a sequence-formatted (SEQ) file was captured at 30 frames per second and flight speed of 2.7 m/s at 30 m flight altitude.

### 2.3. Thermal Video Frame Mosaic

Raw UAV thermal video itself does not contain geometric information. However, DJI Matrice 200 V2 and Zenmuse XT2 provide telemetry data for full orientation (position and altitude) in subtitle format (SubRip Subtitle: SRT) along with the recorded thermal video. The time sync function of OSDK V3.8.1 embedded in the flight controller of DJI Matrice 200 V2 lines up the observation time of the video, GPS time, and the flight controller clock at 1 Hz. Thus, the SRT file gives second-by-second full orientation data with a number indicating the sequence, Coordinated Universal Time (UTC), and full orientation parameters (GPS coordinates, barometer altitude) acquired from the flight controller during the flight. We utilized Thermal FLIR Studio PRO to extract thermal video frames from the SEQ video file. The full frame rate of DJI Zenmuse XT2 is 30 Hz (30 frames per second). According to Hwang et al. (2021) [23], as the frame intervals are short (15 frames/2 s), the obtained
thermal signatures from the video-mosaic are well aligned with the photo-mosaic. Thus, we set the frame intervals for building video-mosaics as 15 frames/2 s with 99% overlapping rates. Autopilot flight is executed over a double-grid path with an overlapping rate of 95%. A mosaic of respective imageries is automatically conducted by utilizing the photogrammetry software Pix4D Mapper following the procedures: (1) Initial processing (key-point extraction, key-point matching, camera model optimization, geolocation GPS/GCP); (2) Point cloud and mesh generation (point densification, 3D textured mesh); and (3) Digital Surface Model (DSM) (photo-mosaic and index) development.

Currently, one of the most widely used methods for geometric correction of UAV imagery is based on Structure-from-Motion (SfM) algorithms. These algorithms provide the opportunity to create accurate 3D models from image structures without prior information about the location at the time of image acquisition or about the camera parameters. With the SfM method, the 3D scene geometry and camera motion are reconstructed from a sequence of 2D images taken by a camera that moves around the scene. The SfM algorithm detects the common 16 feature points in multiple images and uses them to reconstruct the movement of those points throughout the image sequence. With this information, the locations of those points can be calculated and visualized as a 3D point cloud [30]. SfM algorithm is applied to establish the camera exposure position and motion trajectory for building a sparse point cloud [31–35]. The sparse point cloud is then used for camera calibration, and a multiview stereo (MVS) is utilized in conjunction with the DSM generation method based on reverse distance weight interpolation to construct a dense point cloud [36,37]. Figure 2 presents the overlap between the mosaic generated using still imagery (photo-mosaic) and video frames (video-mosaic). Green areas in Figure 2 indicate an overlap by more than five images. The photo-mosaic and video-mosaic are mostly overlapped with more than five images, except borders. The overlap ratios, key-points, and matched key-points are enough to generate high-quality results (Figure 2). Table 2 presents the surface temperature of solar cells (hereinafter referred to as the SCST) that appeared in the photo-mosaic and video-mosaic.

![Figure 2](image-url)
Table 2. Descriptive statistics of detected SCST (°C) in the photo-mosaic and video-mosaic.

| Category                              | Photo-Mosaic | Video-Mosaic |
|---------------------------------------|--------------|--------------|
| SCSTs of solar cells detected in testbeds (°C) |               |              |
| Min                                   | 58.7         | 60.0         |
| Max                                   | 75.8         | 76.3         |
| Mean                                  | 68.0         | 68.6         |
| Standard deviation                    | 2.00         | 2.15         |
| Numbers of detected solar cells       | 8316         | 8316         |
| Overlapping rates (%)                 | 95           | 97           |

2.4. Hot Spot Analysis (Getis-Ord Gi*)

Spatial autocorrelation is based on the first law of geography in Tobler’s (1970), “everything is related, but the closer is more related than the distant.” Getis-ord Gi* is one of the spatial autocorrelation techniques, which statistically measures the degree of spatial autocorrelation and tests the null hypothesis that the region of interest does not show any spatial pattern other than accidental distribution [38]. We have explored the adjacent distance and pattern of the SCST in solar cell malfunction caused by soil in the photo-mosaic and video-mosaic through hot spot analysis with ArcMap 9.3. After the hot spot analysis, we have evaluated the distribution of the SCSTs at that location to determine whether the spatial patterns of the SCSTs appear the same in the photo-mosaic and video-mosaic. In this study, the Getis-Ord Gi* statistic is calculated through the weight of the space by using the SCSTs. As a result, the spatial clustering can be determined through the high and low values of the calculated p-values and z-scores. The formula for calculating the Getis-Ord Gi* statistic is as follows [39]:

\[
G^*_i = \frac{\sum_{j=1}^{n} w_{ij}x_j - \overline{X} \sum_{j=1}^{n} w_{ij}}{\sqrt{\frac{\sum_{j=1}^{n} w_{ij}^2 - (\sum_{j=1}^{n} w_{ij})^2}{n-1}}} 
\]

\[
\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n} 
\]

\[
S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\overline{X})^2} 
\]

where \( x_j \) is the SCSTs for the \( j \) point, \( w_{ij} \) is the spatial weight between the \( i \) and \( j \) points, and \( n \) is the total SCSTs. The Getis-Ord Gi* statistic, calculated by considering the distance between points, determines statistical significance through the z-test. In other words, it is determined through statistical significance how much the high and low values of SCSTs are concentrated. If the z-score is positive (+), it is determined that high values are spatially clustered, and if the z-score is a negative (−) value, low values are determined to be spatially clustered.

2.5. Evaluating the Performance of Video-Mosaic

2.5.1. Ordinary Least Squares (OLS) Linear Regression

Linear regression assumes stationary relationships across the study area. Linear regression and Pearson correlation analyses explain the linear relationship between the two variables based on proportional equations [40–42]. Comparative evaluations with linear regression and Pearson correlation can yield the fitness of the SCSTs of malfunctioning solar cells caused by soil debris detected from the photo-mosaic and video-mosaic. The coefficient and error terms help us determine whether the SCSTs obtained from the video-mosaic are over- or under-measured compared to those of the photo-mosaic in detecting the thermal deficiency on the solar cells. The Pearson correlation indicates that the SCSTs
of the video-mosaic and photo-mosaic have the same directions within the malfunctioning points caused by soil debris in the solar cell.

Given that the coefficient and error terms are close to 1 and 0, individually, when the Pearson correlation values are higher, the respective SCSTs gained from the photo-mosaic and video-mosaic are equivalent and have the similar capability in thermal deficiency inspections of solar cell malfunctioning caused by soil debris in terms of thermal signatures. Therefore, the corresponding linear regression models are established with the SCSTs of detected malfunctioning points resulting from soil debris in the video-mosaic (explanatory variables) and photo-mosaic (dependent variables). These linear models, which are expressed as Equations (5) and (6), are calibrated using ordinary least squares (OLS) estimation.

\[
SCST_{p1} = a_0 + a_1 (SCST_{v1}) + \epsilon_1 \tag{5}
\]

\[
SCST_{p2} = b_0 + b_1 (SCST_{v2}) + \epsilon_2 \tag{6}
\]

where \( SCST_{p1} \) is the SCSTs of hotspots in Testbed 1 detected from the photo-mosaic, \( SCST_{p2} \) is the SCSTs of hotspots in Testbed 2 and Testbed 3 detected from the photo-mosaic, \( SCST_{v1} \) is the SCSTs of hotspots in Testbed 1 detected from the video-mosaic, and \( SCST_{v2} \) is the SCSTs of hotspots in Testbed 2 and Testbed 3 detected from the video-mosaic. In Equations (5) and (6), \( a_1 \) and \( b_1 \) are the coefficients, and \( \epsilon_1 \) and \( \epsilon_2 \) are the random error term of the residuals.

2.5.2. Histogram-Based Correlation

Histogram-based correlation is generally utilized to verify a specific target’s feature extractions or image segmentation by comparing the threshold and distributional similarity between the experimental and control groups [43,44]. For example, the histogram-based correlation can present the differences from extracted features regarding thermal deficiency on solar cells caused by soil debris between the control group (photo-mosaic) and experimental group (video-mosaic) [45,46]. Here, we have conducted a histogram-based correlation to evaluate the distributional properties within hot spots on solar cells caused by soil debris between the control group (photo-mosaic) and experimental group (video-mosaic) with MATLAB R2021a. Note that because the sample is not bivariate, i.e., observations are not measured at the same time instances, we base our measures on the histograms. For example, let us assume \( X_i \) and \( Y_j \) are distributed according to size to \( N \) equidistant bins with resulting relative frequencies \( f_n \) and \( g_n \), \( n = 1, \ldots, N \). Then, the histogram-based correlation is computed as:

\[
\rho_{hist} = \frac{\text{Cov}(f_n, g_n)}{\sqrt{\text{Var}(f_n)\text{Var}(g_n)}} = \frac{\sum_n (f_n - \bar{f})(g_n - \bar{g})}{\sum_n (f_n - \bar{f})^2 (g_n - \bar{g})^2} \tag{7}
\]

3. Results

A single video frame has a lower resolution than the still photo. However, the video frame has a greater number of key-points per cubic meter (48.5–53.4/m³) in the process of building a mosaic, compared to the still photo (14.1–26.2/m³), as shown in Table 3. Furthermore, the video shows far more matched key-points (100–110) than the photos (29–54) per solar module (162 solar cells). Therefore, the video-mosaic has approximately 2.5–3.4 times more matched key-points per solar module than the photo-mosaic. Since autopilot takes pictures over a large area at a higher altitude, only three still photos can be used to generate the mosaic on the investigated solar panel [47]. Contrary, 24 video frames acquired on the solar panel can guarantee more matched key-points due to the constant and consecutive overlap.
Table 3. Comparative evaluation of point cloud between the video-mosaic versus the photo-mosaic.

| Category                | Matched Key-Points per m$^3$ | Matched Key-Points per Solar Module |
|-------------------------|------------------------------|-------------------------------------|
|                         | Testbed 1 | Testbed 2 | Testbed 3 | Testbed 1 | Testbed 2 | Testbed 3 |
| Photo-mosaic            | 26.2      | 21.8      | 14.1      | 54        | 45        | 29        |
| Video-mosaic            | 52.4      | 53.4      | 48.5      | 108       | 110       | 100       |

Figure 3. Differentiated distribution density of matched key-points between solar cells of the photo-mosaic and video-mosaic. (A) photo-mosaic; (B) video-mosaic; (a1,b1) Testbed 1; (a2,b2) Testbed 2; (a3,b3) Testbed 3. Solar panel includes one or more solar modules assembled as a pre-wired, field-installable unit [48]. The typical solar module is the aggregation of solar cells, 60 (6 by 10) or 72 (6 by 12) [1]. The magnified picture (red box) of the photo-mosaic (bottom-left) contains only two matched key-points, while the video (bottom-right) shows ten.

Figure 4 and Table 4 contain the results of the hot spot analysis of SCSTs in Testbed 1 to 3 between the photo-mosaic versus the video-mosaic. Mean z-scores are lower in Testbed 3 (soil debris occupying under 1% of a solar module) and higher in Testbed 1 (soil debris occupying over 80% of a solar module) than other testbeds from both the photo-mosaic and video-mosaic. The results of hot spot analysis exhibit that high values of SCST are clustered on malfunctioned solar cells resulting from soil debris in both the photo-mosaic and video-mosaic (Figure 4). The video-mosaic shows similar mean z-scores (2.04–3.03) to the photo-mosaic (2.22–3.14) from Testbed 1 to 3. This implies that the video-mosaic has similar spatial patterns to hot spots derived from the photo-mosaic. The similarity of the spatial patterns of hot spots is over 90% in Testbed 1 and 3 between the photo-mosaic versus the video-mosaic. Testbed 2 (soil debris taking up under 10–20% of a solar module) shows the lowest similarity as 81%. In Figure 5, we present the magnified portion of the photo-mosaic and video-mosaic with hot spot boundary and in situ photos in Testbed 2. Higher values of SCSTs are well presented on most soil-covered solar cells in the video-mosaic. Higher values of SCSTs are more scattered in the video-mosaic than photo-mosaic (Table 4).
Higher values of SCSTs are more scattered in the video-mosaic than photo-mosaic (Table 4).

Table 4. Results of the hot spot analysis (Getis-Ord Gi*). The similarity is calculated by dividing hot spots by the matched numbers of hot spots between the photo-mosaic and video-mosaic.

| Category                          | Photo-Mosaic | Video-Mosaic |
|-----------------------------------|--------------|--------------|
|                                   | Testbed 1    | Testbed 2    | Testbed 3    | Testbed 1    | Testbed 2    | Testbed 3    |
| Numbers of pixels                 | 809          | 106          | 2            | 767          | 88           | 2            |
| z-score of Getis-Ord Gi*          |              |              |              |              |              |              |
| Min                               | 1.962        | 1.963        | 2.112        | 1.961        | 1.962        | 2.041        |
| Max                               | 6.199        | 5.958        | 2.218        | 5.292        | 5.766        | 2.046        |
| Mean                              | 3.139        | 2.905        | 2.215        | 3.027        | 2.881        | 2.044        |
| SCSTs in hot spots (°C)           |              |              |              |              |              |              |
| Min                               | 69.6         | 68.7         | 70.0         | 70.4         | 69.7         | 70.4         |
| Max                               | 75.8         | 73.3         | 70.4         | 76.3         | 74.1         | 70.9         |
| Mean                              | 71.8         | 70.3         | 70.2         | 72.4         | 71.1         | 70.6         |
| Standard deviation                | 1.03         | 0.95         | 0.21         | 0.98         | 0.97         | 0.26         |
| The similarity of spatial patterns of hotspots between photo-mosaic vs. video-mosaic (%) | 94           | 81           | 100          | 99           | 97           | 100          |

* p-value < 0.05.
Figure 5. Comparison of magnified image and hot spots between the photo-mosaic and video-mosaic. (a1) in situ photo and hot spot boundary detected from photo-mosaic; (a2) photo-mosaic and hot spot boundary detected from photo-mosaic; (b1) in situ photo and hot spots detected from video-mosaic; (b2) video-mosaic and hot spot boundary detected from video-mosaic. See the location of the image in Figure 4.

4. Discussion

Table 5 and Figure 6 show the results of the regression analysis to examine the SCSTs detected common hot spots from both the video-mosaic and photo-mosaic in testbeds. \( SCST_{v1} \) and \( SCST_{v2} \) exhibit strong correlations with \( SCST_{p1} \) and \( SCST_{p2} \) because the Pearson correlation coefficients are higher than 0.98 (0.981–0.991). Moreover, the model fitness values are extremely high at 0.981–0.962. Furthermore, the unstandardized coefficients representing the direction and strength of SCSTs detected from the photo- and video-mosaic is 0.973–1.003, indicating a strongly positive (+) linear correlation. That means that the increases in SCSTs from defective solar cells are likely to point in the same direction. By contrast, the model for Testbeds 2 and 3 has a lower unstandardized coefficient than Testbed 1. Therefore, this indicates that the \( SCST_{v2} \) has higher SCSTS than \( SCST_{p2} \) (Figure 6) [49].
Table 5. Results of the ordinary least squares linear regression with SCSTs (°C) in matched hot spots between the photo-mosaic and video-mosaic.

| Frame Intervals | Testbed 1 | Testbed 2 & Testbed 3 |
|-----------------|-----------|----------------------|
| Numbers of pixels | 762 | 88 |
| Unstandardized coefficient (°C) | 1.003 * | 0.973 * |
| t-statistic | 199.847 * | 46.949 * |
| VIF | 1.000 | 1.000 |
| Pearson correlation | 0.991 | 0.981 |
| R² | 0.981 | 0.962 |
| RMSE (°C) | 0.136 | 0.183 |

*p-value < 0.05; VIF: Variance Inflation Factor; RMSE: Root Mean Square Error.

Figure 6. Scatter plots of SCSTs in matched hot spots between the photo-mosaic and video-mosaic. (a) Testbed 1; (b) Testbeds 2 and 3.

Similar results can be found when testing the null hypothesis that the individual models’ coefficients \((a_i, b_i)\) are zero. To validate the null hypothesis, we calculated the t-statistics and p-values. The p-value denotes the highest error probability at which we cannot reject \(H_0\): “There is no difference between both distributions” against an alternative \(H_a\): “There is a statistically significant difference between both distributions.” Since all p-values are under 0.05, we can reject \(H_0\) based on our data. The identical result holds for the t-statistics: \(\sqrt{n} \times \bar{X} / S\), where \(\bar{X}\) and \(S\) are defined as the sample mean and standard deviation. \(N\) denotes the sample size. Generally, higher t-statistic values indicate that we can reject \(H_0\), that is, that the corresponding coefficients are more likely to be significant. The precise boundary between significance and insignificance depends on the sample size and the Student t-distribution [50]. In Testbeds 2 and 3, the t-statistic values are lower than Testbed 1 (199.847 → 46.949). The RMSE in Testbeds 2 and 3 is slightly higher than Testbed 1 (0.136 °C → 0.183 °C). However, in general, the benchmark of the t-statistic is lower than 3. Hence, the coefficients are statistically significant given the t-statistic values in Table 5.

The distributional similarity of SCSTs in matched hot spots on malfunctioning solar cells caused by soil debris between the photo-mosaic and video-mosaic could present the distributional properties of the recorded observations—both from Testbed 1 and Testbeds 2 and 3. For this purpose, we first must adjust both sets of observations by the mean to account for the temporal recording difference of about 30 min, which is enough to significantly skew the measured temperatures. Let \(a_{ui, b_{ui}}\) denote the \(i\)th temperature observations...
from a photo-mosaic and video the \( j \)th temperature observed using video-mosaic. Then, we consider \( X_i = \text{auto}_i - \text{auto}_j \) and \( Y_j = \text{video}_j - \text{video}_j \).

There are different options to compare the distributional properties. Most methods assume that the underlying observations are Gaussian distributed [51]. A quick look at the histograms (Figure 7) and the skewness values (see Table 6) indicate that all distributions are significantly skewed to the right. For \( n = 20 \) the Testbed 1, we find a histogram correlation of \( \rho_{\text{hist}} = 98.95\% \); for Testbeds 2 and 3, the value lies slightly lower at \( \rho_{\text{hist}} = 90.52\% \). These values vary with the number of bins, but the size stays the same and hence the interpretation: we see very high correlation values close to +1, which indicate that both histograms are highly correlated, i.e., fairly identical.

![Figure 7](image.png)

**Table 6.** Descriptive statistics of the histogram with the mean-adjusted SCSTs in matched hot spots between the photo-mosaic and video-mosaic.

| Testbed | Min  | Max  | Mean | Standard Deviation | Skewness | Kurtosis | \( \rho_{\text{hist}} \) (%) |
|---------|------|------|------|--------------------|----------|----------|------------------|
| 1       | Photo-mosaic | 70.1 | 75.8 | 72.1 | 0.99 | 0.48 | 2.72 | 98.95 |
|         | Video-mosaic  | 70.4 | 76.3 | 72.5 | 0.98 | 0.50 | 2.74 |       |
| 2 & 3   | Photo-mosaic  | 69.2 | 73.5 | 70.6 | 0.95 | 0.96 | 3.18 | 90.52 |
|         | Video-mosaic  | 69.7 | 74.0 | 71.0 | 0.96 | 1.04 | 3.49 |       |

5. Conclusions

This is arguably the first study exploring the tracking capability of soil debris defects between UAV video and photo-mosaic for a single solar cell to the best of our knowledge. Previous literature has not considered the constraints caused by insufficient key-points and data redundancy in thermal deficiency inspection of solar cells as the minimum survey unit for the solar panel. Due to this reason, most previous studies were implemented with autopilot flight focus on evaluating the tracking ability of UAV in the inspection of area-wide solar farms and plants, as a target much wider than a solar cell unit. This study experimentally validated that the video-mosaic can track the solar cell malfunction caused by soil debris at the level of the photo-mosaic in terms of detecting the spatial patterns and distributional property. Furthermore, this study shows that the video-mosaic has good
performance, tracking soil debris defects on the single solar cells with 2.5–3.4 times more matched key-points per solar module than the photo-mosaic. The results of this study can serve as significant evidence for applying video stream to thermal deficiency inspection on single solar cells.

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