Defect Detection in PV Arrays Using Image Processing

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***Abstract*—Renewable energy continues to be an important part of the energy field. New wind, photovoltaic (PV) and hydro plants continue to be installed. Many PV farms have been in operation for years and are exhibiting defects and less efficient operation due to age as well as being constantly exposed to weather conditions, such as rain, ice, cold, heat and hail. In this research image processing operations are applied to PV panels to determine defects or damaged areas/panels. The proposed method can be utilized in real-time to determine the damaged areas and count the number of damaged panels.**

Keywords—renewable energy, image processing, solar panels, photovoltaic, edge detection, morphological erosion, blob analysis.

I. INTRODUCTION

Renewable energy and green technology continue to be fields of interest to the energy sector and governments. Common renewable energy sources include wind, solar, biomass, geothermal, tidal and hydro [1],[2]. Many applications and microgrids include a combination of different renewable energy sources connected to the grid. To improve the design phase, system level modeling can be utilized to efficiently take into account the expected system interfaces, communications and expected constraints and requirements [3]. Generally, more complete system level modeling for a complex system design will lead to fewer redesigns thereby lowering design costs and design time. Increases in energy demand can be modeled using time series analysis to forecast the expected energy needs [4]. With this information, companies can increase renewable energy production and installations to account for the forecasted energy requirements.

Photovoltaic (PV) farms capture solar energy in areas that experience high amounts of sunlight as a renewable energy resource. Many PV farms have been in operation for years and are exhibiting defects and less efficient operation due to aging as well as being constantly exposed to weather conditions, such as rain, ice, cold, heat and hail. With the large number of panels in a typical PV plant, an automated system to detect damage or defects in the panels is needed to efficiently monitor the PV farms. Unmanned aerial vehicles (UAVs) can be utilized to obtain images of the panels in the PV array or plant where many panels are installed. UAVs can image the panels in locations that are hard to access or costly to reach [5]-[7]. Image processing has been utilized in many applications to detect PV damage or solar panel conditions [8]-[11]. Thermal images have been utilized for fault detection in solar panels [8]-[10]. Variations in the thermal images indicate regions of interest which may be indicative of damage to the panels. More recently, visual spectrum images of solar panels have been studied using convolutional neural networks to determine solar panel defects [11].

In this research visual spectrum images are analyzed to determine damaged or defective regions on the panels. The results of this work can then be used to enable the PV plant to replace or service the necessary PV panels. The image processing steps in this research to determine defects in or damage to the solar panels can be performed in real-time. The next section (Section II) summarizes methodology. In this section the image processing techniques used in this research are discussed. Section III Results shows images at various steps in the process to determine panel defects, and provides a discussion of results. Finally, Conclusions are presented in Section IV.

II. METHODOLOGY

Installed PV panels are subjected to weather conditions that can vary from day to day. A major concern is hail storms as hail can damage the panels. In this research image processing operations are applied to PV panels to determine defects or damaged areas/panels. The proposed method is detailed in the following two sub-sections *A and B.*. The steps can be implemented in real-time to determine the damaged areas of the solar panels.

A. Steps to Determine Panels in the PV Array

The following steps were applied in this research to process the images to determine the PV panels in the image. These steps are discussed in more detail in [12].

1. Obtain the visual spectrum image for the PV panel(s); many applications are utilizing drones to accomplish this step. [5]-[7]. The image can be capture in red, green, blue (RGB). In the case of large PV farms, images can be mosaicked to produce an image of the entire PV farm installation if an image of the large array is not possible using the UAV's camera.

2. Determine the region of interest (ROI) for the image and the image is appropriately cropped.

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3. Convert the image into the Hue, Saturation, Value (HSV) space. Convert the image to grayscale.

4. Implement thresholding to binarize the image. This will remove some image artifacts that are not part of the solar panels. The resulting image is then filtered.

5. Apply morphological erosion operation to separate the solar panels in the image. Remove other unwanted artifacts from the image outside the ROI.

6. Detect blobs in the image and determine bounding boxes.

7. Apply area thresholding to the image to remove any other artifacts.

8. Fill in holes.

9. Determine number of PV modules.

B. *Steps to Determine Damaged Panels in the PV Array*

The following steps were applied in this research to process the images to determine damaged areas of the PV panels. These steps are discussed in more detail in [12].

1. Obtain the visual spectrum image for the PV panel(s).

2. Determine the region of interest (ROI) for the image and crop the image appropriately.

3. Convert the image to grayscale.

4. Perform nonlinear edge detection using Kirsch operator

5. Apply morphological erosion operation to separate the solar panels in the image. Remove other unwanted artifacts from the image outside the ROI. The image is then binarized in order to be utilized by the blob detection. Filtering is applied to remove image artifacts.

6. Detect blobs in the image and determine bounding boxes. Next, determine borders for damaged areas.

7. Implement area thresholding. This will remove some image artifacts that are not part of the solar panels. The resulting image is then filtered.

8. Fill in holes.

9. Determine number damaged PV modules

C. *Image Processing Operations*

For the determination of cracks in the solar panel as well as other damage detection, common image processing operations such as thresholding, erosion/dilation and edge detection were performed. The panel images were first inspected to determine regions of interests (ROIs). The image processing steps to determine the PV panels in the PV array and the damaged areas of the PV panels in the PV array are listed in the previous section. Partial panels on the edges of the image are removed during image processing.

For the damage detection algorithm, the edge detection technique, namely Kirsch edge detection, was utilized. The Kirsch edge detection determines the intensity q_k in the *kth* direction [5]. To simplify the calculations, masks (M_1 - M_4) for only diagonal directions at 45º, 135º, 225º, 315º are used as defined in [5]:

$$M_1 = \begin{pmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{pmatrix} \qquad M_2 = \begin{pmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{pmatrix}$$

$$M_3 = \begin{pmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{pmatrix} \qquad M_4 = \begin{pmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{pmatrix}$$

and the edge intensity, q_k, in the k^{th} direction is found by Eq. (1), as defined in [5]:

$$q_k = M_k I_n(i,j), \tag{1}$$

where I_n is the 3x3 matrix centered at pixel (i,j) in the gray-scale image. At each pixel *(i,j)*, the corresponding maximum edge intensity, *S(i,j)*, is determined by Eq. (2) as in [5]:

$$S(i,j) = \max\{q_k\}$$

For the other common image processing operations such as thresholding, erosion and dilation utilized in this research, please refer to [13] for more details.

III. RESULTS

The following images, Figs. 1-7, resulted from applying the Steps 1-9 in *Section II - A*. Fig. 1 shows the original image, extracted and adapted from [14], with the damaged PV panels after cropping. The cropped image is then converted to hue, saturation and value (HSV) color space, which is shown in gray scale in Fig. 2.

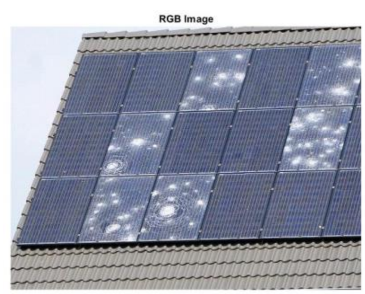

Fig. 1. Input Example Image of PV Panels with Hail Damage, cropped from the image in [14]

Thresholding is then applied for a two-level segmentation to obtain a binary image, as shown in Fig. 3. Binarizing the image will remove some image artifacts that are not part of the solar panels. After the application of morphological erosion operation to separate the solar panels in the image, Fig. 4 is obtained. Fig. 5 is the resulting image after area thresholding is applied.

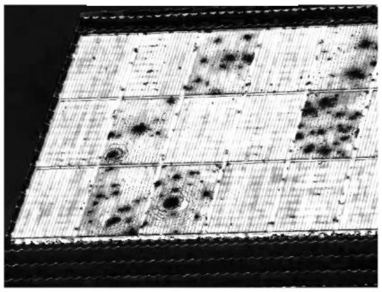

Fig. 2. Image of Damaged PV Panels Converted from RGB to HSV, Represented in Gray Scale Color Map

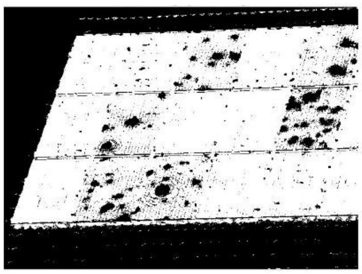

Fig. 3. Binarized Image of Damaged PV Panels

Fig. 4. Erosion Applied to Image of Damaged PV Panels to Demonstrate Panel Separation

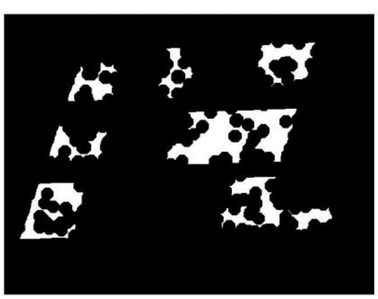

Fig. 5. Area Thresholding Applied

Fig. 6 is the resulting image after filling in holes. The detected panels in the image are then shown in Fig. 7. Nine PV panels that are not damaged are detected. Partial panels on the edges of the image were removed during image processing and are not included in the determined number of PV panels.

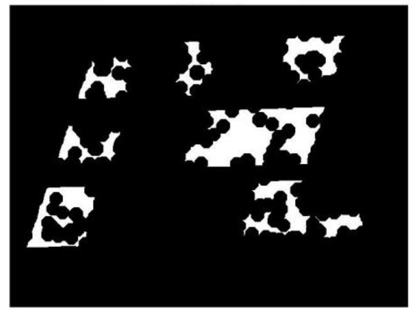

Fig. 6. Holes Filled In in Image of Damaged PV Panels

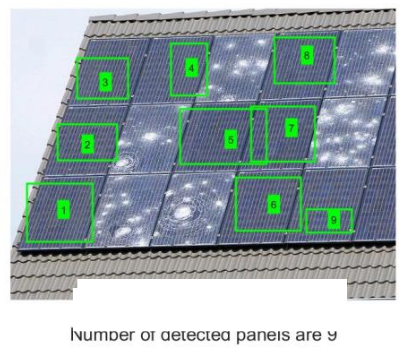

Fig. 7. Detected Undamaged PV Panels (total 9) (image adapted from [14])

The following images, Figs. 8-16, resulted from applying the Steps 1-9 in *Section II - B.* Fig. 8 shows the original image with the damaged PV panels after cropping. This is then converted to grayscale as seen in Fig. 9.

Fig. 8. Input Example Image of PV Panels with Hail Damage, cropped from the image in [14]

The Kirsch edge detection is then utilized to determine the edges in the image as seen in Fig 10. Using this image, morphological erosion operation is used to separate the solar panels in the image as seen in Fig. 11. Thresholding is then implemented to binarize the image. The resulting binary image is depicted in Fig. 12. The image in Fig. 12 is next filtered to remove noise. The filtered image is shown in Fig. 13.

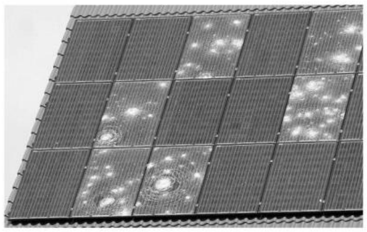

Fig. 9. Grayscale Image of Damaged PV Panels, converted from Fig 8.

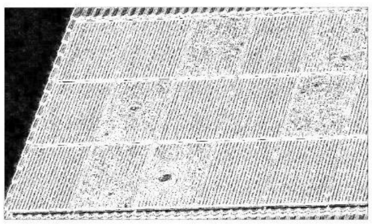

Fig. 10. Edge Detection in the Image of Damaged PV Panels using Kirsch Operator

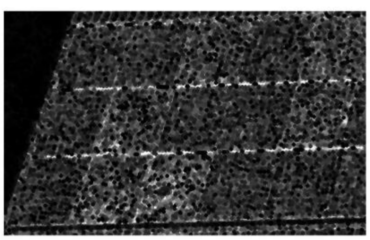

Fig. 11. Morphological Erosion Applied to Image of Damaged PV Panels

Fig. 12. Binarized Image after Morphological Erosion

Fig. 14 is the resulting image after area thresholding is applied. Holes are filled in as seen in Fig. 15. The detected damaged panels in the image are then shown in Fig. 16. Five damaged PV panels are detected. The image shows six panels are damaged. The algorithm grouped three damaged panels as one group and identified one damaged panel as two. All damaged panels were detected although the total number of individual damaged panels is not correctly determined in the tested image.

Fig. 13. Filtered Image Reducing Salt and Pepper Noise

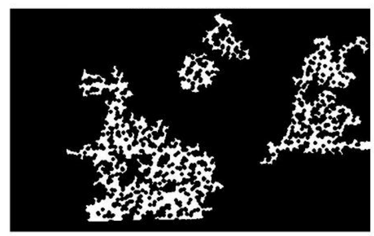

Fig. 14. Area Thresholding Applied to Filtered Image of Fig. 13

Fig. 15. Image of Damaged PV Panels after Filling in Holes

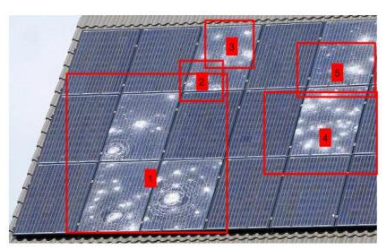

Fig. 16. Detected Cracked PV Panels (image adapted from [14])

Another example for detecting damaged PV panels from an RGB image using the methods described in this research is shown in Fig. 17. Eight damaged PV panels are detected by the algorithm which matches the total number of damaged panels in the image. The algorithm however has erroneously grouped some damaged panels as one group as in group 7 and identified some damaged panels as two separate damaged panels. Even then, all damaged panels were detected in the image. Although the total number of individual damaged panels is correct, the detection of individual damaged panel needs further testing and refinement to correctly identify individual panels in cases with large amounts of damage on adjacent panels.

Fig. 17. Detected Cracked PV Panels (see [12]; original image adapted from [15])

IV. CONCLUSIONS

The proposed algorithms for determination of photovoltaic panels and cracked or otherwise damaged photovoltaic panels from visual spectrum images were evaluated to determine the efficacy of the proposed methods. The results demonstrate that the methods can be applied effectively to RGB images, but may generate errors due to various issues, such as reflections, shadows, panels being occluded by dirt, snow or rain, or adjacent panels exhibiting so much damage that the proposed methods erroneously group adjacent damaged panels into a larger group.

Future work entails improving the detection accuracy of individual damaged panel in cases with large amounts of damage on adjacent panels. The uniform dimensions of the panels will be used as a constraint to improve the results. The work can also be extended by registering thermal images with the visual images to detect hotspots. The proposed method can be utilized in real-time to determine the damaged areas and count the number of damaged panels. In addition, an image database will be developed for more extensive testing. Finally, the proposed algorithms for PV defect detection will be compared with other methods such as convolutional neural networks.

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