2017 8th International Conference on Information Technology (ICIT)

Fault Detection in Photovoltaic System Using SLIC and Thermal Images

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***Abstract* - Solar energy has been gaining a strong momentum as the future clean and renewable source of energy. Optimum utilization of this energy propelled research efforts into many areas of the solar energy system such as photovoltaic (PV) where significant improvement will lead to better systems' efficiency. PV systems operate without any supervisory mechanism but they still can have many faults internally and/or externally hindering its efficiency. In this work, we are focusing on creating a framework for automating defect detection in a solar energy system using thermal imaging to create an accurate and a timely alert system of hazardous conditions. We are proposing to use Simple Linear Iterative Clustering (SLIC) Super-pixel technique as technique for hot spot detection. Experimental results show that the hot spots in the solar panels can be accurately detected using infrared images using SLIC, in a real time implementation. Detection results will give alerts as to where the solar panels may not be working under normal conditions.**

Keywords—Solar Panels; Fault detection; SLIC Super-Pixel; Thermal images.

1. INTRODUCTION

Solar energy has been utilized since the 1950s mainly to generate power for businesses, homes, and fuel technology. The most popular type of solar energy system is Photovoltaic (PV) based as shown in Fig. 1. The solar cells in the PV are connected in series allowing control on output voltage or in parallel with more control on output current. The serial connection between the solar cells in the PV module has a drawback because when one of the cells is damaged, the performance of the PV panel will be reduced [1]. Solar cell efficiency is divided into four individual efficiencies; thermodynamic, reflectance, charge carrier separation, and conductive efficiency. The product of each of these efficiencies is the overall efficiency [2]. In order to enhance efficiency, it is very important to detect a fault as soon as possible to minimize harmful impact and save energy and money.

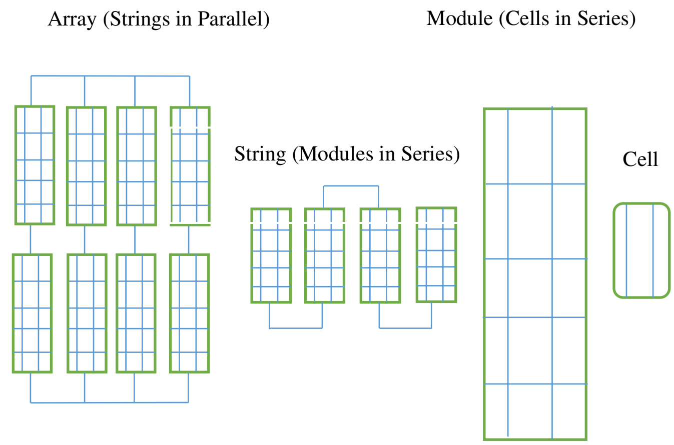

Fig. 1. Solar PV Configurations, Cell, Module, String, and Array

Faults in a solar panel can occur for a variety of reasons and they canbe referenced as hot spots. Some of the known reasons are having, defects in the anti-reflective coating, bubbles in the solar modules, delamination over cells and interconnections, protruding interconnections, and browning and yellowing [3]. The faults inside PV arrays usually cause an overcurrent causing heat and damages to PV components [4]. There are three types of faults in PV arrays; these are the line-line fault, open circuit fault, and ground fault. A line-line fault occurs when an accidental connection goes through a low resistance path between two points in the solar panel [4]. A line-line fault may occur between two adjacent strings or between two points on the same string, during open fault, or Arc fault, a current might be established due to insulation breakdown in the Current Carrying Conductors (CCC) [5]. Open fault is generated in CCC from cell damage, rodent damage, solder disjoint, or corrosion of connectors. The ground fault generates an accidental low impedance path between the ground and one of the CCCs. Using a Ground Fault Detection Interrupt (GFDI) device helps to detect the ground faults and interrupt the fault current [5]. However, the solar panel may also have other sources of electrical faults, such as the shunting in cells, erroneous bypass diode functionality, reverse-biased heating, high series resistance, nonlinear weak diode, or resistive solder bonds [6-8]. Once the fault is detected in its earlier stage, the power consumption and the efficiency can be improved by taking the appropriate action and prevent any further damage such as fire or any other electric dangers that may arise and comprise safety. In this paper, we propose to use infrared images to automate fault detection in solar panels. Infrared imaging technique has a proven record in non-destructive testing, such as in detection of defects within building walls, faulty engines, plastic manufacturing quality control, and many other detection problems in industrial applications and electrical systems. This is because of the warm objects with a temperature above absolute zero can produce infrared radiation because there is no molecular and atomic activity at absolute zero [9].

II. BACKGROUND

Current characterization techniques help to identify problems in photovoltaic cells; these techniques include infrared thermal imaging (IR), photoluminescence imaging, and electroluminescence imaging (EL). Problems caused by high series resistance, linear shunt defects, nonlinear weak diodes, and radiative and non-radiative recombination centers can be identified using the current characterization techniques [8]. Thermal imaging techniques are used for solar cells inspection where temperature-sensitive polymer-dispersed cholersteric liquid crystal foils covered the solar cell whose shunts can be localized by detecting the temperature variations in reverse-bias [10]. In 1998, fluorescence microthermography (FMT) is the same technique which can be used to locate hot spots in circuits and devices. FMT is based on the efficiency of the temperature-dependent luminescence of rare earth chelate dyes [10]. In 2000, a survey of the infrared imaging applications was done for shunts in solar cells, such as reverse-bias heating, resistive solder bonds, by-pass diode functionality, and other component defects [10]. In 2001, non-destructive testing was done using infrared methods, for example, IR sensor and optics, thermal emission, and imaging and analysis for response to thermal excitation and heat sourcing probing [10]. In 2002, the cracked solar cells were inspected by thermographic imaging [10]. In 2011, the IR camera was used in the field to monitor the solar module’s performance [10]. Infrared images can localize the shunting in cells, bypass diode functionality, hot spots in modules, batteries during charging, and temperature of electronic components [7].Gao et al proposed a method for defect detection and solar panel recognition using infrared images; their proposed method is based on recording a video sequence, the camera mounted on a cart [11]. The infrared video is first collected for each array of solar panels; the image processing segments the solar panels. Optical flow is used to establish frame-to-frame association which helps to count the number of panels with any given array. They recognize the panels using Hough Transform (HT); once the edge is extracted from the incoming frame, the lines can be detected [11]. The DBSCAN clustering was used to detect the hot module by comparing it with its neighbours. The local defects can be detected using the adaptive thresholding by comparing its value with the value of the mean added to the multiplied standard deviation value. The comparison based on any sample having a mean larger than a threshold will be considered abnormal spot [11]. The drawbacks of the Gao et al method is the following: the top row is missed and the first column of an array cannot be recognized. Then the image has a bad registration from optical flow and the algorithm is highly dependent on the image registration by optical flow [11]. Tsai et al used Independent Component Analysis (ICA) basis images to detect defective solar call sub-images of a large solar module using Electroluminescence EL image[12]. The defects are presented as a dark spot in EL images, for example, breaks, finger interruptions, and micro-cracks. These defects have been detected using EL images. Tsai et al used two approaches based on ICA. The first one is based on the cosine distance of future vectors between all training samples and the test image. The minimum cosine distance is considered as a discrimination measure [12]. The second approach is based on the reconstruction error between the test image and the reconstructed image. The drawback of the Tsai et al method is that it is considered to detect only the global approach. This method cannot classify the local defects. Tsanakas et al proposed the use of standard thermal image processing and the Canny edge detection. This method proposed for module-related faults that have a hot spot heating. The main objective was the applicability of thermal image processing and edge detection to detect the defective PV modules. The proposed method did not classify the fault types. Another limitation is the unwanted grey-level variations that caused by any specular object present in the background, which conflicting with the actual variations related to hot spots, and thus the false alarm will take place. There are further limitations referring to emissivity uncertainties [13].

III. PV FAULT DETECTION SYSTEM USING THERMALDATA

The proposed framework is shown in Fig. 2, thermal images have been taken for different defectsin solar panel. These thermal images are the input data for the Simple Linear Iterative Clustering(SLIC) super-pixel algorithm in order to determine the defected regions in the solar panel.

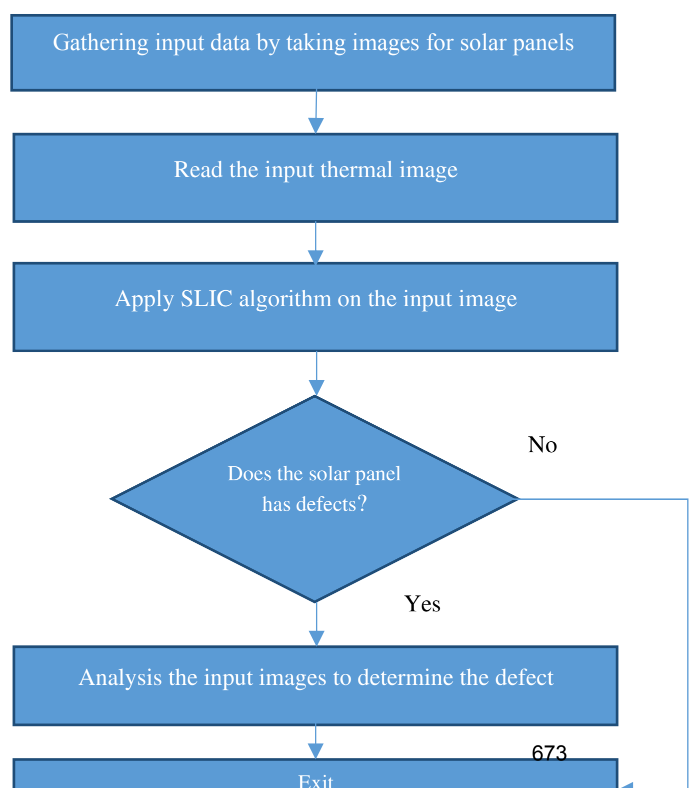

Fig. 2The proposed framework using SLIC

The SLIC super-pixel technique is based on a spatial localization of K-mean clustering version. SLIC is an excellent tool for decomposing an image into small homogeneous regions, that is to locally group pixels and thus to provide a perceptual understanding of content [14]. Super-pixel reduces the complexity of the images from hundreds of thousands of pixels to only a few hundred [14]. SLIC may include a pre-processing phase including Gaussian smoothing filter to minimize outliers that would skew the results. Achanta et al proposed a SLIC algorithm to efficiently generate superpixels [15]. Fig. 3 shows the main steps for SLIC algorithm. The main parameter of the SLIC algorithm is the desired number of approximately equally-sized superpixels$k$[15]. the first step in SLIC is initializing cluster centers$C_k$by sampling pixels at regular grid step using (1), where N is the number of pixels. In the next step, the cluster is moving to seed location, to the lowest gradient position in 3x3 neighborhood. For each pixel in the 2Sx2S region around C_k for each cluster center, the distance is computed between the pixel and the cluster center using (2).

$$S = \sqrt{\frac{N}{k}} \qquad (1)$$

$$D = \sqrt{\left(\frac{d_s}{S}\right)^2 m^2 + \left({d_c}^2\right)} \qquad (2)$$

SLIC corresponds to clusters in *labxy* color space [15], which means the spatial distance and color distance should be calculated using (3) and (4) respectively. The two distances are combined in (5) in order to normalize spatial proximity and color proximity by their respective maximum distances with a cluster, N_s and N_c.

$$d_s = \sqrt{\left(x_j - x_i\right)^2 + \left(y_j - y_i\right)^2} \qquad (3)$$

$$d_c = \sqrt{\left(l_j - l_i\right)^2 + \left(a_j - a_i\right)^2 + \left(b_j - b_i\right)^2} \qquad (4)$$

$$D' = \sqrt{\left(\frac{d_s}{N_s}\right)^2 + \left(\frac{d_c}{N_c}\right)^2} \qquad (5)$$

The expected maximum spatial distance $N_s$within a given cluster should equal to the sampling interval S. The maximum color distance N_c is considered as a constant value m in (2) because the color distance can vary from image to image and cluster to cluster [15]. Once the pixel is assigned to the nearest cluster, the new cluster centers will be computed and recalculate the distance until the residual error between the new cluster center and the previous cluster center is less than threshold value.

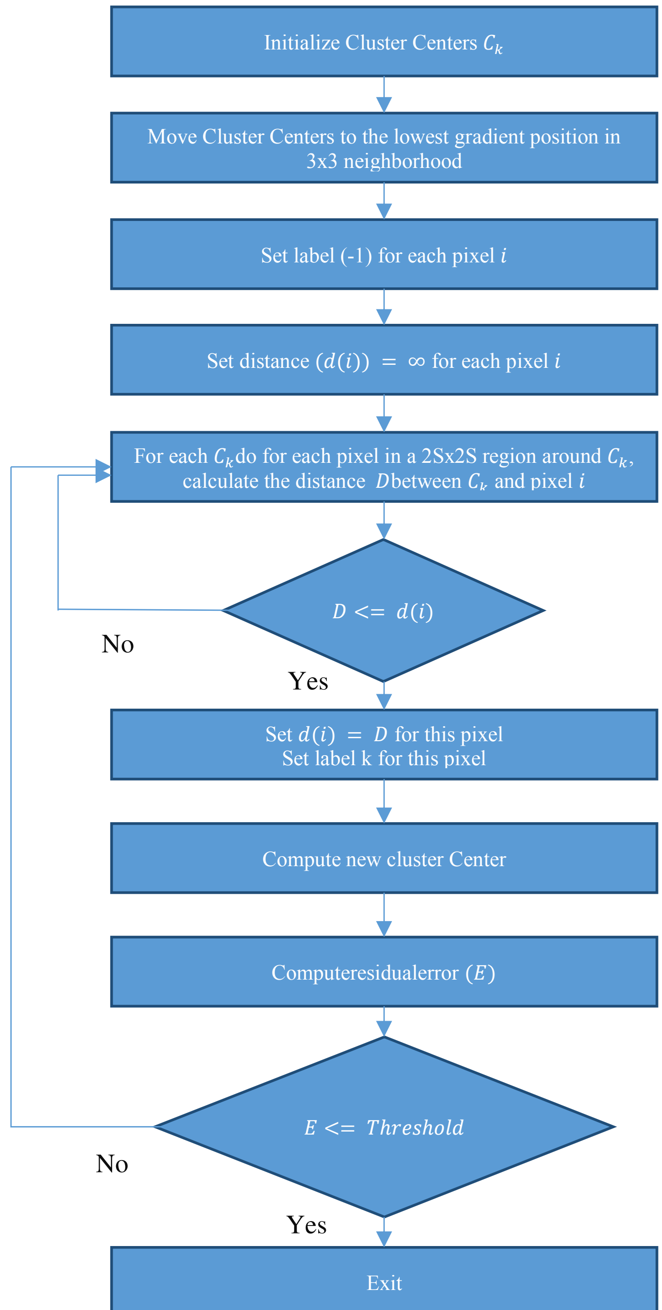

Fig. 3. SLIC Super-Pixel algorithm

VI. EXPERIMENTAL RESULTS

To validate our proposed work, we used images from the solar panel in the Digital Image and Signal Processing (DISPLAY) lab at Western Michigan University (WMU) for different defects, our solar system composed of two panels of SUNIVA OPTIMUS 60 Cell modules (Model OPT285-60-4-1B0); each panel produces 285 W.Some images have been capturedfor the solar panel at the main campus of WMU. The camera we used is FLIR Vue Pro with resolution of 336x256 pixels. This resolution is high enough to show an accurate thermal resolution from the solar panels. The input data were processed using the Python 2.7 on the Eclipse IDE platform. Python was installed on Windows 10 environment, and other modules, extensions and libraries were installed using pip command, for example, skimage, NumPy, and matplotlib. Python provides multiple modules for image processing in which used OpenCV. We also used Windows 10 Home, Intel(R) Core(TM) i5-4210M CPU @2.60 GHz with 8 Giga Byte RAM to implement offline system.SLIC was implemented to detect the hot spots in the solar panel. The thermal image in Fig.4 (a) shows the two solar panels system in DISPLAY lab at WMU. The panel on the left is healthy while the second one is defected. We have imposed an external defect by placing a Polystyrene behind the panel, on the sides causing heating to take place as hot spots. The hot regions are surrounded with big areas for the input image in (a), 50 segments in (b), 150 segments in (c), and 500 segments in (d).

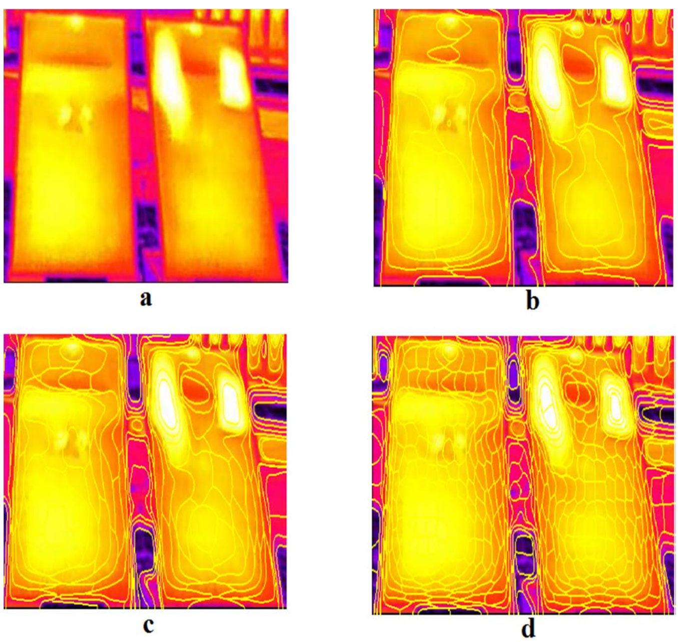

Fig. 4. WMU healthy and defective solar panels by polystyrene: (a) installed solar panel in DISPLAY Lab at WMU, (b) SLIC output for 50 segments, (c) SLIC output for 150 segments, (d) SLIC output for 500 segments

External defects have been applied on our solar panel system in DISPLAY lab. The first defect was an Adhesive paper; it is used to write WMU on the panel glass. Fig. 5 shows how the defects have been detected using SLIC algorithms for different segment sizes. WMU's letters are surrounded with regions using different sizes of segments. In Fig. 6, we show the thermal images for the solar system in DISPLAY lab. A piece of gum was placed on the solar panel glass to mimic a small external defect; this defect is marked by (D1) in Fig. 6. This defect has been detected as shown in Fig. 6. In the same experiment, a small piece of Polystyrene behind the panel is placed behind the solar panel; this defect is represented by (D2) in Fig. 6. You can observe that the Polystyrene glued at the back of the panel has been detected.

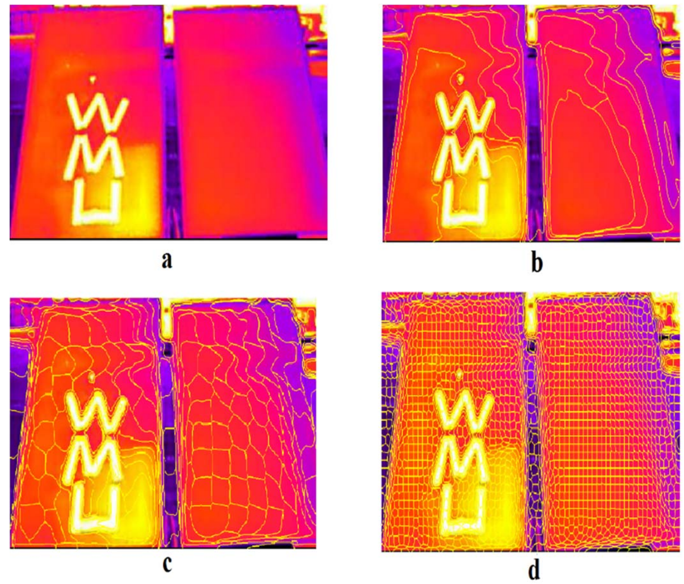

Fig. 5. WMU healthy and defectivesolar panels by adhesive paper: (a) Installed Solar panel in DISPLAY Labat WMU, (b) SLIC output for 20 segments, (c) SLIC output for 200 segments, (d) SLIC output for 2000 segments

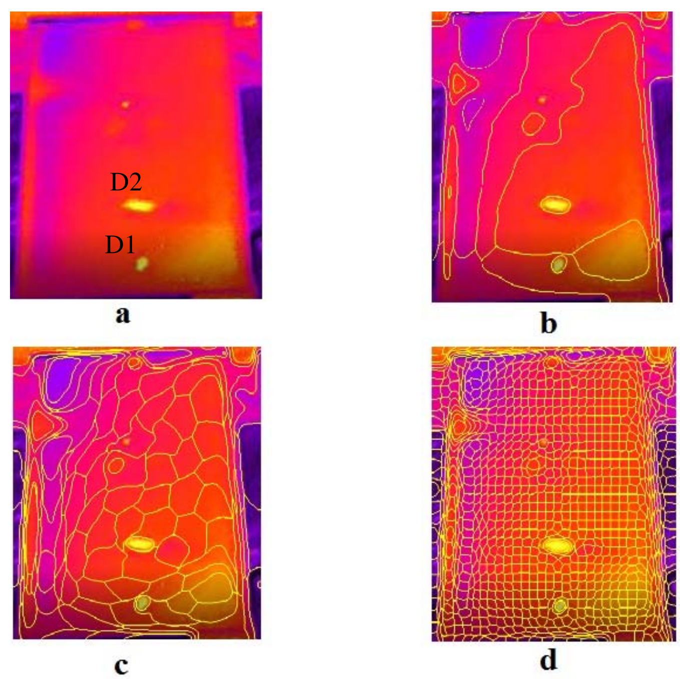

Fig. 6.Smalldefectsby gum and polystyrene: (a) input image, (b) 10 segments, (c) 100 segments, (d) 1000 segments.

Fig.7 shows defectiveregions in one of the solar panels in the main campus of WMU. The defective areas in the solar panels are segmented in regions using SLIC algorithm for different size of segments. The hot regions are surrounded with big areas.

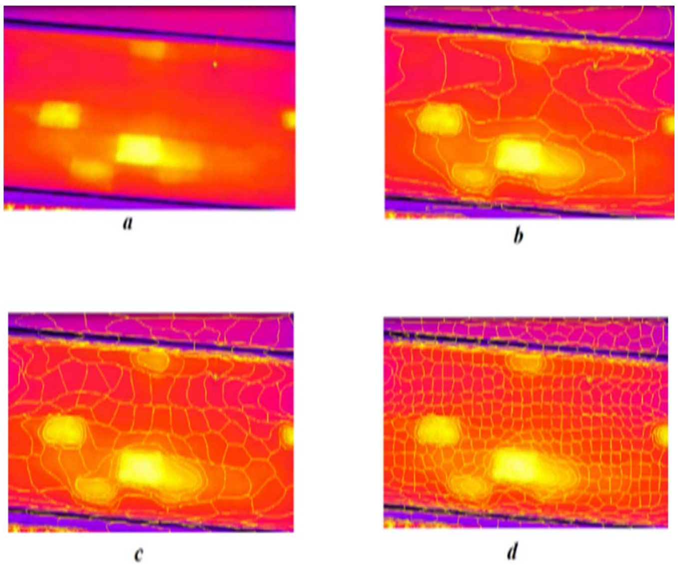

Fig.7.Hot spots detection in solar panel using SLIC Super-Pixel: (a) input image, (b) 50 segments, (c) 150 segments, (d) 500 segments.

V. CONCLUSION

A fault detection framework is proposed in this paper to detect the defects within a solar panel using thermal images. The detection algorithm is based on SLIC Super pixel where the hot spots regions are surrounded with clusters. The importance of using this algorithm is to automate the fault detection process that saves maintenance time for the solar panels, saves the power production and efficiency of the solar panel system, and protects the surrounding places in the solar garden from any further danger such as a fire. Results are very significant in terms of detection accuracy and real-time implementation of this framework is in progress.

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