A Short Analysis of Feature Extraction in Electroluminescence Images of Photovoltaic Module Cells

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Abstract
There has been an exponential increase in the use of photovoltaic (PV) systems, most notably, the photovoltaic solar panel or solar cell. This naturally gives rise to the difficulties of operation and maintenance. With the combined use of unmanned aerial vehicles (UAV) and electroluminescence (EL) imaging, detailed aerial imagery of the PV systems may be collected and inspected for defects. The analysis of these images is a tedious and expensive manual process that can be alleviated by machine learning. An automated approach makes monitoring and upkeep of PV cells feasible.

Goal:
Using a collection of images that convey high spatial resolution, employ a suite of image processing and feature detection / description techniques to produce accurate and cost effective feature extraction.

Keywords
Data Mining — Photovoltaic — Electroluminescence — Feature Extraction — Edge Detection — Solar Fault — Image Processing

Contents

1. Introduction

The increasing role of solar power in the realm of renewable resources has led to noticeable growth in the use of photovoltaic plants. These systems are designed to require large geographical scale and dispersed location placement. Naturally, manual inspection of these units through visual assessment and direct measurement can be prone to error, increase cost or not physically possible. Two pieces of technology may be married to solve this issue of intense nurture at such a large scale. First, the infrared (IR) and electroluminescence (EL) imaging both have been established as non-destructive technology with the means to capture high resolution photographs for fault detection. Secondly, unmanned aerial vehicles have proved extremely useful in civil areas, for example, power line inspection. In conjunction, UAV fitted with high performing EL imaging can take accurate and descriptive photos that not only will make locating defective cells less labor intensive but also create vast datasets upon which models may be fitted to more accurately classify defective cells. Figure 1 shows the angles at which the drone (UAV) would capture the imagery of the PV cells [1].

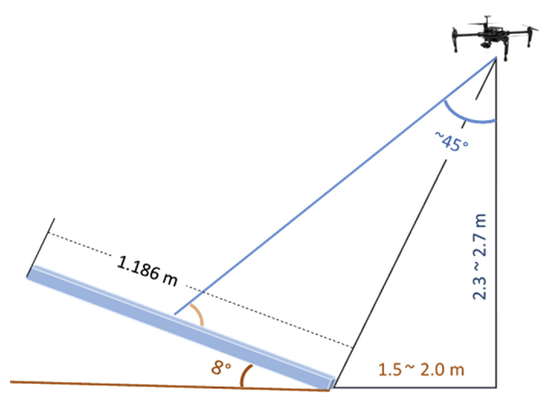

Figure 1. Positioning of UAV with respect to solar panels.

1.1 Data Overview

The dataset consists of high resolution EL images extracted by the means previously described. The dataset contains 2,624 samples of 300x300 pixels 8-bit grayscale images of functional and defective solar cells with varying degree of degradations. These images were extracted from 44 different solar modules. The defects in the annotated images are either of intrinsic or extrinsic type and are known to reduce the power efficiency of solar modules.

All images are normalized with respect to size and perspective. Additionally, any distortion induced by the camera lens used to capture the EL images was eliminated prior to solar cell extraction.[**2**; **3**; **4**]

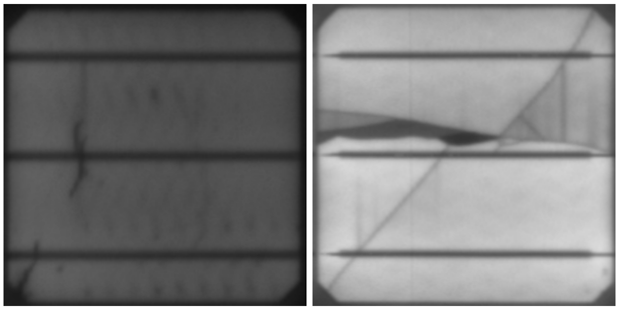

Figure 2. sample images(300x300)

Every image is annotated with a defect probability (a floating point value between 0 and 1) and the type of the solar module (either mono- or polycrystalline) the solar cell image was originally extracted from.

1.2 Outline

The remainder of this paper is organized as follows. Section 2 presents the different approaches to feature extraction and image processing. Due to time constraints sections 3,4 and 5 will be completed at a later date. Section 3 discusses related work on the topic. Section 4 evaluates and discusses results and lastly, Section 5 concludes this paper's findings. Sections may be swapped and improved upon in later iterations.

2. Computer Vision

Each solar panel module is broken down into its individual cells. This focuses the analysis to the smallest meaningful unit of the PV interconnected system. As described in the introduction, images with lens distortion impairments were removed and all images may be assumed normalized in size, that being 300 x 300 pixels EL images. This is a previously cleaned dataset and other sets, either downloaded from a repository or collected on site, should not be expected to mirror the aforementioned set.

The general approach to identifying the most potent feature vector is as follows: given a small set of images that represent the whole, apply an array of feature detection methods to create a baseline for performance. Next apply masking techniques to highlight different attributes and reapply the feature detection methods. Compare and contrast against the baseline to conclude if a more accurate feature vector was achieved.

The mask transformations include: Canny Edge Detection, Histogram Equalization and Hough Line Transformation.

The feature detection methods include: Features from Accelerated Segment Test (FAST), Harris Corner Detection and Oriented FAST and Rotated BRIEF (ORB). The methods SURF and SIFT were not used in this experiment as their patent prevents them from use in the current version of OpenCV.

2.1 FAST

The FAST algorithm begins by selecting a pixel, ***p***, which is to be identified as an interest point or not. The pixel is a corner if there exists a contiguous set of points, ***n***, around ***p*** in which all are brighter than ***Ip + t*** or all darker than ***Ip - t***. This process is iterated upon for all pixels in the image. To maintain performance, if at least three of the four-pixel values ***I1, I5, I9, I13*** are not above or below ***Ip + t***, then *p* is not an interest point (corner).[**5**]

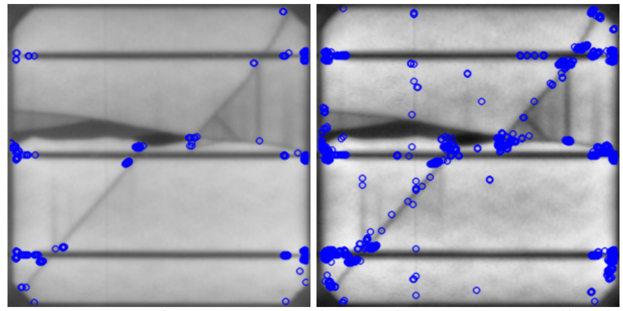

Figure 3. Left: No Mask, Right: Histograms Equalization

It can be seen that FAST easily locates and denotes the most damaged part of the cell. This is in part due to the plethora of brighter cells surrounding the cite in question. The draw back of the algorithm can be seen directly to the left of the damaged center. Though it is clear shattering has occurred here as well, no pixels have been marked as points of interest. This is due to the large amount of dark pixels within the cracked cell and the large amount of bright pixels outside of the crack. These pixels offset the necessary ***n*** contiguous points needed for either the ***Ip + t*** or ***Ip - t*** to be true.

The same phenomenon can be seen on the image on the right in the same area. However, this image has had the Histograms Equalization mask applied in which, while taking into account the neighboring pixels' brightness, the contrast of the image has been heightened. The difference is readily apparent. In general, the many thin lines, representing cracks in the cell, have been identified, most notably the large horizontal crack spanning the entire image. Overall, the feature vector of this image better represent the condition after the histograms equalization mask was applied.

2.2 Current Conclusion

Unfortunately, due to time constraint, the written report of these experiments is not yet complete. However, the Jupyter notebook that was used to explore the feature extraction and masking transformations is available to view and download at your convenience: CLICK HERE

Citations

OpenCV Documentation

Full list of citations is include in biblio.txt