Design and Evaluation of a Machine Vision System for Identifying Cracked PV Panels

Jerome Wynne

July 7, 2017

1 Problem Description

This work developed a system for automatically identifying cracks in PV panels from their 2D grayscale computed tomography images. 50 images were provided, of which 38 were deemed to be cracked. Several of these images are shown in Figure 1. The median

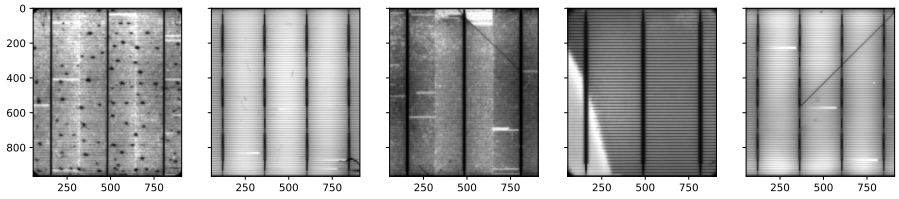


Figure 1: Scans of the PV panels that were analyzed for damage. The first, third, fourth, and fifth panels from the left contain cracks. Pock-marks similar to those seen on the first panel were not regarded as cracks.

frame height for these images was 965 pixels; their width was similar.

The criteria for labelling a given mark as a crack were as follows:

- A dark line propagating diagonally for at least 50 pixels
- Was no more than 15 pixels in width (transverse to crack axis, see Figure 2

As can be seen in Figure 3, it was sometimes difficult to ascertain whether a given mark was a crack or a scratch. For the purposes of this work, the latter were considered to be fainter and wigglier - heuristic measures in the absence of any conveniently quantifiable differences. The labels themselves consisted of manually drawn binary masks, an example of which is shown in Figure 4. Each pixel in a mask was in effect indicators representing whether the associated image pixel was part of a crack. The masks were validated by a panel inspector. The centers of thick cracks were not labelled on the basis that they were too similar to other dark regions in the images (such as the vertical and horizontal bars).

Desirable properties of this sytem

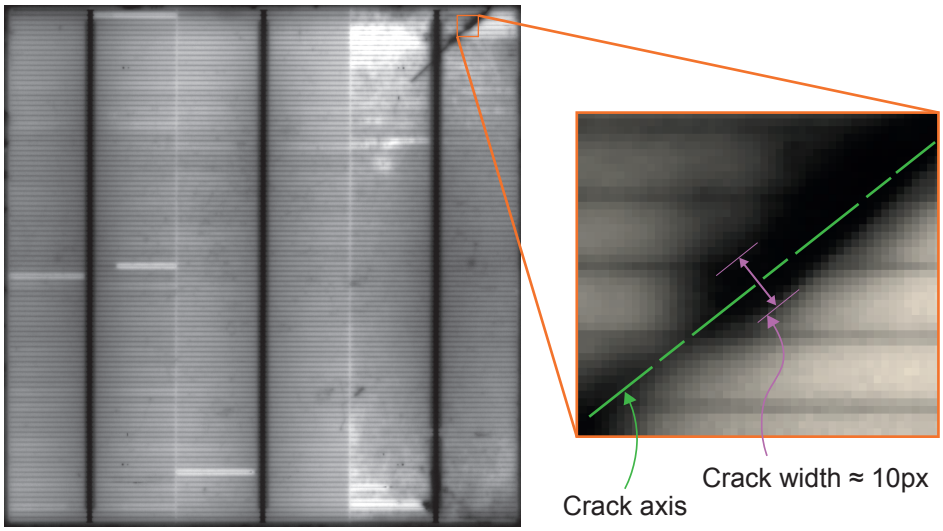


Figure 2: Crack anatomy.

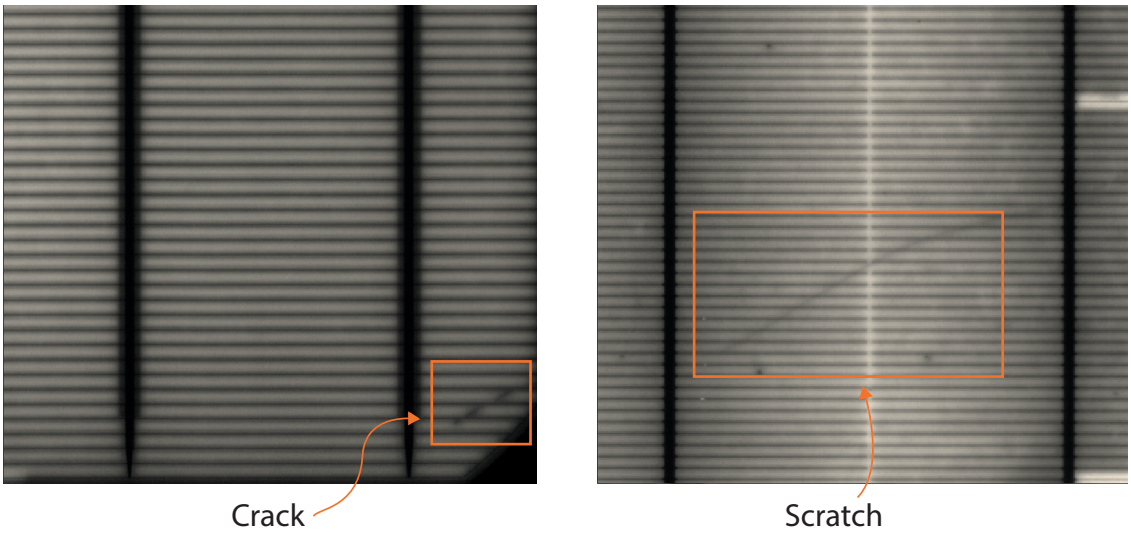


Figure 3: Distinguishing between cracks and scratches was difficult in certain cases, making ground truth labels somewhat subjective.

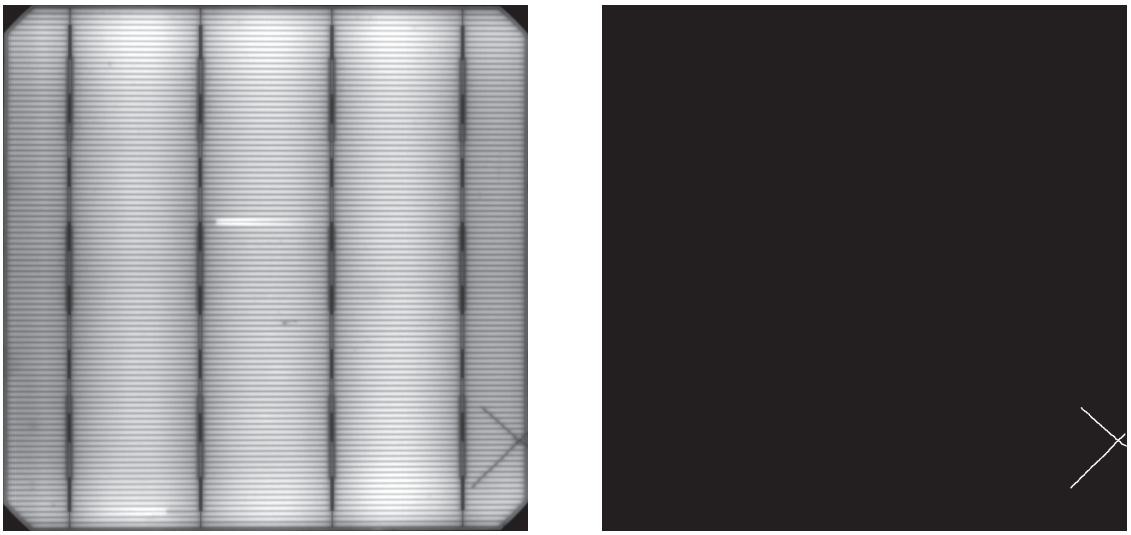


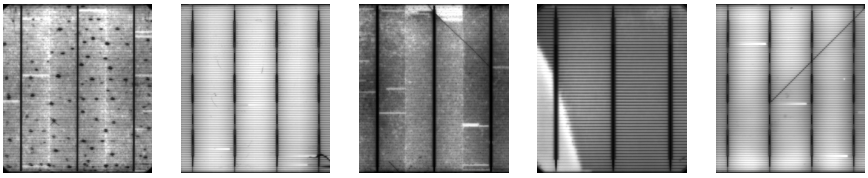
Figure 4: A panel image and its associated set of labels.

1.1 Pre-Processing

Various filters were applied to the images in an attempt to emphasize cracks or suppress other features.

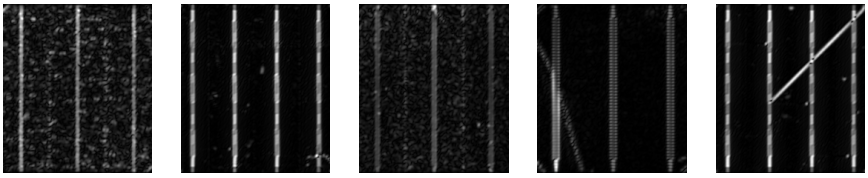
The most successful was as follows:

1. Invert.
2. Vertical Sobel filter.
3. Gabor filter differencing.

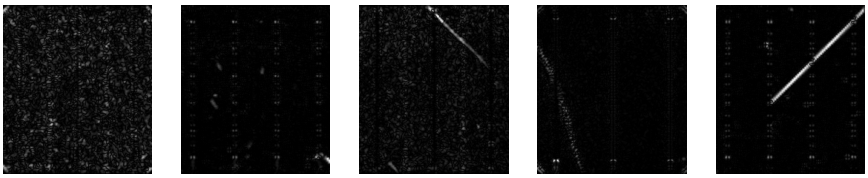


(a) Raw images.

(b) Vertical Sobel filter.



(c) Vertical Sobel filtering followed by a Gabor filter.



(d) Vertical Sobel filtering followed by a difference of two Gabor-filtered images.

(e) Original image masks (i.e. ground truth).

Figure 5