Using DFT to find Defects in Solar Cells Through Image Processing

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1 Introduction

Our experiment utilizes discrete fourier transform (DFT) to analyze the defects found in solar panels. Given the repetitive nature of the glass layer on a solar panel, one could utilize DFT to find potential defects on the glass shield of the solar panel. We would expect a uniform wave from the DFT given a uniform panel, so given any irregular occurrence were to appear in our wave, we would have derived a defect.

1.1 Engineering Application and Societal Need

Our experiment uses discrete Fourier transform (DFT) to analyze the defects found in solar panels. As we move more into renewable energy and solar panels, it is important for us to automate checking solar panels for defects to reduce the time and labor intensive work of doing it ourselves. Automating this process also means that we can spot smaller irregularities than just seen by the human eye. It is important to detect these defects because undetected micro-cracks in photovoltaic glass can propagate into electrical hot spots, reducing panel efficiency, shortening operational lifetime, and increasing maintenance costs for large-scale solar installations.

1.2 Key Decisions

In order to create this algorithm, engineers have to have a good understanding of how images are going to be taken and centered so that a bad image doesn't immediately read as a defect. We are assuming periodicity and regular structure in both the image and in the solar panel glass. We are also making the decision that we are only looking for glass layer defects, not electrical faults or performance degradation modeling. We are also assuming any glass defects we do detect correlate with panel performance issues. The final decision we make is the type of noise filtering and how aggressive it will be. Too much filtering might miss defects and if it is too lenient, the algorithm will falsely detect a defect.

1.3 Periodic Behavior

Mono crystalline solar cells are manufactured with a highly regular grid structure consisting of evenly spaced bus bars, fingers, and crystal domains. This spatial regularity produces dominant, well-defined frequency components in the Fourier domain. Physically, these correspond to repeating geometric features with fixed spacing. When cracks or fractures occur, this periodic structure is locally disrupted, introduing non-periodic, broadband high=frequency components that appear as irregular energy in the Fourier spectrum. This physical periodicity justifies the use of high-pass filtering, since defects manifest as deviations from the expected frequency peaks. Given the repetitive nature of the glass layer on a solar panel, one could utilize DFT to find potential defects on the glass shield of the solar panel. We would expect a uniform wave from the DFT given a uniform panel, so if any irregular occurrence were to appear in our wave, we would have derived a defect.

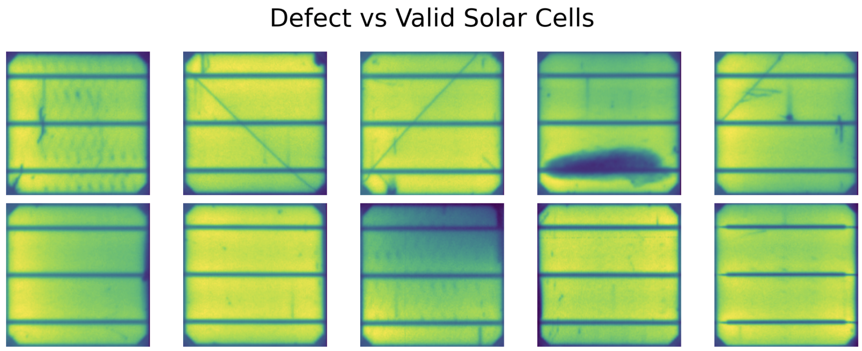

Figure 1: Unprocessed images from the dataset we are using to test and make our algorithm on. The first row of images are all regular panels while the second row shows defects.

2 Data Collection

For our data, we used a publicly available solar panel image dataset we found on github: Electroluminescence Photovoltaic (PV) Dataset. This data set contains electroluminescence images of panels with annotated defects and have been used in other research and algorithm detecting. The images were taken using an electroluminescence camera with a sampling rate of 300x300 pixels per image. The images have both defective and non-defective panels to allow for testing and validation. We chose to use a data set because we don't have access to solar panels in person - especially those with defects. In order to minimize noise, for example from the size, we cropped them to be smaller. We also converted the images to grayscale and used a high pass filter to get rid of the noise.

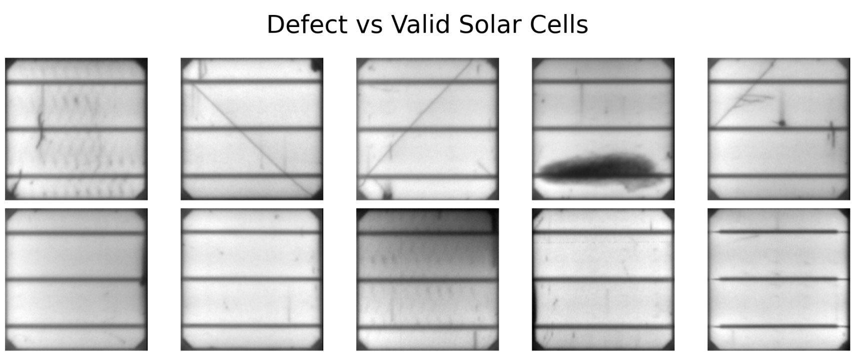

Figure 2: Grayscale images of the valid and invalid solar cells

3 Analysis

To analyze our data, we used python and the numpy and matplotlib libraries. For consistency, we only used mono-crystalline cells. Once we had test images, we converted them to gray scale because the DFT operates on color intensity, not color values. Each image was then converted from the spatial domain into the frequency domain using 2D FFT.

Each image is modeled as a discrete 2D signal:

$$f(x,y), x = 0, ..., M-1, y = 0, ...N-1$$

where x, y are spatial indices, M, N are the number of indices in the x and y direction, and $f(x, y)$ is the pixel intensity.

The 2D DFT of an image $f(x, y)$ are then defined as:

$$F(u,v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) e^{-j2\pi \frac{ux}{M} + \frac{vy}{N}}$$

where u and v are the horizontal and vertical spatial frequency indices and $j = \sqrt{-1}$. Each Fourier coefficient $F(u, v)$ represents the contribution of a 2D complex complex exponential basis function. The basis functions are:

$$e^{-j2\pi \frac{ux}{M} + \frac{vy}{N}}$$

These basis functions correspond to 2d sinusoids with spatial frequency u/M along x and v/N along y where the orientation is determined by the ratio u:v.Thus, the DFT decomposes the image into planar waves of varying spatial frequency and direction. Because the transform is complex:

$$F(u, v) = A(u, v)e^{j\phi(u,v)}$$

where $A(u, v) = |F(u, v)|$ is the magnitude spectrum and $\phi(u, v) = arg(F(u, v))$ is the phase spectrum. The magnitude encodes the strength of each frequency component while phase encodes the spatial alignment and structure. Low frequencies ($u, v \approx 0$) mean that the image has a smooth variation and global illumination whereas high frequencies ($|u|, |v| >> 0$) means that there are sharp edges, cracks and discontinuities.

Once we had our sinusoids and magnitudes, we computed the log-scaled magnitude of the Fourier transform, which compresses the large range of frequency magnitudes, making subtle frequency differences caused by defects more visible. A defective cell shows irregular high-frequency components which are disruptions caused by cracks, fractures, and micro-defects.

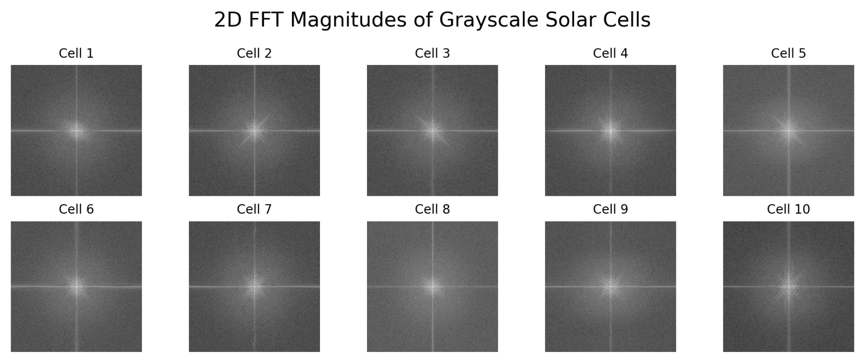

Figure 3: Log scaled version of our DFT on sample images. Bright off-axis frequency components indicate non-periodic disruptions in the otherwise regular lattice structure, consistent with cracking or material defects.

Looking at just the log scale plot of the the image after 2D DFT isn't super useful, so we did some high pass filtering to isolate defects. This was done because cracks and defects correspond to abrupt intensity changes, generating high frequency energy. By removing low frequencies, we suppress uniform regions and highlight any structural damage. The high pass filtering is done by shifting the FFT to modify the frequency components and reconstruct a defect-enhanced spatial image via the inverse transform.

The same frequency-domain representation is re-indexed by shifting the frequency to center the low frequencies and apply a high pass filter mask. The mask is defined by:

$$H(u, v) = \begin{cases} 1, & |u - u_0|^2 \leq r \text{ and } |v - v_0|^2 \leq r \\ 0, & \text{otherwise} \end{cases}$$

In this case, u, v are frequency coordinates instead of spatial pixels so high values are sharp edges or cracks while low values are slow intensity changes. $H(u, v)$ is the binary filter applied in this frequency space. When $H(u, v) = 0$ so when the frequency in less than the cutoff radius (r), it gets cutoff or set to zero and if the frequency is outside the cutoff, it remains unchanged. In order to improve our model, we adjusted and calibrated the frequencies to try and get the algorithm to be more accurate.

Once we filtered the data, we reconstructed the image using inverse 2D DFT.

$$g(x, y) = \frac{1}{MN} \sum_{u=0}^{M-1} \sum_{v=1}^{N-1} G(u, v)e^{j2\pi(\frac{ux}{M} + \frac{vy}{N}}$$

We can visualize this on a 3d plot to better see the different frequencies.

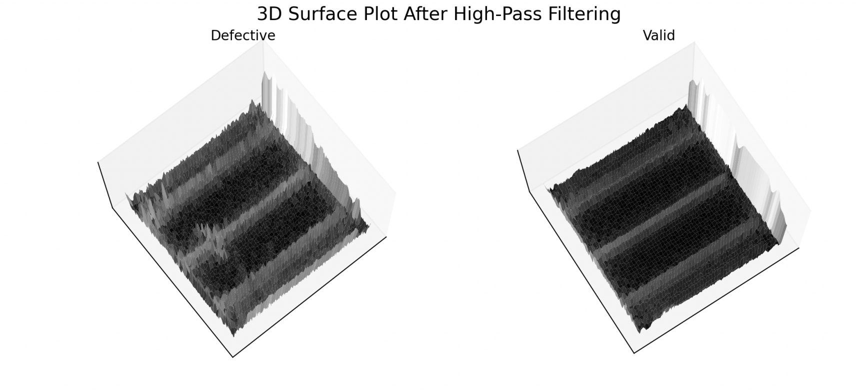

Figure 4: 3D Surface visualization given the High-Pass Filtered Picture. Because the signal is spatial rather than temporal, frequency is expressed in cycles per pixel rather than Hz.

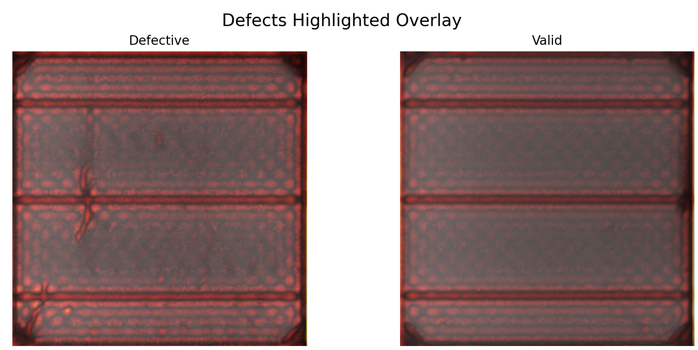

Figure 5: Final Filtered Image showing the Defects in the cell

4 Conclusion

Given the numerical visualization and understanding of defects within a uniform structure–such as a protective shield for a solar panel–we can better infer the structure's state, whether its invalid or valid, and be able to identify disruptions in the cells, whereas the naked eye may not be able to notice. Finding these defects or micro-cracks in photovoltaic glass can propagate into electrical hot spots, reducing panel efficiency, shortening operational lifetime, and increasing maintenance costs for large-scale solar installations. Given this output, we are adequately capable of addressing minor issues with our photovoltaic glass. With adequate filtering, we were able to highlight the defects of importance, accomplishing our goal for this project.