Detection of Micro-Cracks in Solar Cell Images

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Abstract— This paper presents an algorithm for detection of micro-cracks in solar cell images. The detection goal is challenging due to the presence of inhomogeneous background of the images. A customized filter is implemented to remove finger interruptions in the images. An algorithm comprising of image enhancement and object classification is proposed in the paper and was tested on a set of Electroluminescence images of multi-crystalline solar cells.

Keywords— Multi-crystalline, micro-crack, histogram, frequency domain filtering, canny edge detection, thresholding, SVM.

I. INTRODUCTION

The increasing demand for solar electrical energy has raised the need for photovoltaic arrays resulting in requisiteness for solar cells in recent years. It prospects for the automation in solar cell industry because millions of solar cells are manufactured daily worldwide. Finished solar cells are occasionally found to be defective or faulty. Their occurrence seems relevant due to thermal stress in the production process or physical stress during transportation and is directly related to the breakage rate in the cell production process. The defects are classified into two groups: (i) intrinsic (ii) extrinsic. Grain boundaries are an example of intrinsic defect, while micro-cracks belong to the extrinsic defects.

The intrinsic type of defects diminish the short-circuit current of the cell, and this leads to loss in the efficiency. The extrinsic defects form a class of cracks that are entirely invisible to the naked eye. With dimensions smaller than 30 mm, this type of defect can only be visualized electronically like using the electroluminescence (EL) or photoluminescence (PL) technique and high-resolution cameras. It is important to have high-quality, defect-free cells in the production of PV modules.

In practice, there are various shapes and sizes of microcracks in a solar cell depending on how they are formed. For example a line-shaped micro-crack is caused by scratches, and it generally occurs during cell fabrication. This type of defect can also be due to wafer sawing or laser cutting, which propagates and causes the detachment or internal breakage of the grainy materials within the solar cells. In contrast, star-shaped micro-crack is formed due to a sharp point impact which induces several line cracks with a tendency to cross each other. There are other types of micro-crack defects, but these two are the most commonly found in solar cell production. So it is necessary to recognize the type of cracks and the effect caused by it on the efficiency of the cell. To distinguish between cracks, classification based on shape of cracks is important.

The features extracted from shape analysis are used to train the artificial classifier. Support vector machines (SVMs), Adaboost, K means are types of classifier used in machine learning and artificial intelligence. SVM is a supervised learning algorithm originally developed for two-class classification problems. Therefore, this classifier is suitable for this type of application. Micro-crack shape features are assigned as positive class, while arbitrary shape features are assigned as negative class

Optical inspection systems are composed of a camera, illumination, and a system that presents the wafer to illumination and a handling system. Micro cracks can appear as contaminations when the wafer is transparent and the light is penetrating the wafer in a direction parallel to the surface. Light sources for micro-crack inspections operate therefore typically at a wavelength of 1.5 µm and above. In order to meet and deliver the reliability criteria as stated above, the wafers must be presented in the most probable and controlled way to both light and camera. The inspection system is used for "in-line characterisation". With the difficulty of micro-crack inspection on wafers being overcome, the industry is anxiously waiting for reliable inspection systems with the ability to find micro-cracks in processed solar cells. Only such systems can potentially save the module manufacturers from the issues of breakage brought on by micro-cracks.

II. METHODOLOGY

The proposed block diagram of the algorithm is given below:

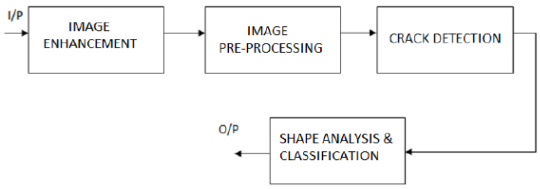


Fig 1: Block Diagram

The input image is obtained from a CCD or a si-cooled CCD camera. Electroluminescence technique is used to obtain the image of the solar cell. The algorithm comprises of three basic steps. Histogram Equalization is performed to enhance the quality of the input image, followed by frequency domain filtering to remove finger interruptions and finally a classifier to distinguish cracks from other impurities.

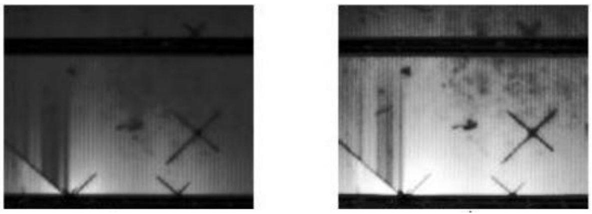
A. Image Enhancement.

The micro-cracks are of order of few micrometre. Due to their small size it is impossible to perform image pre-processing on the images obtained from the Camera. So the images need to be enhanced before they are processed further.

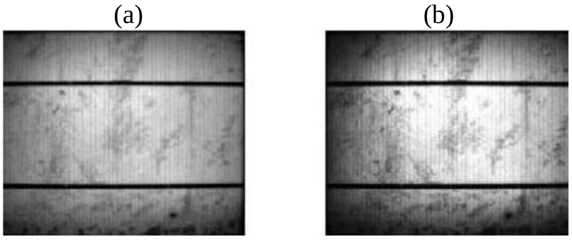
The principal objective of image enhancement is to process a given image so that the result is more suitable than the original image for a specific application. It accentuates or sharpens image features such as edges, boundaries, or contrast to make a graphic display more helpful for display and analysis. The enhancement doesn't increase the inherent information content of the data, but it increases the dynamic range of the chosen features so that they can be detected easily.

Histogram equalization is used to increase the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through

this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. When the CCD camera takes an image, it might not be able to fully use the 8-bits of image depth (Gray value of 0 to 255).Histogram equalization to enhance the gray scale difference between the micro-cracks and grain boundaries, so that the entire available range can be utilised. Figure 2(a) shows the Original image. Figure 2 shows the images before and after equalization. It is seen from figure 3 that the contrast is enhanced and occupies the entire available intensity range in the equalized image(refer fig 3(b)).



(a) (b)



(c) (d)

Fig 2: (a)defected sample (c) good sample (b)-(d) respective histogram equalized images

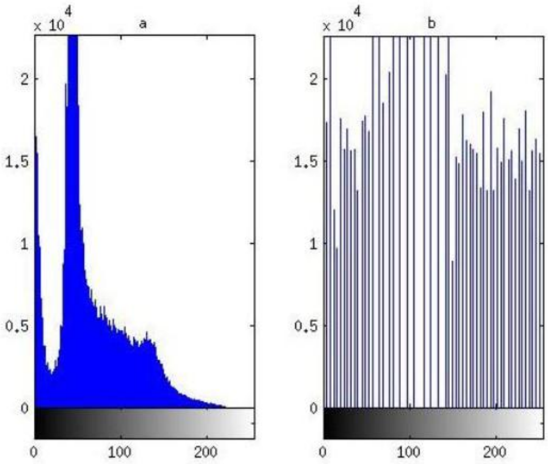


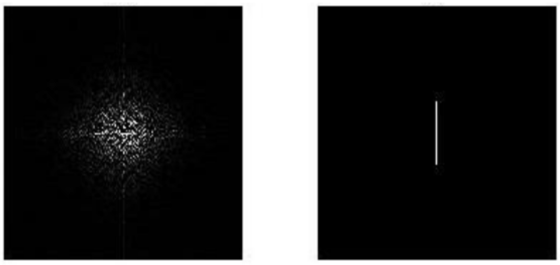
Fig 3: (.a) Histogram of input image (b)histogram of equalized image

B. Image pre-processing

As seen in the fig 2(b), the electroluminescence image of a solar cell contains different impurities like finger interruptions, grain clusters along with cracks. Due to the presence of these impurities, crack detection becomes difficult. So these finger interruptions has to be removed to make the background homogeneous. This is done by filtering in the frequency domain. The Fourier spectrum is shown in fig 4(a).

Fingers are characterised by high gradient and they correspond to high frequency regions in the Fourier spectrum whereas cracks and other impurities correspond to low frequency regions. Let ip(i,j) be the input image and f2 be its Fourier image. Due to its orthogonal properties, fingers in the frequency spectrum appear as a straight vertical line located at the centre of the spectrum. This is characterised by high frequency regions whereas the low frequency regions appear away from the centre. A filter H(i, j) as seen in fig 4(b) was implemented using the following equation:

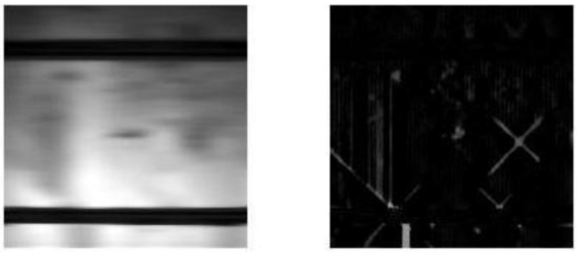
$$H=\{^{1}_{0}, \sqrt{\left(i-\frac{m}{2}\right)^{2}} < a and \sqrt{\left(j-\frac{n}{2}\right)^{2}} < b \text{---}(1)$$



(a) (b)

Fig 4: (a) FFT spectrum of input image (b) Filter H

The filter is then convolved with Fourier spectrum shown in fig 4(a) and an inverse Fourier spectrum is obtained of the resulting image. This image contains only fingers which are shown in fig 5(a). Finally input image (fig 2(b)) is subtracted from this image to obtain an image free of finger interruptions shown in fig 5(b).



(a) (b)

Fig 5: (a) inverse Fourier image (b) fingers free image

C. Thresholding

Global thresholding was used in the algorithm due to its fast computational ability. To highlight cracks from the background, intensity histogram corresponding to the image is plotted. Objects and background have intensity values grouped into two dominant modes. Thresholding techniques partition image directly into regions based on intensity values and properties of these values. To extract the object from the image is to select a threshold T that separates these modes

$$g(x,y) = \begin{cases} 1, & \text{if } f(x,y) > T \quad \text{object point} \\ 0, & \text{if } f(x,y) <= T \quad \text{background point} \end{cases} \qquad (2)$$

When T is a constant applicable over an entire image.

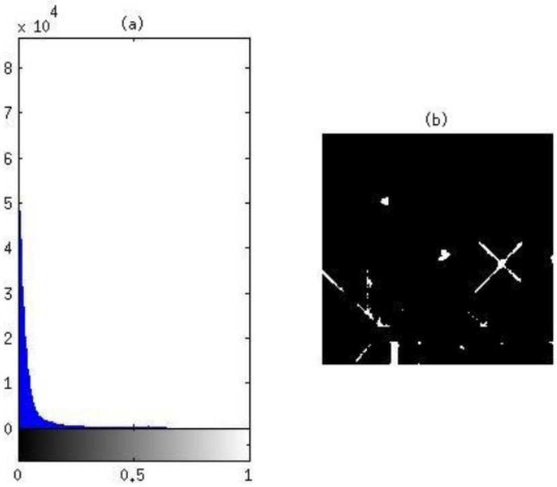


Fig 6: (a) histogram of image 5(b) Thresholded image with 50 intensity value

D. Edge detection.

After removal of fingers our next objective is to detect crack pixels. Cracks are characterised by high gradient and low intensity level, whereas the background is characterised by high intensity but low gradient. This characteristics of the edges is used in our algorithm to detect cracks. Edges are low level features. They occur at boundaries between – Regions of different colour, Intensity or Texture. It is preferable to detect edges using only purely local information. Edges occur at locations of steep slopes. A mathematical way to define the slope and direction of a surface is through its gradient. Thus, cracks can be visualised as edge pixels and can be detected using edge detection algorithm. Canny edge algorithm was used to detect edges in the filtered image. Figure5(a) shows cracks identified by canny edge algorithm. Whereas figure 5(b) shows with sobel operator. As can be seen from the images canny detection algorithm yields better results.

(a) (b)

Fig 7 : (a) crack detection using canny algorithm. (b) Crack detection using sobel edge detection algorithm.

III. PROPOSED HARDWARE

Fig 9 : Proposed hardware for implementing algorithm.

Further, this algorithm can be implemented on a hardware module to have in-line inspection of solar cell in an industry. The Fig 9 shows shows a set-up of black fin processor connected to a video camera and a solar cell in line of sight of the camera. The image acquired is then fed to a computing machine where the processing is done.

Such a system can be used as a standalone system in the quality assurance unit of a solar cell production house.

IV. RESULTS

The algorithm was tested on a set of images, result of four of which are shown in fig 8. Two defected and two defect-free images were taken as input images and the algorithm was successfully implemented on them. The corresponding results indicate that the the output yields cracks distinguishably well in the defected solar cells. But along with the cracks some impurities are obtained as well. Hence, further classification is needed to reject impurities which do not have similar properties to that of micro-cracks.

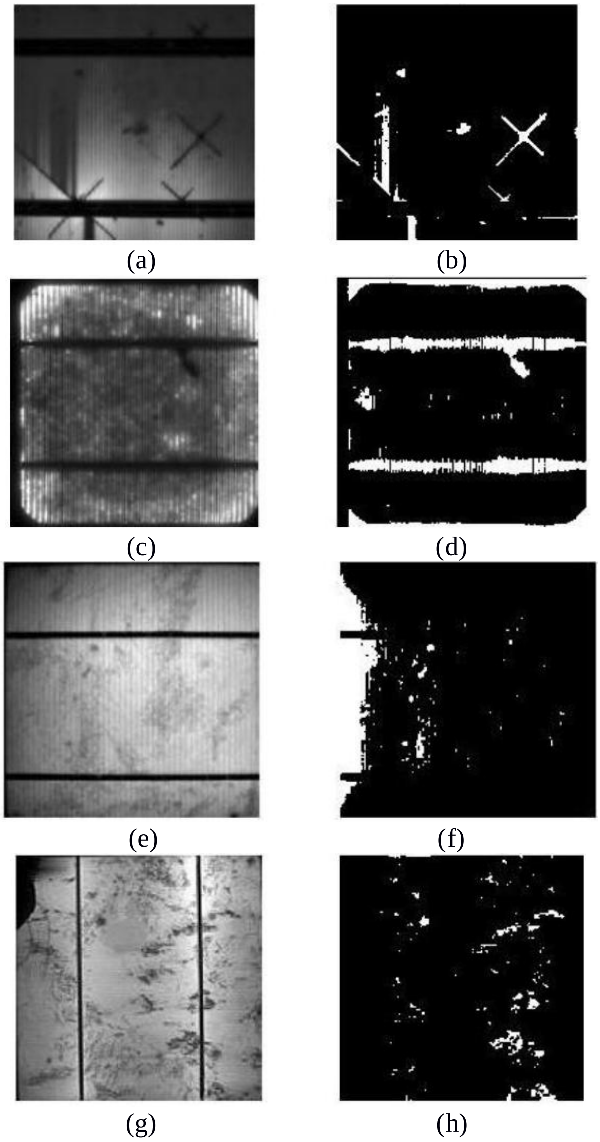


Fig 8: (a),(c) Defected solar cells (e),(g) defect-free solar cells. (b),(d),(f),(h) Respective outputs.

V. CONCLUSION

For the optimum production and quality assurance of solar modules, the early detection of defects is essential. The algorithm developed, presents the efficient way to detect micro cracks in the electroluminescence image of solar cell. The algorithm is supported with Image Enhancement technique to increase the dynamic range of the micro-crack, Edge Detection and Low pass filtering to separate the cracks from other contaminations in the cell. It will give the result in fraction of seconds with a better efficiency, sensitivity and accuracy.

VI. FUTURE SCOPE

Our further emphasis is on the shape analysis. It is necessary to distinguish micro-cracks from the other defects present in the solar cell. Micro-cracks are present in different shapes like line or star patterns. Power loss depends on the type and shape of solar cell and thus the efficiency. With shape analysis the features of cracks is extracted. The extracted features are used to train the artificial classifier. In this study, support vector machines (SVMs) are used in machine learning and artificial intelligence. It is a supervised learning algorithm originally developed for two-class classification problems. Therefore, SVM classifier is suitable for this type of application. Micro-crack shape features are assigned as positive class, while arbitrary shape features are assigned as negative class. The positive class is accepted, rejecting the later. Therefore classifier is the integral part for crack detection.

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