Solar Cell Micro-Crack Detection Using Localised Texture Analysis

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***Abstract*—A novel method to classify micro-cracks in Photoluminescence (PL) images of polycrystalline solar cells is proposed. Micro-cracks in PL images are difficult distinguish as they're easily confused with noises that are present which may share the same size and shape features. Instead of relying on shape analysis to classify micro-cracks, the proposed method takes advantage of the patterns that are present at the end points of micro-cracks. Textural features are extracted via grey level co-occurrence matrix at the end points and then used as feature vectors in a SVM classifier. The proposed method is compared against existing shape analysis method and a preliminary experimental result has shown a significant improvement in sensitivity, specificity and accuracy.**

***Index Terms*—solar cell, photoluminescence, micro-crack**

I. Introduction

Micro-crack is a type of defect that may be present in crystalline silicon solar cells which can be completely hidden and invisible to naked eyes. The presence of micro-cracks in solar cells not only compromises the structural integrity of the product but also poses a safety risk where solar cells containing micro-cracks may produce 'hot-spots' in solar modules which can potentially be a fire hazard. On average, 5 – 10% of fully completed solar cells coming out of a production line contain some form of micro-crack and this represents an ongoing problem to solar cell manufacturers.

As a quality control process, an automated system that is capable of inspecting each and every solar cell coming out of a production line would be beneficial to manufactures. Several specialised techniques and methods currently exist to inspect fully completed crystalline silicon solar cells for micro-cracks. These include the Light Beam Induced Current (LBIC) [1], the Electron Beam Induced Current (EBIC) [2], the Electroluminescence (EL) [3] and the Photoluminescence (PL) [4] method. A good review on the various methods has been published elsewhere [5]. It would appear that the PL method is potentially suitable to be used in an in-line inspection without the need of extensive modifications to existing production lines.

Although the PL method is able to meet the inspection speed and other practical demands of an in-line inspection, it also poses several challenges in image processing, especially for micro-crack detection for polycrystalline solar cells in particular. An example of a PL image of a polycrystalline solar cell is shown in Fig. 1. The base solar wafer of a polycrystalline solar cell is made from multiple silicon crystals. Each silicon crystal will emit slightly different PL intensities and therefore would produce a random heterogeneous background due to the multiple crystals in the solar cell. Furthermore, the grain boundaries produce noises in PL images which consist of random curvilinear structures that are very similar to micro-cracks, especially when compared against shorter examples.

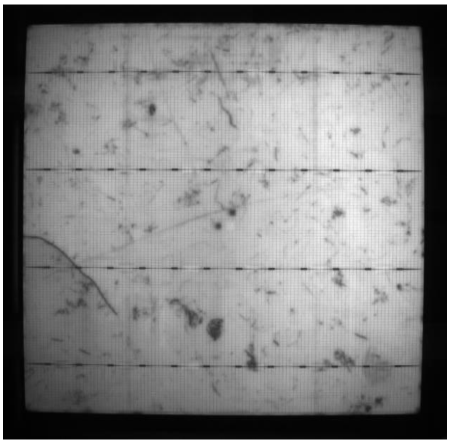

Figure 1. PL image of a polycrystalline silicon solar cell containing a micro-crack originating from the left edge.

Several studies [6], [7] has attempted to segment micro-cracks via shape analysis techniques. However, based on our observation, it would appear that in polycrystalline solar cells, micro-cracks cannot be reliably distinguished based on shape analysis alone as the micro-cracks can also exhibit very similar shape features with the surrounding noises. Furthermore, they

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usually occupy the same gray scale values as noises and this further limits the ability of the previously proposed techniques.

In this study, we propose a novel technique using localised texture analysis on each curvilinear structure that can be extracted from a PL image. Instead of extracting shape features of the segmented structure, the textural features and its immediate surrounding areas are used for classification. Classification is then performed using Support Vector Machines (SVM) based on the extracted textural features.

II. Methodology

A. Hardware Overview

A PL imaging system consists of an excitation light together with a camera with appropriate lens and optical filters. Fig. 2 shows a layout of a PL imaging system for crystalline silicon solar cells where a camera is placed directly above the inspected sample. The solar cell sample is transported into the field of view of the camera with the sunny side (the side of the solar cell which faces the sun) facing the camera either by a belted conveyor or a walking beam, both which are common in solar cell production lines.

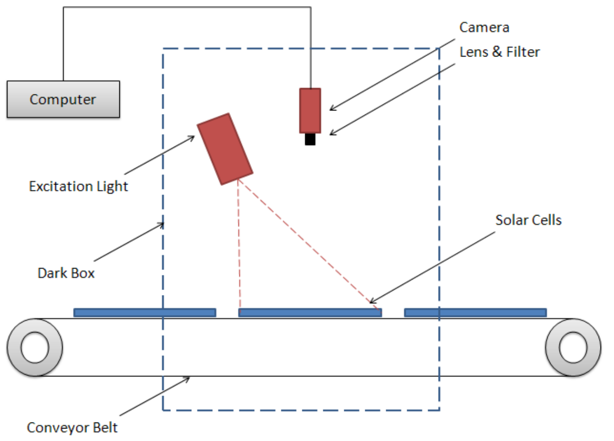


Figure 2. Schematic layout of an in-line PL system showing important elements.

A monochromatic light source with wavelengths shorter than the PL emission spectrum is used as the excitation light. The reflected light from the surface of the sample would be blocked by a long pass filter allowing only the PL emission to be captured by the camera.

The acquired PL image from the camera is then processed by software to identify and segment defects if present. PL signals are relatively weak compared to ambient light and are prone to interference from external light sources. To minimise exposure from external light sources, the entire PL imaging set-up would be enclosed in a dark box. A detailed design for a practical in-line PL imaging set-up was proposed in our previous study [8].

B. Curvilinear Structure Extraction

Micro-cracks in PL images of solar cells consist of curvilinear structures. Therefore, all curvilinear structures that are present in a PL image are extracted as potential micro-crack candidates. A differential geometric approach to extract the curvilinear structures as proposed by Steger [9] was used. Fig. 3 shows the result of the extraction of the curvilinear structures from the original image shown in Fig. 1. It should be noted that the bus bars of the solar cell and the printed grid like patterns in the PL image was masked out prior to the curvilinear structure extraction and therefore do not form part of the extracted image.

Figure 3. Extracted curvilinear structures of the original image as shown in Fig. 1.

C. Region of Interest

Once the curvilinear structures are extracted, a square shaped Region of Interest (ROI) is created at both ends of the extracted structures. Fig. 4 illustrates the position of the ROIs at the end points of an extracted region. The ROIs are created at these positions as we have found that the textural patterns at the end points of each curvilinear structure in PL images would be able to provide the best distinction between micro-crack and noises. From our observation, micro-cracks can be classified into 3 distinct types, where their end points can be used to distinguish them. They are the edge cracks, bus bar cracks and the ‘toolmark’ cracks.

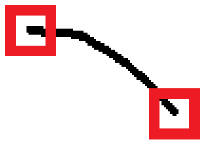
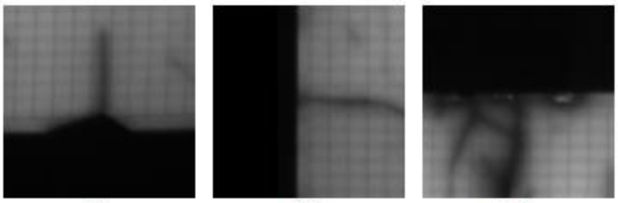


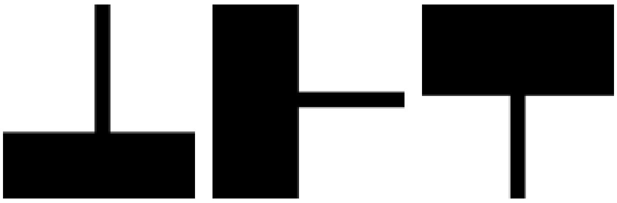
Figure 4. Illustrated example of the position of the ROIs at the end points of an extracted curvilinear structure.

Edge cracks are defined as micro-cracks that originate from the edges of a solar cell which are usually caused by an impact to the edges and would sometimes exhibit a visible chip. Examples of edge cracks are shown in Fig. 5 Edge cracks when observed from the end point ROI closest to the edge of a solar cell will exhibit a distinct feature of a sharp line against a background which consists of a part of the solar cell and also a part of the background. The basic model of an edge crack is shown in Fig. 6.



(a) (b) (c)

Figure 5. Examples of edge crack at the bottom edge (a), left edge (b) and the top edge (c) of solar cells under PL.

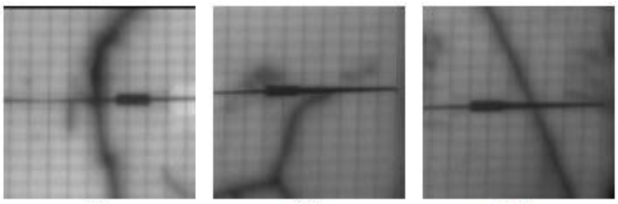


(a) (b) (c)

Figure 6. Examples of edge crack basic models (a), left edge (b) and the top edge (c) of solar cells.

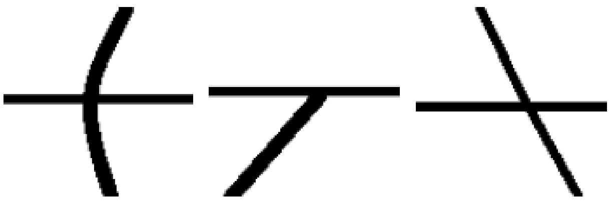
Bus bar cracks are defined as micro-cracks that originate or cross the bus bar area of a solar cell. These are usually caused by an impact to the bus bar area by a probing tool, i.e. an IV tester or a hotspot tester. Examples of bus bar cracks are shown in Fig. 7. Bus bar cracks when observed in the ROI at the intersection point with a bus bar will exhibit a cross like feature which contains part of the crack along with part of a bus bar. The basic model of a bus bar crack is shown in Fig. 8.

'Toolmark' cracks describes micro-cracks that can occur in any location on a solar cell that would exhibit multiple crack lines that resemble a star or the letter 'X', 'Y', or 'T' caused by a sharp impact on the solar cell. Examples of 'toolmark' cracks are shown in Fig. 9. When observed at the intersection point of origin, the ROI will exhibit a cross like feature with multiple crack lines that can be traced back to a single point of origin. The basic model of a 'toolmark' crack is shown in Fig. 10.



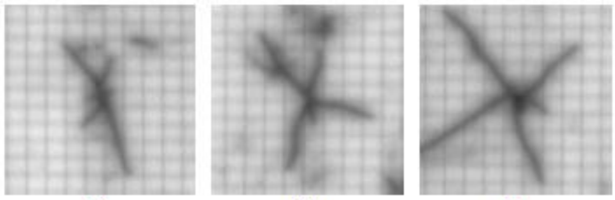
(a) (b) (c)

Figure 7. Examples of cracks intersecting the bus bar of solar cells under PL.



(a) (b) (c)

Figure 8. Examples of basic models of cracks.



(a) (b) (c)

Figure 9. Examples of 'toolmark' cracks on solar cells under PL.

(a) (b) (c)

Figure 10. Examples of basic models of 'toolmark' cracks on solar cells.

D. Texture Analysis

To distinguish micro-crack curvilinear structures against noises in each ROI, each basic model of a crack type has to be extracted. Methods such a pattern matching of each distinct micro-crack types has been previously proposed to be used to classify intact and micro-cracked solar cells. However, based on our observation, pattern matching cannot be reliably used as the variation of noises and cracks vary too much which makes basic pattern matching rather challenging.

Instead of an attempt to extract shapes for pattern matching, a statistical approach based on texture is proposed. Based on our observation, due to the crack line characteristics along with the distinct immediate surrounding background features at the end point and intersection points of the 3 micro-crack types, it is useful to use a statistical approach such as the grey level co-occurrence matrix (GLCM) to provide textural characteristic information about the relative position of neighbouring pixels.

Haralick [10] proposed 14 statistical features that can be extracted from GLCM. In this study, 4 features of GLCM are used, they are; energy, correlation, local homogeneity and contrast. These 4 GLCM features were chosen as they represent the best features to be used to distinguish the different crack types and noises. They are calculated as follows:

$$Energy = \sum_{i,j=0}^{width} c_{ij}^2 \tag{1}$$

$$Correlation = \frac{\sum_{i,j=0}^{width} (i-u_x)(i-u_y)c_{ij}}{s_x s_y} \tag{2}$$

$$Homogeneity = \sum_{i,j=0}^{width} \frac{1}{1+(i-j)^2} c_{ij} \tag{3}$$

$$Contrast = \sum_{i,j=0}^{width} (i-j)^2 c_{ij} \tag{4}$$

where

$$width = \text{Width of co-occurance matrix} \quad (5)$$

$$c_{ij} = \text{Entry of co-occurance matrix} \quad (6)$$

$$u_x = \sum_{i,j=0}^{width} i * c_{ij} \quad (7)$$

$$u_y = \sum_{i,j=0}^{width} j * c_{ij} \quad (8)$$

$$s_x^2 = \sum_{i,j=0}^{width} (i - u_x)^2 * c_{ij} \quad (9)$$

$$s_y^2 = \sum_{i,j=0}^{width} (i - u_y)^2 * c_{ij} \quad (10)$$

It should be noted that the textural features calculated in this study is the mean of the four different directions of GLCM at 0°, 90°, 45° and 135°.

E. Classification

The type of micro-cracks to be identified is first determined by the location and feature of the ROI. ROIs which are in close proximity to the edges of the solar cell are used to identify edge cracks, while ROIs which intersects with the bus bar are used to identify bus bar cracks. In situations where multiple ROIs intersect each other, these ROIs are then used to identify 'toolmark' cracks where the crack intersections would create multiple overlapping ROIs.

The textural features extracted from each ROIs is then used for binary classification of cracks and non-cracks using standard SVM. In total, 3 separate SVM classifiers are used, each used to classify each type of micro-cracks.

Images are processed using a computer equipped with an Intel Core i3-3220 Processor (3M Cache, 3.30 GHz), 4GB of RAM. On average, classification results can be obtained within 300 ms after image acquisition. This would mean that the entire cycle time to inspect a single solar cells sample is well within 1000 ms which is appropriate for an in-line application.

III. Experimental Results

To evaluate the classification capability of the proposed method against our existing shape analysis method [11], a dataset as shown in Table I was used. The polycrystalline solar cell samples in the dataset consist of randomly selected pieces directly off a production line to mirror an actual production run. Training of both methods was conducted using 50 pieces of defective samples along with 200 pieces of intact samples contained within the dataset.

TABLE I. Dataset Containing Defective and Intact Samples of Polycrystalline Solar Cells

Total number of samples	921
Number of defective samples	231
Number of intact samples	690

Defective and intact samples were identified by examination of the acquired PL images by an experienced human observer. A physical stress test was later conducted on the samples and retested using the PL imaging system to observe any event of elongation of potential micro-crack lines to confirm the presence of actual micro-cracks.

The classification performance is assessed using several commonly used quantitative measures, namely sensitivity, specificity and accuracy. These measures are based on the calculation of true positive *TP*, true negative *TN*, false positive *FP* and false negative *FN*.

$$Sensitivity = \frac{TP}{TP + FN} \quad (11)$$

$$Specificity = \frac{TN}{TN + FP} \quad (12)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (13)$$

The classification results are summarised in Table II. It can be observed that the proposed method yields a significant improvement to the regular shape analysis method with good sensitivity, specificity and accuracy.

TABLE II. Classification Results of the Test Data Set

Method	Sensitivity	Specificity	Accuracy
Texture Analysis	0.979	0.896	0.952
Shape Analysis	0.799	0.452	0.539

It was observed that the system tends to over-reject based on specificity figures. The over-rejected samples was further re-examined by a physical examination by the means of a stress test. It was found that some samples which have passed the physical stress tests contain certain features that are indistinguishable with actual micro-cracked samples even to an experienced human observer in PL images. Examples of such samples are shown in Fig. 11 and a comparison with actual verified micro-cracked samples is shown in Fig. 12.

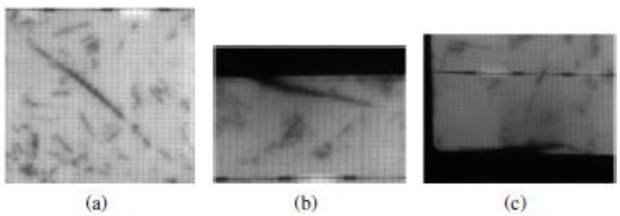


Figure 11. Examples of intact solar cells exhibiting features which are indistinguishable from micro-cracks samples.

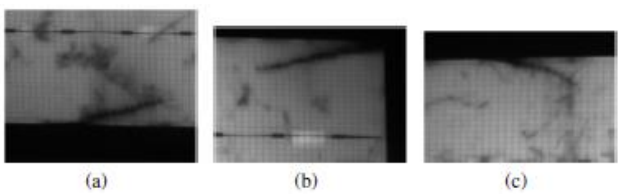


Figure 12. Examples of actual verified micro-cracked samples.

Most of these micro-crack like lines under PL was later found to be scratches on the solar cell's surface due to handling. Although scratches are not desirable, they should not be misclassified as micro-cracks. The similarity with micro-crack still poses a challenge not only in the classification but also the selection of images used for training.

It should be noted that the classification results presented here are still preliminary and a large scale test shall be conducted to test if these figures are still valid as noises contained within polycrystalline solar cells can vary greatly between different batches of solar cells. Efforts to conduct a large scale test are currently being actively pursued in a commercial polycrystalline solar cell production facility.

IV. Conclusion

The detection of micro-cracks in polycrystalline solar cells is very challenging due to the similar looking noises that share the same gray scale values in PL images. Previous methods which rely on shape analysis do not perform well as there's no significant shape distinction between micro-cracks and the noises that may be present. In this study, a novel method to classify micro-cracks based on localised texture analysis was proposed. Preliminary results have shown significant improvements over current method and a large scale test is currently in progress. The existing results have also shown that the system tends to over-reject due to similar looking features which are not micro-cracks such as scratches. Further research is recommended to be carried out to better distinguish scratches and cracks in solar cell PL images.

Acknowledgment

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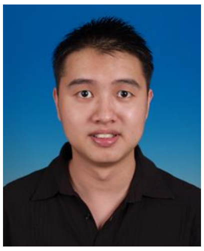

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