GRAIN SEGMENTATION OF SOLAR CELL WAFERS USING REGION GROWING

Shu-Kai S. Fan
Taipei Tech, Taiwan
morrisfan@ntut.edu.tw

Wei-Che Chuang
Taipei Tech, Taiwan
kgarnett_19@hotmail.com

Pei-Hua Sung
Taipei Tech, Taiwan
cat051320@gmail.com

Abstract:
In the era of rapid high-technology growth, the energy allocation problem influences not only in economic development, but also seriously affects the environment and ecology. Recently, solar power becomes an attractive alternative source of energy. The multi-crystalline solar cell has been widely accepted in the market due to its significantly reduced manufacturing cost. Multi-crystalline solar wafers own larger average grain size surfaces and less grain boundaries that bring about higher quality and conversion efficiency. In this article, we propose a new image processing method to segment solar wafers for grain analysis. The pre-processing step via a median filter is applied first for the image contrast enhancement. Then, an adaptive segmentation algorithm based on region growing is developed, with an attempt to retain the fast algorithmic convergence and appropriate regional growth. The separate closed regions, called grain, are culled from the wafer by using the proposed region growing algorithm, and then the average grain size and number on a single wafer surface can be evaluated to dictate the quality of solar wafers in conversion efficiency.

Keywords: green cultural events, event management, environmental management, ecological certification

1. INTRODUCTION

Since the oil crisis in 1970s and the environmental awareness arise, the development of new energy source is pursued urgently. Solar power is an attractive alternative source of electricity. Silicon solar cells are the main components that convert photons to electricity. For current solar cell technologies, the multi-crystalline solar cell has become more popular in the market than the mono-crystalline solar cell because of their lower manufacturing and material costs. Nowadays, multi-crystalline silicon is the material with the largest market share in photovoltaic (PV) cell and modules production. Multi-crystalline silicon (mc-Si) is usually produced in form of square shaped ingots that are crystallized by directional solidification of molten silicon feedstock. The obtained ingots are cut into bricks and wafers, which are then used for the processing of solar cell.

Recent research has demonstrated that machine vision can be successfully applied to the defect detection on multi-crystalline solar wafer surface [1]. Online surface inspection of solar wafers in the PV industry can ensure product quality and prevent unsatisfactory wafers from reaching the back-end processing. In the past, surface defect detection hinges on the inspector's subjective judgment. Image processing techniques have been popularly accepted in industry for automatic visual inspection. The currently available machine vision algorithms for solar cell inspection are mainly applied to mono-crystalline solar wafers that contain only uniform surfaces, or to the detection of shape-related faults such as finger interruptions, chip and necking in a solar cell.

To evaluate the quality of the multi-crystalline solar cells systematically, an image segmentation method is proposed using region growing in this paper. Upon completion of image segmentation, the grain number and the average grain size can be readily computed as new measures to assess the quality of solar cell wafers. It is well known in practice that the conversion efficiency showed a quasi linear dependence on the mean grain size [2]. The challenge to be faced in solar wafer inspection results from the complex distribution of the grain size, geographical shape and also irregular intensity contrast. To ensure an initial good quality image, first, the image contrast enhancement via a median filter is performed, which has the merits of enhancing image contrast and reducing noise while preserving the contour image. To alleviate the aforementioned difficulty during segmentation, we develop an automated threshold based adaptive region growing approach, while retaining the fast convergence and a robust regional growth. After the closed regions segmented by using the region growing approach are obtained, then the quality of solar cell wafers can be quantitatively evaluated. Due to the page limitation, only the proposed region growing approach will be addressed in this paper.

2. IMAGE SEGMENTATION BASED ON REGION GROWING

To begin, the multi-crystalline silicon image is considered the input image that is processed through image enhancement and smoothing. Second, the image is processed by conducting the proposed region-growing approach until all the pixels of the solar cell image are already labeled. At last, the resulting image is processed by merging extremely tiny segmented areas into the adjacent area as a post hoc operation. Through the aforementioned steps, it is hoped that the grains of the multi-crystalline solar cell wafer can be accurately segmented. In doing so, the resulting grain analysis makes it possible for practitioners to assess the conversion efficiency of the multi-crystalline solar wafer.

2.1. Image Pre-processing

Operation of Image Contrast Enhancement

It is well known from practice that nearly every multi-crystalline silicon solar wafer image is of low-contrast in intensity. The pre-processing of image enhancement will help to improve results of later processing for grain segmentation. Most contrast enhancement methods make use of the gray-level histogram, created by counting the number of times each gray-level value occurs in the image, then dividing by the total number of pixels in the image to create a distribution of the percentage of each gray level in the image. The simplest contrast stretch is a linear transform that maps the lowest gray level $GL_{\min}$ in the image to zero and the highest value $GL_{\max}$ in the image to 255 (for an -bit representation), with all other gray levels remapped linearly between zero and 255, to produce a high-contrast image that spans the full range of gray levels. This linear transform is defined by

$$g'(x,y) = \mathrm{INT}\left\{\frac{255}{GL_{\max} - GL_{\min}}\left[g(x,y) - GL_{\min}\right]\right\} \quad (1)$$

where $g(x,y)$ is the input gray-level. The INT function returns the integer value, and $g'(x,y)$ is the output gray-level after conversion.

Image Smoothing based on Median Filter

The median filter [3] comes under the class of non-linear filter. The median filtering is very widely used in digital image processing since, under certain conditions, it preserves edges while removing noise. The main idea of the median filter is to run through the signal importation from entry, replacing each entry with the median of neighboring entries. Typically, a 3×3, 5×5, or 7×7 kernel of pixels is moved over the entire image. Because the median value must actually be the value of one of the pixels in the neighborhood, the median filter does not create new unrealistic pixel values when the filter straddles an edge.

2.2. Automated threshold-based adaptive region growing

In what follows, we will present a new approach, based on region growing, for the grain segmentation of the multi-crystalline solar cell wafer. The proposed approach is executing rapidly and automatically set in the starting seed and stopping criterion. In general, the seed point will definitely affect the convergence speed and segmentation result, so the “initial position” of the seed point needs to be carefully selected [4]. The concept adopted here is that the seed point to be selected should be located near the region around the center of the crystalline silicon wafer image, rather than the image boundary. Such an arrangement of seed point selection intuitively facilitates the speed of region growing. In this light, we apply an edge detection method to the entire multi-crystalline image. In this paper, we take Sobel operator to obtain the edge intensity image. The operator uses two 3×3 kernels which are convolved with the original image to calculate approximations of the derivatives, one for horizontal changes, and one for vertical changes. Essentially, the gradient near the image center is much less than the one near the boundary. Thus, the unlabeled pixel with the minimum gradient so far will be chosen as the seed point for region growing.

Adaptive Threshold Mechanism

The initial threshold is set to be the maximum gray level value minus the minimum gray level value over the entire image under investigation, as given by the following equation:

$$T_{int} = \max(f_{image}(x,y)) - \min(f_{image}(x,y)) \quad (2)$$

where T_{int} is the initial threshold of region growing, and $f_{image}(x,y)$ indicates the gray-level at any point in the image. At the outset, a loose threshold is automatically given in the proposed approach to run the conventional region growing segmentation until all the pixels are labelled. Then, a new performance measure is created to evaluate if the segmentation result is satisfactorily delivered. The performance measure is designed based on the entropy computation, as will be introduced shortly. If the termination criterion is not met, then the initial threshold is reduced by 1 as the new threshold to re-run region growing for the next iteration until all the pixels are re-labelled.

Termination Criterion (TC)

In this section, the termination criterion for the proposed region growing approach is introduced, where the entropy, a measure of the uncertainty in a random variable, is utilized to characterize the uniformity (i.e., homogeneity) of pixel intensity within the segmented grain. The term, uncertainty, usually refers to the Shannon entropy, which quantifies the expected value of the information contained in a message. Shannon entropy is the average unpredictability in a random variable, equivalent to its information content. Shannon entropy provides an absolute limit on the best possible lossless encoding or compression of any communication, assuming that the communication may be represented as a sequence of independent and identically distributed random variables. In this case, for the segmented region R_i with n outcomes, $\{x_1, x_2, \ldots, x_n\}$ indicate the pixels' gray levels within the segmented region R_i. The Shannon entropy is a measure of uncertainty and denoted by $H(R_i)$, as defined by

$$H(R_i) = -\sum_{i=1}^{n} p(x_i) \log_b p(x_i) \quad (3)$$

where b is the base of the logarithm used; $p(x_i)$ is the probability mass function of outcome x_i .

The entropy of the gray levels within every segmented region is computed. If the entropy of the segmented region's gray levels is less than termination criterion (TC), this region is deemed a "classified" grain (i.e., further segmentation is no longer necessary). On the contrary, if the entropy of the segmented region's gray levels is greater than termination criterion, this region is deemed "unclassified" and needs to be further segmented. The termination criterion (TC) is defined by means of the percentage decrease (PD) in the entropy of the whole image. The termination criterion is formulated as follows:

$$TC = H_{image}(x) \times (1 - PD \times 100\%) \quad (4)$$

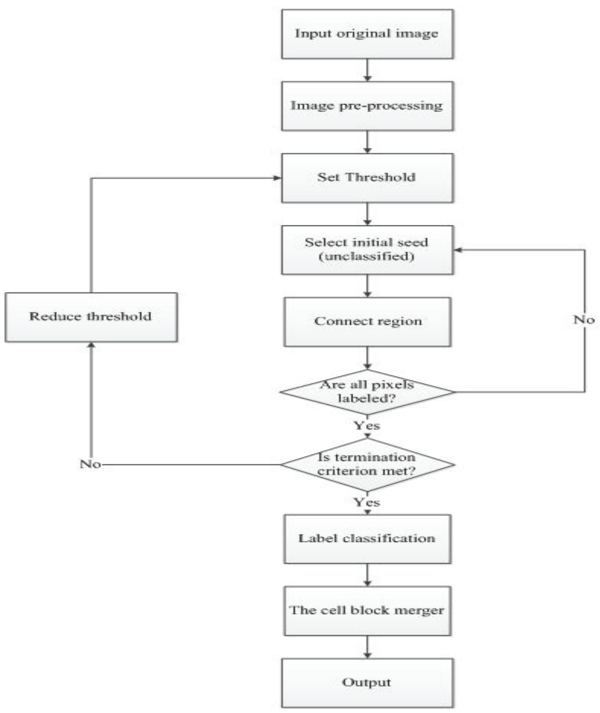
where PD is pre-specified by the user.

With the termination criterion mentioned previously, the segmented region can be determined "classified" or "unclassified" as follows:

$$R_i \begin{cases} H(R_i) \le TC, & \text{classified} \\ \text{otherwise}, & \text{unclassified} \end{cases} \quad (5)$$

Note that the entropy calculation in (3) and (5) is in relation to all the pixels of the original image. Figure 1 shows the flowchart of the automated threshold-based adaptive region growing approach in the following.

Figure 1: The flowchart of the automated threshold-based adaptive region growing approach.



After all the segmented regions are classified as grains, the cell block merger is triggered to combine all the really tiny grains. Now, the formal procedure of the automated threshold-based adaptive region growing approach is presented below.

step 1: Establish the termination criterion (TC) and given the initial loose threshold;

step 2: Select a seed point that must be unclassified;

step 3: Use the threshold of the current iteration to perform region growing to segment and then label the pixels for the entire image except the classified pixels;

step 4: Compute the entropy for each segmented region, and classify them as compared to the termination criterion (TC). If all the segmented regions are classified as grains, then go to Step 7, else go to Step 5;

step 5: Reduce threshold by 1;

step 6: Repeat Steps 2 to 5 until all the labels are classified in the image;
step 7: Merge the extremely tiny classified grains (less than or equal to M pixels) to the adjacent grains, and return the classified grain image.

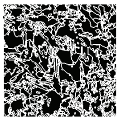
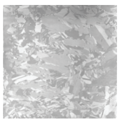
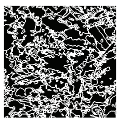
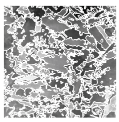
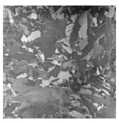
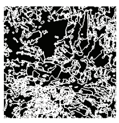
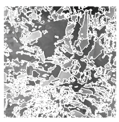
3. RESULTS AND DISCUSSIONS

To assure that the termination criterion is practically feasible for on-line production, the following issues in parameter setting should be taken into account. First, the termination criterion (TC) should be general-purpose and case-independent. That is, the termination criteria (TC) must be pre-determined by the user for every multi-crystalline solar cell image. Second, without losing generality, the percentage decrease (PD) in entropy with less than two decimal points is particularly recommended.

In this section, all the test images are of size 256×256 pixels. For the verification purpose, the histogram of the intensity data of corresponding pixels in the test solar cell image is created with 256 bins due to the 8-bit grayscale representation. Based on an earlier simulation study, the parameter setting of using $PD = 0.25$ and $M = 5$ produces satisfactory segmentation results for the proposed automated threshold-based adaptive region growing approach.

The three test images are exhibited in Table 1, from A1 to C1. The pre-processing results after enhancement and smoothing are displayed in A2-C2. Displayed in A3-C3 are the region-growing boundaries of the segmentation results, and the boundary lines placed on the enhanced images are shown in A4-C4. .

Table 1: Segmentation results returned by using the proposed automated threshold-based adaptive region growing approach

			
A1	A2	A3	A4
			
B1	B2	B3	B4
			
C1	C2	C3	C4

It has been demonstrated that the proposed region growing approach is not only fully automated in image segmentation, but also able to render satisfactory segmentation results. As compared to the original region growing approach, the threshold parameter selection of region connection for the original version is often determined according to the best segmentation results decided upon the human visual. In terms of the same test images, the segmentation results obtained by using the original and proposed approaches are tabulated in Table 2. Note that both approaches perform the processing of region growing on the solar cell image after pre-processing. The comparison between these two approaches mainly rests on the matching of physical objects and the number of small regions on the segmented image. The better segmentation result is presented as fewer really small regions are generated by the segmentation approach. In Table 2, the segmentation outputs contain the original images, the pre-processing results, and the segmentation results of the original and proposed region growing approaches. Obviously from this table, the proposed approach yields a better presentation of grain segmentation with much fewer really small grains than the original approach. Evidently, the original region growing approach can, at best, produce over-segmentation results as long as a fixed parameter setting is opted throughout the entire segmentation process.

To further compare these two region growing approaches, the numbers of small regions (≤ 5 pixels) prior to Step 7 are recorded in Table for images A1-C1. By using the proposed approach, the number of small regions significantly drops around 46-65%. Taking a close look at the segmented images in Table 2, it has been discovered that the original region growing approach tends to generate a large number of really small grains near the wafer boundary. Conversely, the proposed approach shows much better segmentation results that closely match the major details in the studied image, accompanied by a significant drop in the number of small regions. The drop in number does not influence the evaluation of the conversion efficiency remarkably but facilitates the merge of small regions in step 7. The most prominent merit of the proposed approach is that the entire region growing process for every studied image is automatically executed as long as two constant parameters are given beforehand. To our experience, these two constant parameters could be universally set for a specific application. In the case of solar cell image segmentation, the setting of $PD = 0.25$ and $M = 5$ is currently found to be working satisfactorily for a very large number of test images.

4. CONCLUSION

This paper investigates the performance evaluation of the proposed region growing approach for solar wafer image segmentation. The test images considered here are targeted at multi-crystalline solar cell wafer images. It is well known from the literature that the larger average grain size, the better quality of multi-crystalline solar cell. Thus, segmentation is the first image-processing step for grain size analysis. Particularly, entropy computation is used as termination criterion in the proposed approach to improve segmentation quality while seeking the appropriate, adaptive threshold for every segmented region. Through a set of three test images of solar cell wafer, the comparison between the original and proposed region growing approaches is presented. As evidenced by the comparison results, the proposed region growing approach presents much better segmentation results for the following grain analysis than the original version of region growing. A necessary and interesting future study will be how to develop suitable grain analysis indices to dictate conversion efficiency based on the segmentation results implemented in this paper.

Table 2: Segmentation results obtained by using the original and proposed region growing approaches.

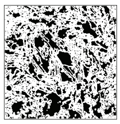
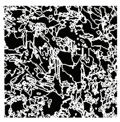
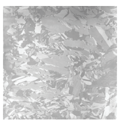
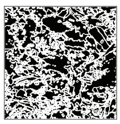
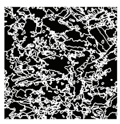
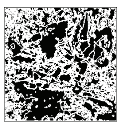
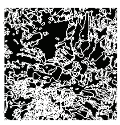
Image	Original image	Pre-processing result	Original region growing	Proposed region growing
A				
B				
C				

Table 3: The number of small regions generated by using two different region growing approaches.

Image	Number of small regions		Drop rate
	Original region growing	Proposed region growing	
A	7167	2447	65.90%
B	5104	2374	53.50%
C	4863	2596	46.60%

REFERENCE LIST

1. M. A. Ordaz and G. B. Lush. (2000). "Machine vision for solar cell characterization," *Machine Vision Application in Industrial Inspection VIII 3966*, 238-248.
2. M. B. Lee, K. H. Song, K. M. Park, J. H. Jung and S. L. Bae. (2012). "A Study on the Correlation Between the Grain Size and the Conversion Efficiency of Mc-Si Solar Cells," *Journal of Nanoscience and Nanotechnology 12*(7), 5691-5695.
3. S. Dangeti. (2000). *Denoising Techniques-A Comparison*, Master, Thesis, Louisiana State University, Visakhapatnam, India, 2000.
4. R. Adams and L. Bischof. (1994). "Seeded Region Growing," IEEE *Transactions on Pattern Analysis and Machine Intelligence 16*(6), 641-647