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Micro-crack inspection in heterogeneously textured solar wafers using anisotropic diffusion

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ABSTRACT

This paper proposes a machine vision scheme for detecting micro-crack defects in solar wafer manufacturing. The surface of a polycrystalline silicon wafer shows heterogeneous textures, and the shape of a micro-crack is similar to the multi-grain background. They make the automated visual inspection task extremely difficult.

The low gray-level and high gradient are two main characteristics of a micro-crack in the sensed image with front-light illumination. An anisotropic diffusion scheme is proposed to detect the subtle defects. The proposed diffusion model takes both gray-level and gradient as features to adjust the diffusion coefficients. It acts as an adaptive smoothing process. Only the pixels with both low gray-levels and high gradients will generate high diffusion coefficients. It then smoothes the suspected defect region and preserves the original gray-levels of the faultless background. By subtracting the diffused image from the original image, the micro-crack can be distinctly enhanced in the difference image. A simple binary thresholding, followed by morphological operations, can then easily segment the micro-crack. The proposed method has shown its effectiveness and efficiency for a test set of more than 100 wafer images. It has also achieved a fast computation of 0.09 s for a 640×480 image.

1. Introduction

Solar power has become an attractive alternative of electricity energy recently due to growing environmental concerns and global oil crisis. Solar cells that convert the photons from the sun to electricity are mainly based on crystalline silicon in the current market because it can generate good performance in usable lifespan and conversion efficiency among the currently available techniques. Multi-crystalline material dominates the production volume of silicon cells. Polycrystalline solar cells are more popular than mono-crystalline solar cells owing to lower manufacturing costs.

One critical category of defects found in solar wafer manufacturing is "micro-crack". Wafer breakage during processing results in high recovery cost and reduction in production yield. It may also cause electrical failure in postprocessing stages of solar cells and solar modules. In this paper, we develop a fast machine vision scheme for detecting micro-crack defects on polycrystalline solar wafers. The proposed method concentrates on the micro-crack that can be visually observed on the wafer surface. The non-observable internal micro-crack inside the wafer is beyond the scope of the paper. Fig. 1(a) displays the image of a polycrystalline solar wafer. It shows multiple grains of random shapes and sizes, and variations in direction on the surface and, therefore, results in a heterogeneous texture pattern. Fig. 1(b) demonstrates the image of a partial solar wafer surface that contains a diagonal micro-crack on the upper right of the image. It is hardly to be distinguished from the normal elongated grains on the lower right of the image. The heterogeneous multi-grain pattern of a polycrystalline solar wafer makes the micro-crack detection task extremely difficult.

Texture analysis techniques in image processing have been used extensively for automated visual inspection of material surfaces. The traditional texture analysis techniques for defect detection have been mainly focused on homogeneously textured surfaces, in which repetitive, periodical patterns give harmonic visual perception in the whole image. A set of texture features extracted from the spatial-domain or the spectral domain are generally used as discrimination measures, and then a classifier such as Bayes [1], maximum likelihood [2] or neural networks [3] is applied to distinguish defective regions from the faultless background pattern. The texture features are calculated based on a small neighborhood window by assuming that the texture patterns enclosed in the window are approximately identical everywhere in the inspection image. This assumption is only true for homogeneous texture surfaces.

In spatial-domain approaches, the commonly-used texture features are the second-order statistics derived from spatial gray-level co-occurrence matrices [4]. They have been applied to industrial

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inspection tasks such as wood inspection [5], carpet wear assessment [6] and roughness measurement of machined surfaces [7]. In spectral-domain approaches, texture features are popularly derived from the Fourier transform [8,9] for fabric defect detection [10,11] and patterned wafer inspection [12] in semiconductor manufacturing. Gabor transform [13–15] is also commonly used to design a bank of convolution filters that represent the characteristics of the textured patterns, and has been applied to the inspection of wooden surface [16], granite [17], steel surfaces [18] and textile fabrics [19]. Wavelet transform [20,21] is a popular alternative in recent years for texture feature extraction. It has been applied to industrial inspection of LSI wafers [22], woven fabrics [23] and homogeneously textured surfaces [24].

Instead of using the texture features for defect detection, image reconstruction schemes have been applied to eliminate the repetitive background pattern and preserve defects of arbitrary types in the reconstructed image by using Fourier transforms [25,26] and wavelet transforms [27,28]. Khalaj et al. [29] presented a self-reference technique to detect defects embedded in structurally textured surfaces that comprise only horizontal and vertical structural patterns. The repetitive periods are first evaluated by a spectral estimation technique. A synthetic reference template was then generated from the acquired image itself based on the pixel values in subsequent periods, and was used for comparison with the inspection image. The image-reconstruction and self-reference methods do not require the tedious process of texture feature design and extraction, but can only be applied to the surface images with repetitive patterns.

The local feature extraction and global image reconstruction methods described previously perform well for defect detection in homogeneously textured surfaces. However, they fail to detect local defects in heterogeneously textured surfaces that do not present repetitive patterns. As seen in Fig. 1, the local texture patterns in a small neighborhood window are distinctly different from each other in the polycrystalline wafer surface. The resulting local feature values could vary in a wide range and make the quantitative measures indistinguishable between defect-free and defective regions. The global representation of the heterogeneous textures cannot be abstractly described for background removal.

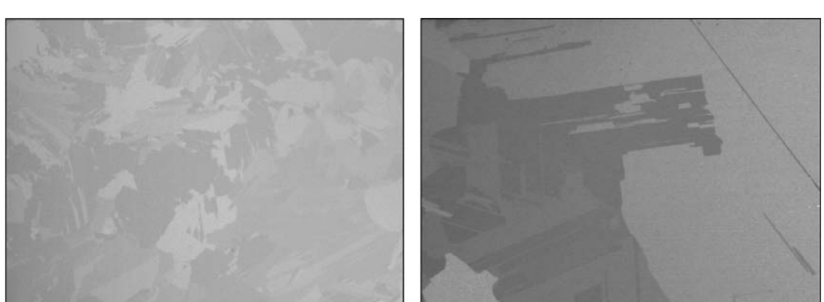
Only a few relevant papers in the literature discuss defect detection in the surfaces of solar cells or solar modules. Fu et al. [30] presented an image processing scheme for solar cell crack inspection. The solar cell images they investigated contained only simple structural patterns. They also assumed the cracks on the edge of the cell and those on the surface of the cell had distinct gray values with respect to the whole image. Simple image enhancement processes were first carried out to extract the contours of potential defects. Then cracks were verified based on geometrical criteria of the contour. Ordaz and Luch [31] discussed the solar cell characterization of conversion efficiency based on the intensity distribution of electroluminescence (EL) images. Pilla et al. [32] proposed an infrared thermography method for crack inspection in solar cells. The system had the thermal front propagating along the surface. It took advantage of the large thermal resistance at the interface created by the crack. Then surface cooling was generated by blowing air temperature over the surface. An infrared camera was used to capture the surface image. Simple edge detection was finally carried out in the IR image to identify the crack. The crack inspection methods discussed previously mainly focus on the solar cells that contain non-texture or structural texture patterns. They cannot be applied to micro-crack detection in polycrystalline solar wafers.

Since micro-cracks affect the structural integrity of solar wafers, they should be detected in an early stage of the manufacturing process so that the overall production yield can be greatly improved. In this paper, an anisotropic diffusion scheme is proposed to detect the subtle defects of micro-crack embedded in heterogeneous textures of solar wafers. Anisotropic diffusion model was first introduced by Perona and Malik [33] in image processing for scale-space description and edge detection. It has been used as an adaptive edge-preserving smoothing process for image segmentation [34,35] and texture segmentation [36].

The continuous anisotropic diffusion model is given by

$$\frac{\partial \boldsymbol{I}_t(x,y)}{\partial_t} = \boldsymbol{div}[c_t(x,y) \cdot \nabla \boldsymbol{I}_t(x,y)] \tag{1}$$

where $\boldsymbol{I}_t(x,y)$ refers to the image at time t, $\boldsymbol{div}$ the divergence operator, $\nabla \boldsymbol{I}_t(x,y)$ the gradient of the image, and $c_t(x,y)$ the diffusion coefficient at pixel coordinates (x,y). If $c_t(x,y)$ is a constant, Eq. (1) is reduced to the isotropic diffusion model. It is then equivalent to convolving the image with a Gaussian function, and only the smoothing process is performed. In the anisotropic diffusion model, the diffusion coefficient $c_t(x,y)$ is adaptively determined based on the local gradient magnitude of individual pixel at coordinates (x,y) so that the intra-regions are effectively smoothed while edges of the inter-regions are well preserved in the image. In our previous study [37,38], we have proposed two modified versions of the Perona–Malik anisotropic diffusion model to detect low-contrast defects in non-textured surface images. The improved models can effectively smooth the rough background and enhance the defective region in the diffused image. A simple statistical control limit based on the gray-level mean and standard deviation of the diffused image is then used as the threshold to locate the defective region. The approach that smoothes the background as a uniform region and enhances the intensity contrast of a defective region has worked successfully for low-contrast, non-textured surface images. Owing to the multi-grain patterns in the polycrystalline wafer surface, the faultless background with multiple intensities in random grain regions cannot be smoothed by using such an approach.



(a) (b)

Fig. 1. Two sample images of polycrystalline solar wafers: (a) defect-free multi-grain wafer surface and (b) defective wafer containing a micro-crack on the upper right of the image.