DENOISING OF IMAGE DATA FOR DWS WAFER CHARACTERIZATION USING GENERATIVE ADVERSARIAL NETWORKS

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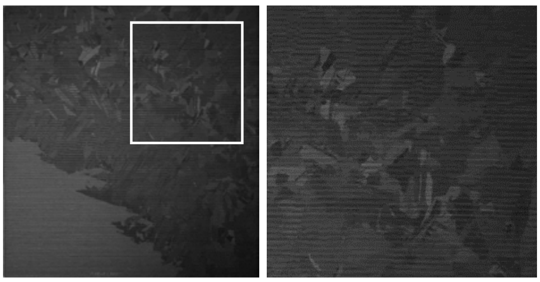
ABSTRACT: Diamond wire sawing is the wafering technique which recently replaced slurry-cut wafering, due to reduced kerf-loss, lower process expenditures and increased speed. While this technology is successfully used to wafer the ingots, it introduces a strong macroscopic saw damage on the surface of the wafers. These saw marks introduce artifacts in images recorded by multiple characterization methods which lead to poor quality inspection of silicon wafers and solar cells. Instead of a cost intensive update of the implemented measurement systems for the inspection of saw-damaged wafers, we propose a novel denoising technique of the images of diamond-cut wafers using generative adversarial networks.

Keywords: Characterization, Multi-Crystalline, Grain, Experimental Methods, Machine Learning,

1 INTRODUCTION

According to ITRPV 2018 [8], diamond wire sawing (DWS) [1] is a unique approach to wafering technology that has almost replaced slurry-based wafering for both monocrystalline and multi-crystalline silicon wafers. Diamond wire sawing has several advantages over slurry cutting, which include: (i) higher throughput, (ii) lower cost, and (iii) cleaner/environmentally friendly slurry system. However, these advantages occur only if the quality of the cut is as good as or better than slurry-cut [6]. Diamond wire sawn wafers show strong saw damage on their surface because of the wafering process. Differences or problems in the sawing process can cause strong inhomogeneities and variations in reflection on the wafer surface, which disturb the imaging methods and can cause problems in the detection algorithms[3]. In this work, we inspect the grain boundary imaging (GBI) system for mono-cast and multi-crystalline silicon wafers. Due to the inhomogeneities, the grain boundaries are not wholly visible which affects the overall characterization. Figure~1 shows an image example of a diamond wire sawn wafer captured by the grain boundary imaging system. Here, one can see the artifacts caused by the saw marks on the wafer.



Figure~1: Grain boundary image of a DWS wafer with zoomed in patch (right) shows the artifacts due to sawing damage

Hence our goal is to optimize the grain boundary imaging methods for diamond wire sawn wafers that are implemented for slurry-cut wafers. We approach this problem by digitally removing the saw marks using deep learning technologies. Since the noise patterns are heterogeneously distributed over each wafer, classical image processing techniques are not applicable for denoising the diamond-cut wafer images.

Most machine learning tasks call for supervised learning, i.e., training with paired data which consists of an input and its true target label. In our case, we would need a noisy image with artifacts and a clean image without the artifacts of the same wafer. This is unattainable because a silicon brick can only be cut into wafers by one wafering technology. Hence, we have unpaired data of diamond-wire-sawn and slurry-cut wafer images. An approach using adversarial training with the help of Generative Adversarial Networks (GANs) [2] is used to denoise the diamond wire sawn wafer images. In addition to the unpaired data, we use an experimental strategy to generate paired datasets to aid the adversarial denoising.

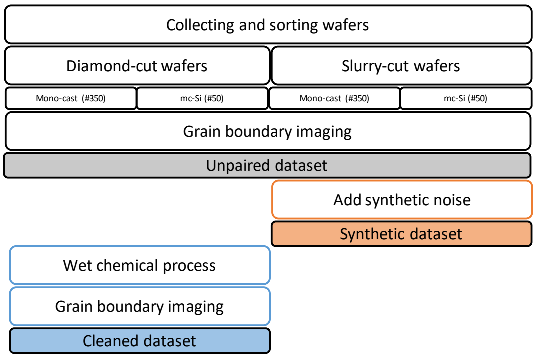
2 APPROACH

We use the generative power of deep learning models to denoise images. Therefore, we develop two approaches to overcome the challenges of unpaired data: (a) create pairs of noisy and clean wafer images, (b) implement machine learning models that work for both, paired and unpaired data. For the first approach, two paired datasets are generated, a synthetic dataset by inducing fake saw marks onto slurry-cut wafer images and an experimental dataset by removing the saw damage from the DWS wafers by undergoing an acidic texture process. For the second approach, a network called “ResidualGAN” is implemented which uses adversarial learning to tackle the lack of paired data. The generative power of GANs helps the network to estimate the heterogenous noise patterns and produce noise-free measurements.

2.1 Dataset creation

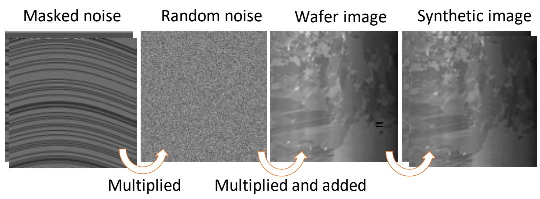
An informative dataset is crucial to train a machine learning model. We generate three different datasets: one unpaired and two paired, for our denoising task. The experimental flow of obtaining the data is shown in Figure~2. To create the different datasets, we collected 400 diamond-cut wafers and 400 slurry-cut wafers which are of mono-cast [7] and multi-crystalline material. These wafers were sorted out from different points along the brick height to provide a variety in data, e.g., different grain structures along the height of the brick. The data acquisition is explained below based on the complexity, from the easiest to the most difficult achievable data.

Unpaired dataset. To create an unpaired dataset, each DWS wafer and slurry-cut wafer were measured using a grain boundary imaging system. This system records a wafer from eight different angles using an LED illumination and therefore produces eight images of the same wafer. This dataset contains about 2900 images of both diamond-cut and slurry-cut wafers each of 400 wafers. As this dataset is an unpaired dataset, it contains a batch of DWS wafer images as the noisy images batch and a batch of slurry-cut wafer images as the clean images batch as shown in Figure~4 (see Unpaired data).



Figure~2: Experimental flow of dataset creation with unpaired (marked in gray), synthetic (marked in orange) and cleaned (marked in blue) data. The processes marked in black are common irrespective of the dataset.

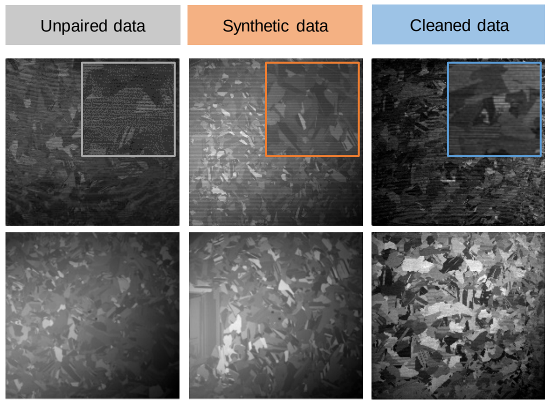
Synthetic dataset. The second dataset is a paired data by adding synthetic noise to the slurry-cut wafer images. It is challenging to synthesize data in such a way that the data correspond to the real data. In our case, it is difficult to reproduce such saw marks due to its unique and very noisy structures across the DWS wafer. To be able to replicate the saw marks accurately, the saw marks on the DWS wafer were analyzed and reproduced on slurry-cut wafer images. Here, we use slurry-cut wafer images because of their artifact-free wafer images. An example pair is shown in Figure~4 (see Synthetic data). Some sample images contain artificial saw mark structures that look more curved than the real saw marks. This allows the model to denoise not only uniform but also uniquely structured saw marks from the DWS wafer images.



Figure~3: Process flow of noise synthetization on slurry-cut wafer images

Figure~3 shows how the addition of synthetic to the slurry-cut wafer images is performed. First, a mask is created that imitates the line-like structures of the saw marks. To include some variety in the saw marks for better denoising of the noisy wafer images, the lines are slightly curved in randomly selected wafer images. The mask is multiplied with random normal noise. This masked noise is then added and multiplied with the slurry-cut wafer images to create a synthetic DWS wafer image. The original slurry-cut wafer image that is used to create the synthetic DWS wafer image is the corresponding clean label.

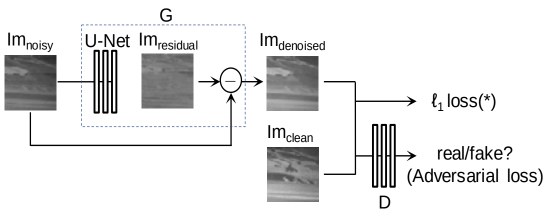
Cleaned dataset. An additional paired dataset, called the cleaned dataset, is generated within an experimental set-up. After recording grain boundary images of diamond-cut wafers, the wafers undergo an acidic texture that etches away the saw marks from the wafer surface. Once the saw marks have been removed, the wafers are measured again with the grain boundary imaging system to generate the cleaned diamond-cut wafer images. In Figure~4 (see Cleaned dataset), one can see that the grains on the DWS wafer image look slightly different from the wafer image after surface cleaning. This is due to the change in the optics of the wafer surface related to the texture process.



Figure~4: Example pairs of unpaired (left), synthetic (middle) and cleaned (right) datasets

2.2 Machine learning models

The diamond-cut wafers are denoised using an advanced deep learning approach. A generative adversarial network (GAN) is a network used for training with unpaired data by using adversarial training. It consists of a generative and a discriminative network that try to outplay the other during training. The generator tries to fool the discriminator by generating realistic images while the discriminator tries to classify the generated image as real or fake. In our work, we investigate our adversarial model called ResidualGAN shown in Figure~5. The goal of this model is to generate a clean DWS wafer image, which contains the content of the DWS wafer but has a slurry-like surface.



Figure~5: Schematic of our Residual GAN training architecture; (*) ℓ_1 loss is optional: included for paired datasets, excluded for unpaired datasets

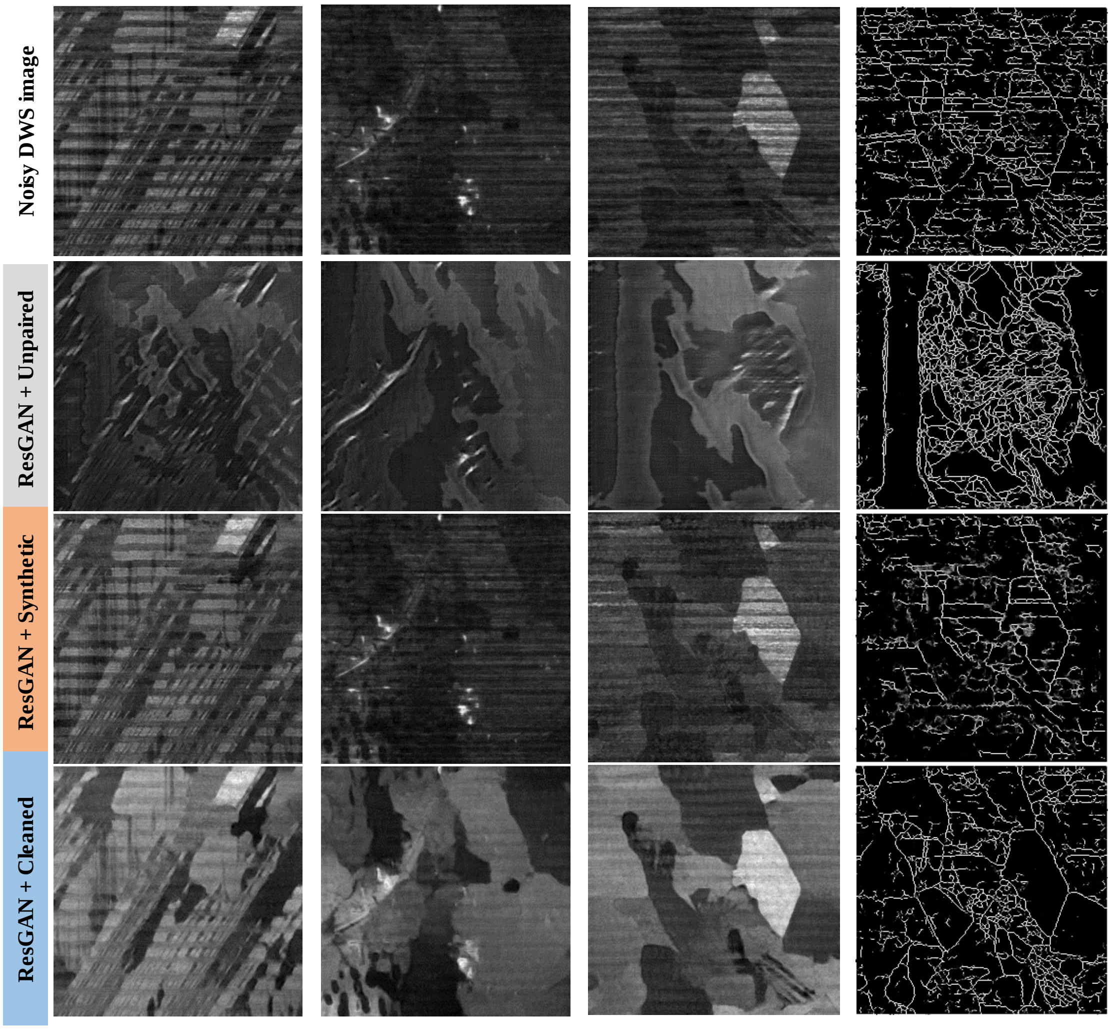
ResidualGAN uses a convolutional neural network, namely, a U-Net [3] in the generator network. U-Net was initially developed for image segmentation but has been extended to other tasks. The generator network of the ResidualGAN learns the noise, i.e., the saw marks and subtracts them from the input DWS wafer image to generate the denoised image. To optimize the generator in this model, a discriminator loss is used. The discriminator is trained on both generated "clean" DWS wafer images as well as slurry-cut wafer images. This allows the discriminator to distinguish between a generated and a real image.

Given a generated input from the generator, the discriminator categorizes the image as real or fake. This is fed back to the generator which tries to improve depending on the discriminator's outcome. If the discriminator correctly classifies the generated image as a fake one, the generator will try to create more realistic images than the previous one. On the other hand, if the discriminator classifies the image as real, it implies that the generator is successful at creating slurry-like DWS wafer images. The generator gets better with time at generating slurry-like DWS wafer images. When training this network with paired data, an additional loss function, here l_1 loss, is used along with the discriminator loss to optimize the generator.

3 EXPERIMENTAL

To achieve the goal, different experiments have been conducted. The implemented model is trained with each dataset and tested on real data, i.e., grain boundary images of diamond-wire-sawn wafers. Following the original GAN paper [2], the discriminator D and generator G are updated once in every epoch. To reduce model oscillation [2], we follow Shrivastava et al's strategy [5] and update the discriminator using a history of 50 previously generated images rather than the ones produced by the latest generators [9]. Both the generator and discriminator are optimized by using the Adam optimizer [4] with their learning rates set to 0.0002 for a stable training. In every experiment, the model is trained for a total of 100 epochs. An epoch indicates a round through the entire dataset by the machine learning algorithm.

The results from each experiment are shown in Figure~6 and discussed below. For each test, eight DWS wafer images recorded with the grain boundary imaging system are selected. These images are denoised with each trained model. To understand the results better, the grain boundaries are extracted from the denoised images using a grain boundary detection model that was trained on slurry-cut wafer images. Each column shows three of the eight denoised images and their detected grain boundaries.



Figure~6: Results of our ResidualGAN trained on unpaired data (second row), synthetic data (third row) and cleaned data (last row) with noisy DWS wafer images (first row); last column shows the detected grain boundaries of the third denoised DWS wafer images

ResidualGAN trained with unpaired data. In the first experiment, the ResidualGAN is trained with unpaired data using an adversarial loss. The network gets a noisy DWS wafer image as the input and is expected to denoise the DWS wafer images. Instead of creating clean DWS wafer images, it generates unrealistic slurry-like images without the grain structures from the DWS wafer. This is due to a phenomenon called mode collapse. Mode collapse occurs when the generator learns how to generate samples from a few modes of the data distribution but misses many other modes, even though samples from the missing modes occur throughout the training data [4]. An example of the generated result is shown in Figure~6 (second row).

ResidualGAN trained with synthetic data. By using an additional direct comparison loss function, the ResidualGAN is trained with the synthetic dataset. The results obtained from this model are better than the ones from adversarial training. The artifacts are less intense and therefore the detection of their grain boundaries partially improves (see third row in Figure~6) when compared to the raw diamond-cut wafer images.

ResidualGAN trained with cleaned data. In the experiment with cleaned data, ResidualGAN did a better job at denoising the wafer images shown in Figure~6 (see ResGAN+Cleaned data). The grain boundaries are sharper than the ones from the previous test. The reason behind it could be that the model was trained on real data instead of synthetic or unpaired data which makes it easier for the model to transfer to real data.

To evaluate the models, a similarity metric called SSIM (Structural Similarity Index Measure) [5] was used. It measures the similarity between the real and generated clean images based on luminance, contrast and structure. An SSIM value of 0 means that the real and generated images do not have any similarity, whereas an SSIM value of 1 represents 100% similarity between the real and generated images. Our model trained with synthetic data achieved an SSIM value of 0.8337 whereas the ResidualGAN trained with cleaned data achieved a value of 0.9779 which indicates that our model performed comparatively better with cleaned data.

4 DISCUSSION

Our model ResidualGAN was trained on three datasets: unpaired, synthetic and cleaned data. In our first experiment, ResidualGAN was trained using unpaired data using an adversarial network. The results obtained from this training scheme turned out to be unrealistic slurry like images, i.e., images with slurry like surfaces but no content from the input image. For the second and third experiments, we used an additional supervised loss function which helped our model to denoise the DWS wafer images. The training with synthetic data aided in a better grain boundary detection than the noisy DWS wafer images. Better results were achieved by training our ResidualGAN on the cleaned data. The results show that most of the saw marks were removed from the wafer images and therefore enables to have a better grain boundary detection with these denoised images. Unlike unpaired data, the training with the synthetic dataset was successful at avoiding mode collapse and generated realistic wafer images. On the other hand, the training with the cleaned data was successful at denoising the DWS wafer images better.

5 CONCLUSION AND OUTLOOK

In this work, we evaluate our model ResidualGAN to denoise the images captured with the grain boundary imaging system DWS wafer of mono-cast and multi-crystalline silicon material. For this approach, we have successfully generated three kinds of datasets. The easiest available dataset is the unpaired data, as no extra effort was required to create this dataset. Additionally, we generated two paired datasets: a synthetic by adding artificial noise to the “clean” slurry-cut wafer images and a cleaned dataset by performing a wet chemical process on the DWS wafers. Our model generates a denoised image of DWS wafers using a combined adversarial and supervised loss mechanism. A purely unsupervised training using adversarial loss led to a failure called mode collapse which led to unrealistic images.

Within the scope of this work, we generated training data for additional imaging systems: photoluminescence and infrared transmission imaging. The denoising task can be extended to these datasets. Additional methods are being investigated to overcome the challenge of mode collapse when training with unpaired data.

6 REFERENCES

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