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Full Wafer Process Control Through Object Detection Using Region-Based Convolutional Neural Networks

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Abstract — Full wafer measurement techniques are used in the semiconductor industry to acquire information at a large scale to control process variation or detect potential defects. This process usually results in the generation of full wafer images, containing various objects that need to be identified to evaluate their impact on the final product performance. Artificial intelligence is very powerful to automate this identification routine. In this paper, we present the application of Region-based Convolutional Neural Networks (RCNN) for enhanced process control from full wafer images gathered by two industrial metrology equipments.

Keywords — Full wafer, Process control, Photoluminescence imaging, Scanning Acoustic Microscopy, RCNN

I. INTRODUCTION

The fourth industrial revolution brings fundamental changes that will redefine manufacturing paradigm especially in the semiconductor industry: artificial intelligence, big data, and cloud computing allows connections between every level of the manufacturing cycle, from the supply chain logistics to the production and test equipments. In semiconductor front-end factories, process control is one of the key concerned areas where major evolutions are being undertaken to adopt those new concepts.

Traditionally, metrology control is carried out on pre-designed target structures located in sacrificial areas of the wafer. Those are limited in number especially at the extreme edge of the wafer and are in some ways not always representative of the real devices. Alternative and innovative approaches are emerging which consist in collecting the metrology signal directly from the dies and ideally at the full wafer scale. The resulting signal can then be treated through a model less approach based on artificial intelligence algorithms. Moreover, the treatment of metrology response at the entire wafer scale by its own can also reveal signature that would be ignored in a die-to-die comparison approach. Here we present two interesting use cases based on Photoluminescence and Acoustic imaging techniques.

II. FULL WAFER MEASUREMENT TECHNIQUES

A. Macroscopic Photoluminescence Imaging

Photoluminescence is an optical technique that can be implemented in manufacturing line to control silicon quality and characterize its properties. In this technique, a laser source ($\lambda = 808\text{nm}$) is used to generate free carriers that will radiate light when they recombine. The emitted light properties (wavelength, intensity, etc.) can be used to determine impurity, defect, or doping levels as well as quantum efficiency and other properties (Fig 1.a). In our case, we used a macroscopic photoluminescence (MPL) imaging acquisition system (Fig 1.b) which provides full wafer images allowing a large-scale control. The key outcome of such control is to detect anomalies which correspond to a decrease in PL band-to-band signal intensity and will be later referred as “dark spots” in the image. This PL signal loss can be due to many different mechanisms [1,2] that will not be detailed in this article. A traditional approach to analyze MPL images and provide quantitative results would consist in reporting the mean and the standard deviation of the measured photoluminescence intensity over the full wafer. This is actually very poor restitution of the collected information especially ignoring any spatial consideration.

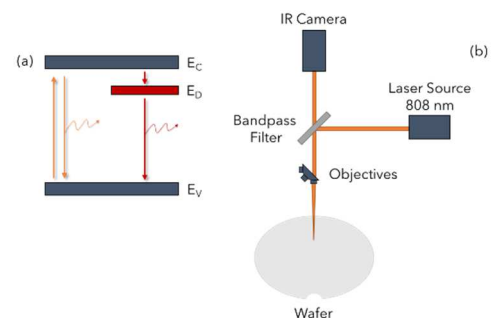


Fig. 1. (a) Energy diagram showing how defects in the silicon induce a reduction in band-to-band signal intensity through photoluminescence and (b) functional schematic of the MPL equipment.

To maximize the outcome, a different approach applying RCNN algorithm was evaluated to detect and localize dark spots directly from the full wafer image. One important background information to mention here is that due to the extreme sensitivity of photoluminescence response, MPL images collected at a given process step of the manufacturing line generally always exhibit dark spots. What is of particular importance is then to differentiate atypical signatures from common ones. So, as a first preliminary study, MPL images were collected at the given process step for a significant number of wafers. The common signature were identified by stacking of the gathered MPL images. This allowed us to identify two classes of common signatures (triangular) that will have to be ignored during the automatic detection (Fig. 2). Any other dark spot will have to be identified as “atypical”, leading to a further action on the affected wafer.

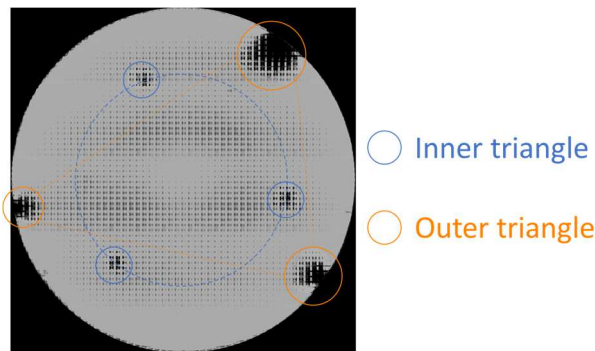


Fig. 2. Example of a MPL cartography with common signatures.

B. Scanning Acoustic Microscopy

Scanning Acoustic Microscopy (SAM) is an acoustic technique that uses focused sound to identify defects by studying the scattered sound induced by the wave encountering the defect (Fig. 3). Further explanations can be found in [3,4]. This technique is widely used to control bonding quality and detect voids in many wafer-on-wafer bonding architecture (temporary, molecular, hybrid...).

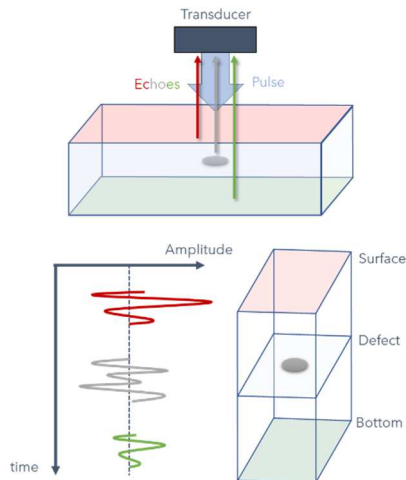


Fig. 3. Functional schematics of the SAM equipment, showing how defects and flat layer surface induce different echoes and can then be identified.

The resulting outcome is also full wafer image (Fig. 4) where voids appear this time as white spots or areas. One possible approach to detect the bonding defects can pass through image treatment techniques notably thresholding. This type of approach requires a very time-consuming recipe creation which is (in addition) specific of the product layout. Moreover, as the expected result is also to further classify the defects depending on their nature (design, particle contamination, etc....) for troubleshooting action, this would lead to a very complex algorithm. Therefore, a RCNN approach seems more promising and was evaluated to detect and classify the voids from full wafer images (Fig. 5). The final objective is to provide a robust solution allowing relevant decisions such as bonding rework or die inking.

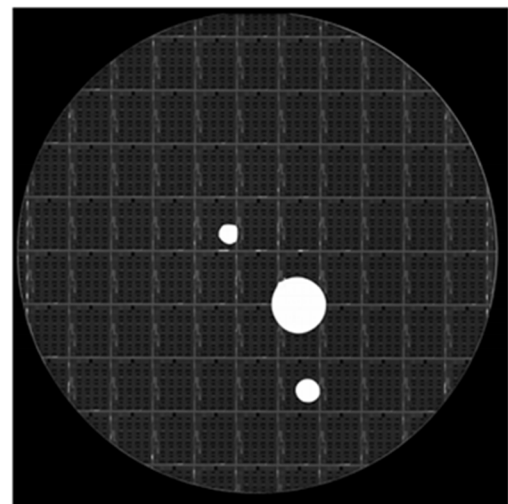


Fig. 4. Example of full wafer SAM cartographie showing white spots from voids of various origins.

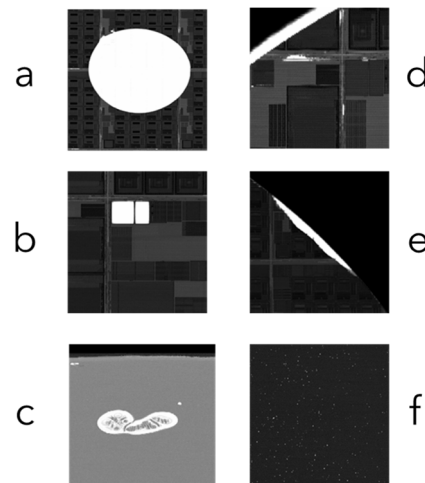


Fig. 5. Typical example of each class.

III. REGION-BASED CONVOLUTIONAL NEURAL NETWORK

Neural networks are now proven to be one of the strongest ways to generate complex models, capable of numerous tasks such as image classification, clustering, or outcome prediction. More advanced architectures are used to perform

object detection, where regions of interest (containing the objects) of images are extracted by a segmentation neural network and classified by a convolutional neural network. Such algorithms are called Region-based Convolutional Neural Networks (Fig. 6). They are notably used for object tracking in autonomous vehicles or cell classification for cancer detection, but also in semiconductor industrial process control to improve accuracy in defect detection [5,6]. They are also able to adapt themselves better to contrast/brightness and product/design variation than the mathematical image treatments commonly used by metrology and defectivity equipments. To train those neural networks, a dataset consisting of images containing the objects to be detected, and an annotation file containing the location, size, and class of said objects must be provided. In our case, to reduce the amount of data and computing time needed for this training, transfer learning from a pre-trained network (RetinaNet [5]) was used. RetinaNet is one of the best one-stage object detection models that has proven to work well with dense and small-scale objects. For this reason, it has become a popular object detection model to be used with aerial and satellite imagery. Transfer learning allows the adaptation of the pre-trained network, commonly used to detect everyday objects (e.g. animals, vehicles...), to our specific dataset by keeping the core capabilities of the original network (namely interest region proposal and feature extraction), but slightly adjusting the neurons weights to better fit the new data. As stated previously, this requires far less data and training time than training a neural network from scratch. It is to be noted that while the training can be computationally intensive (~hours on a commercial GPU), the inference (usage of trained network on new data) can be quickly performed with minimal computing power (~seconds on CPU). RCNN is then a very powerful neural network approach that was tested in a slightly different way depending on the measurement technique's (MPL and SAM) specificity.

For the MPL images, the goal is to detect all the dark spots present on the images, and then to classify them as common or unusual spots depending on their location. A two-step strategy was set. At first, the RCNN was trained to detect all dark spots, regardless of their location on the wafer map. That way, for the inference step, which corresponds to the prediction of the neural network in detecting and classifying new data, all the dark spot signatures are detected. Secondly, once the spots locations on the wafer are found, a subsequent algorithm apply geometrical rules that allows to classify them as common or unusual signature. A training dataset composed of 275 experimental images, gathered with the MPL equipment, containing 1420 annotations was then generated to train this first network.

For the SAM images, the global process is closer to the usual RCNN approach. It was indeed trained to automatically detect and classify of voids on the full wafer images. The individual voids were annotated for the training set and were also classified depending on their origin/nature so that the convolutional neural network will be able, once trained, to

automatically classify and identify the cause of the detected defect. The training was then performed on a dataset containing 12644 classified annotations of defects present on 155 images. In both cases, an additional validation dataset of annotated images was kept in order to evaluate the performance of the trained RCNNs on unseen data.

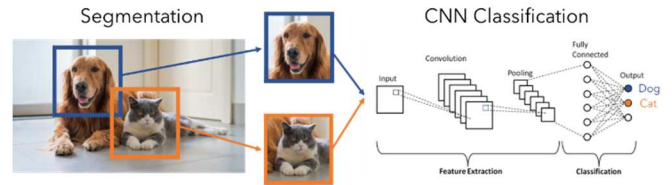


Fig. 6. Schematic diagram of a region-based convolutional neural network, showing the segmented sub-images being classified by the CNN

IV. RESULTS AND PERSPECTIVES

The performances obtained on the validation datasets once both networks were trained on MPL and SAM images are presented in the Table I and Table II. The results are represented in a confusion matrix where predicted classes are compared to the actual class of the defect. We can then determine the detection accuracy (amount of defect detected) and prediction purity (amount of detected defect correctly classified) of both networks.

Table I. Performance results represented in confusion matrix for MPL

MPL		True		
		<i>Common</i>	<i>Atypical</i>	<i>Undetected</i>
Predicted	<i>Common</i>	542	0	11
	<i>Atypical</i>	0	117	0

Table II. Performance results represented in confusion matrix for SAM

SAM		True						
		<i>a</i>	<i>b</i>	<i>c</i>	<i>d</i>	<i>e</i>	<i>f</i>	<i>Undet</i>
Predicted	<i>a</i>	96	0	0	0	0	0	0
	<i>b</i>	5	564	0	14	0	0	4
	<i>c</i>	0	0	73	0	0	0	0
	<i>d</i>	0	1	0	781	0	0	25
	<i>e</i>	0	0	0	0	412	0	51
	<i>f</i>	0	0	0	0	0	254	7

For the MPL full wafer image analysis, the trained RCNN was applied to detect and classify the dark spots present on the validation datasets and the results were compared to the manually annotated spots. Out of 670 annotations on 142 images, the neural network was successful in detecting 659 (98.3%), only missing a few faint common signatures. An example of inferred MPL image is presented in figure 7. For most of those signatures, a standard metrology approach monitoring the mean and standard deviation of the overall MPL signal would be unsuccessful in detecting these

anomalies, because they do not induce a large enough variation in the global photoluminescence signal.

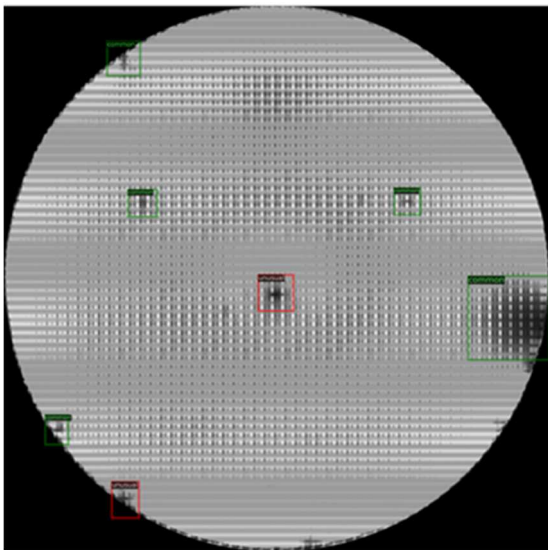


Fig. 7. Inference results on MPL image showing classification of dark spots depending on location – Red = Uncommon , Green = Common

For the SAM images, in the same way, we evaluated the trained RCNNs performance on the validation dataset, and result shows that, in 96.19% (2200/2287) of cases, the algorithm was able to correctly detect the voids and classify them correctly according to their physical origin. Those results are very impressive considering the large number of objects detected per full wafer image in some cases and considering the fact that the defect characteristics from different classes are not always significantly different from one another. Two inferred SAM images originating from the validation dataset are presented in figure 8 and 9.

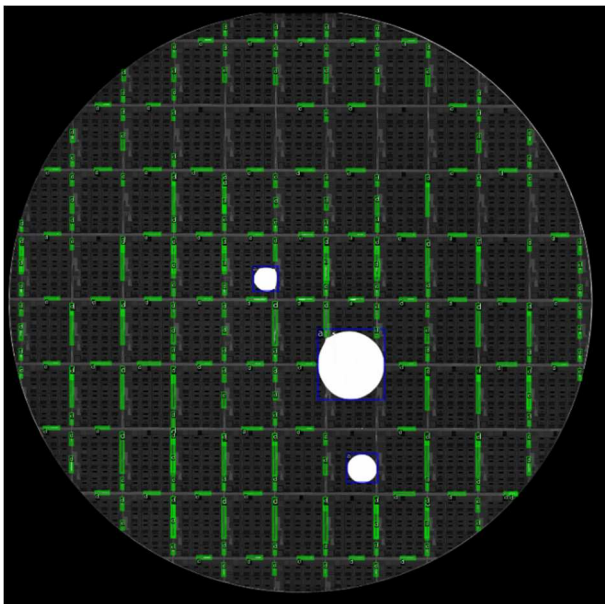


Fig. 8. SAM images with classified voids depending on their origins (Class *a* in blue and Class *e* in green here)

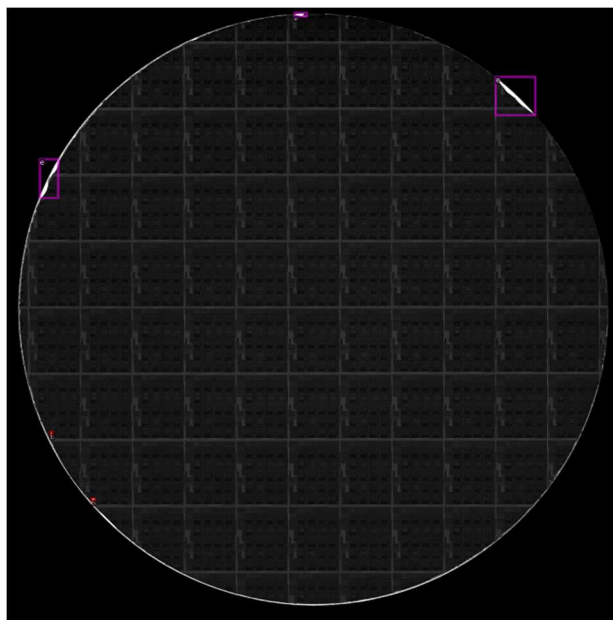


Fig. 9. SAM images with classified voids depending on their origins (Class *b* in purple and Class *f* in red here)

In order to increase the robustness of this approach, and allow for new signatures to be identified, multiple neural networks could be trained with the same datasets and used in parallel. First, signature detection and classification are improved by the redundancy of networks. But most importantly, in the event of a new defect type being present on the wafer images, the RCNNs results can be used to detect them. Indeed, because the classification accuracy of properly trained neural network is very high, any signature classified into different classes by the networks most likely indicates a new type of signature. To test this hypothesis, we trained 4 networks without the Class *c* signature and observed the different inference outcomes. The results are presented in figure 10.

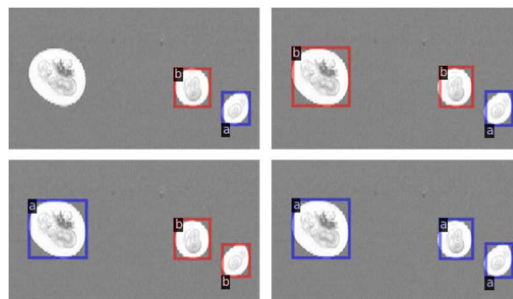


Fig. 10. SAM images containing Class *c* defects, identified as Class *a* or Class *b* defects by the RCNN models trained without this specific class.

The 4 trained RCNN inference results show that they disagree on the classification of the Class *c* voids. This can be used to trigger a new signature alert, or in the case of a false alarm (misclassification of a known defect), lead to re-training of the networks to eliminate this error.

To increase their performance, additional training of both networks will then be done using the inference results from production data, completing the missing detections if needed, and generating additional annotation files.

V. CONCLUSION

Full wafer images were acquired from two metrology equipments and successfully treated by Region-based Convolutional Neural Networks in order to automate the detection and classification of multiple signatures. This innovative approach of using neural networks for process control is less sensitive to image acquisitions variations such as brightness and contrast and is able to detect new signatures, while improving in performance while in production.

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