Enhancing Acoustic Image Analysis Through Machine Learning

Introduction

Acoustic Micro Imaging (AMI) can capture defect information at specific layers of a wafer or advanced package sample. Defects are detected based on their signal amplitude and polarity, and failure criteria is automatically applied based on factors such as size, quantity, and location of defects. Automated in-line acoustic microscopes can inspect multiple samples simultaneously to detect defects early in the production process.

Traditional Digital Image Analysis (DIA) software evaluates defects by binarizing an image into two colors, white representing delamination and black representing a good bond or lack of defects. It then quantifies defects by position, size, etc.

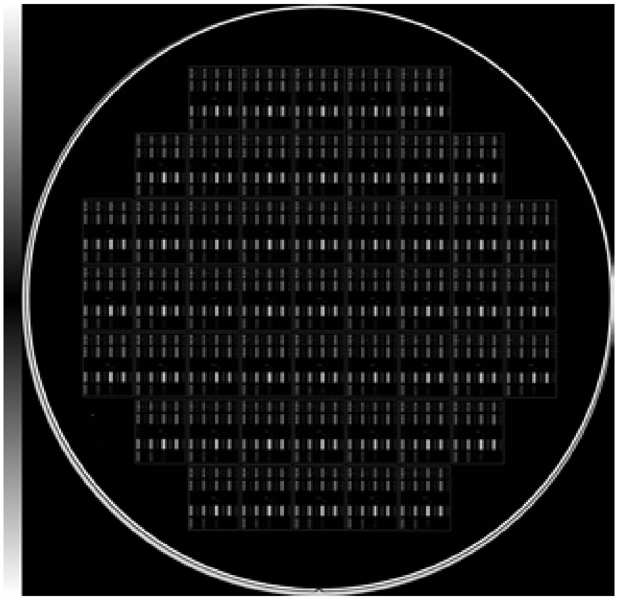

Figure 1: Bonded wafer, calibration void pattern

Challenge

- In more complex wafer structures, die structures such as metallization and via patterns can appear at the same signal amplitude as defects, which prevents traditional pixel value thresholding from isolating defects.
- The bonded wafer shown was constructed with calibration voids arranged in a chip pattern. These calibration marks appear at the same pixel value as the unintended voids.
- This results in both true defects and false defects being included in the total void list.

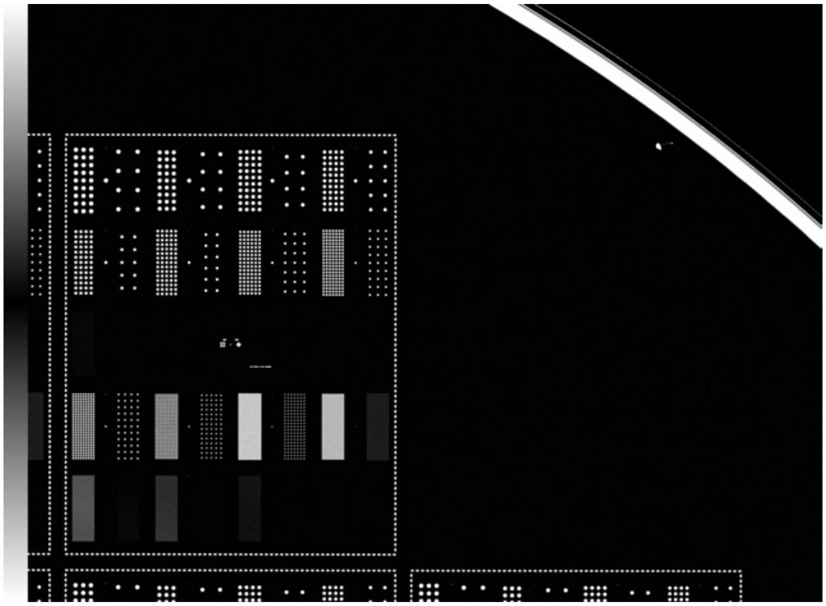

Figure 2: Bonded wafer showing calibration void pattern and defect, zoomed in

Solution

Multi-Gate Image Analysis (MGIA) is an image analysis tool which uses machine learning to recognize good and bad patterns, exclude good patterns from the void count, and combine defect analysis from different acoustic images into one straightforward result based on customized failure criteria.

Using an MGIA machine learning model, it is possible to obtain an accurate defect count and apply relevant failure criteria without artificially inflating the defect count by including vias, metallization, or other patterns. This software model is a precursor to anomaly detection, which will be able to identify defects and anomalies after being trained on a set of known good parts.

Using a calibration wafer as a case study, a machine learning model was trained to differentiate between delaminations and intentionally created calibration voids. This type of model can be integrated into a production recipe to better quantify defects on production wafers or trays.

To train this model, a set of 10 wafers were scanned on the SpinSAM automated acoustic wafer scanner. Data from one wafer was set aside for testing, and data from the other nine wafers was divided for model training and validation. The same images were analyzed using standard DIA software and using a machine learning model to analyze regions which are true voids or calibration voids and quantify only the true voids.

The AI/ML model is able to distinguish three classes of pixels:

1. Background
2. Chip marker (green)
3. True defect (blue)

The model is trained that the calibration voids, with consistent size, shape, and placement, are considered “background” pixels despite having the same pixel value as defects.

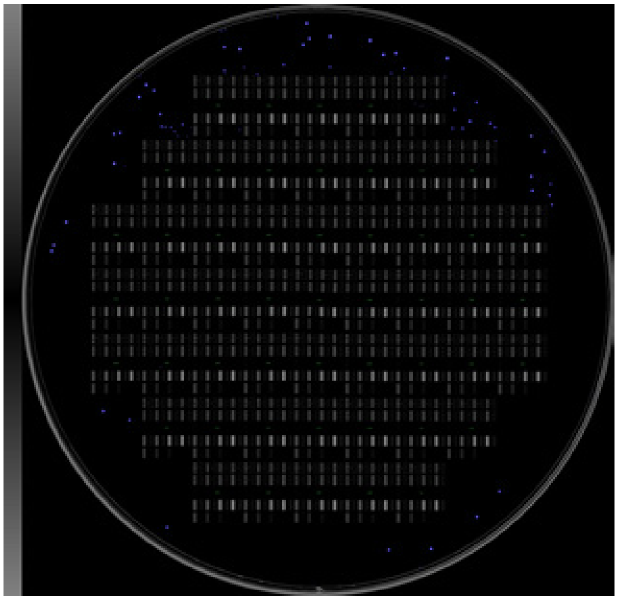

Figure 3: MGIA Classification Image

Conclusion

Using MGIA, defects can be isolated for a count of true voids. The output lists the location, X-Y dimensions, and area of true defects. It excludes acoustically identical calibration voids from the defect list. Integrating AI/ML algorithms into production scale imaging and defect analysis on an inline SpinSAM wafer inspection tool provides results which can improve product yield.

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