반도체디스플레이기술학회지 제22권 제2호(2023년 6월)
Journal of the Semiconductor & Display Technology, Vol. 22, No. 2. June 2023.

Image Processing and Deep Learning-based Defect Detection Theory for Sapphire Epi-Wafer in Green LED Manufacturing

Suk Ju Ko[*,*], Ji Woo Kim[*,***], Ji Su Woo[**,***], Sang Jeen Hong[****] and Garam Kim[*†]**

[*†]Department of Electronics Engineering, Myongji University,
[**]Department of Industrial and Management Engineering, Myongji University,
[***]Semiconductor Equipment Engineering Program, Myongji University,
[****]Department of Semiconductor Engineering, Myongji University

ABSTRACT

Recently, there has been an increased demand for light-emitting diode (LED) due to the growing emphasis on environmental protection. However, the use of GaN-based sapphire in LED manufacturing leads to the generation of defects, such as dislocations caused by lattice mismatch, which ultimately reduces the luminous efficiency of LEDs. Moreover, most inspections for LED semiconductors focus on evaluating the luminous efficiency after packaging. To address these challenges, this paper aims to detect defects at the wafer stage, which could potentially improve the manufacturing process and reduce costs. To achieve this, image processing and deep learning-based defect detection techniques for Sapphire Epi-Wafer used in Green LED manufacturing were developed and compared. Through performance evaluation of each algorithm, it was found that the deep learning approach outperformed the image processing approach in terms of detection accuracy and efficiency.

Key Words : Sapphire Epi-Wafer, LED Defect Inspection, Computer Vision, Convolutional Neural Network

1. Introduction

Recently, there has been a growing emphasis on energy conservation and environmental protection, leading to increased interest in eco-friendly light-emitting diode (LED) components across industries such as semiconductors, automobiles, and displays. Among these components, GaN-based LEDs are particularly favored for their environmental friendliness, chemical stability, wide spectrum coverage, and high electrical conductivity, making them a popular choice in LED manufacturing [1,2].

However, one of the challenges in LED manufacturing is the lattice mismatch between GaN and the sapphire wafer used as a substrate, which amounts to a 16% difference in lattice constant. This lattice mismatch results in stress on the wafer, leading to various defects, including dislocations [3]. In the case of green LEDs, the high In content poses further difficulties, resulting in lower luminous efficiency and the occurrence of various defects [4].

Currently, defect detection research utilizing machine vision is actively conducted for silicon wafers to minimize defects during the manufacturing process. Machine vision offers the advantage of reducing labor requirements and increasing inspection speed by replacing the human eye and judgment with automated systems.

On the other hand, sapphire wafers used in LED manufacturing are predominantly inspected for luminous efficiency after the packaging process, despite the presence of the aforementioned defects. Therefore, performing defect detection inspections using machine vision after the epitaxy process can help identify defective dies, enabling process improvements and cost savings in subsequent stages.

The objective of this research paper is to develop a machine vision-based system for detecting external defects

[†]E-mail: garamkim@mju.ac.kr

on GaN-based layers deposited on sapphire wafers used in LED manufacturing. The study begins by capturing images of the surface defects on the sapphire wafers using a specially designed light source setup. Subsequently, image processing and deep learning-based detection methods are introduced to analyze and identify these defects. The accuracy and performance of these detection methods are then evaluated and compared.

The proposed system aims to determine the presence or absence of defects on the wafers and classify them based on their characteristics. This serves as a starting point for process improvement, particularly in reducing defects during the Epitaxy process, ultimately leading to enhanced LED luminous efficiency. The combined utilization of image processing techniques, which rely on rule-based detection methods rooted in computer vision, and AI-powered deep learning-based detection methods adds significance to this study.

Overall, this research contributes to the field by leveraging both traditional image processing approaches and advanced deep learning techniques to detect and classify defects on sapphire wafers used in LED manufacturing. The findings have the potential to drive process improvements and enhance the overall quality of LED production, with a focus on optimizing the Epitaxy process.

2. Equipment & Data Set

2.1 Equipment

In this research paper, wafer images were captured using optical inspection equipment. The optical imaging technique involves illuminating the wafer with light and observing the reflected light to obtain an optical image of the object under inspection. These optical acquisition methods can be categorized into bright field images and dark field images based on the angle at which the incident light is directed onto the object [5]. In this study, coaxial illumination, a type of bright field imaging where the light is incident vertically, was employed to obtain the images.

The optical inspection equipment utilized in this study is depicted in Fig. 1 and shares the same specifications as described in Table 1.

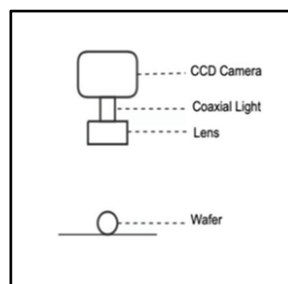


Fig. 1. Optical inspection equipment.

Table 1. Optical inspection equipment specification

Camera	Model	G3-GM11-M2420
	Resolution	5M
	Resolution [H]	2464
	Resolution [V]	2056
	Pixel Size	3.45 μm
	Sensor Size	11 mm
	Mount	C
Lens I/O	Model	VSTC-HR4X110
	Mag.	4×
	WD	110 mm
	F#	22.1
	Image Circle	11 mm
	Lighting Type	Coaxial
	Mount	C
Etc.	Pixel Resolution	0.8625 μm
	FOV [H]	2.13 mm
	FOV [V]	1.77 mm
	DOF	±19 μm (@F#=22.1)

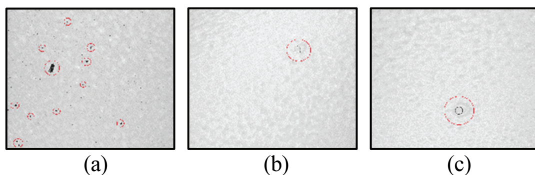
2.2 Data Set

The experimental wafer utilized in this study was a 2-inch sapphire wafer. It served as the substrate on which the GaN-based layer, essential for manufacturing green LEDs, was epitaxially deposited using Metal-Organic Chemical Vapor Deposition (MOCVD) technique. The detailed structure of the wafer is shown in Fig. 2. These layers were grown for research purposes with the cooperation of Soft-Epi, Inc.

Fig. 2. Epitaxial layer structure.

During the experiment, a series of images were captured by placing the wafer on an optical stage and incrementally moving it in small steps. A total of 161 images were obtained for analysis and evaluation.

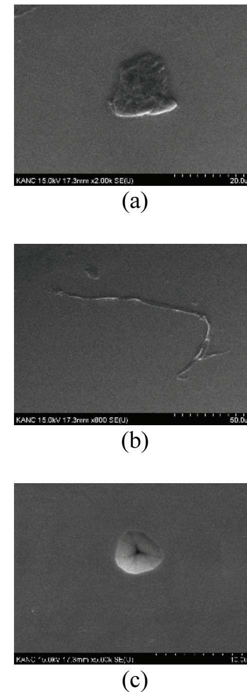
Among the captured images, three distinct types of defects were observed and identified: Particle, Imprint, and Dislocation. Particle defects observed in the images are characterized by the presence of long, thick lines that appear in multiple small shapes or irregular sizes. These lines exhibit a color that is clearly distinguishable from the background. The Imprint defects observed in the images exhibit a thin and short parabolic shape. They appear as small curves or arcs with a narrow width and short length. These defects are typically characterized by a light gray or dark gray color, which distinguishes them from the surrounding background. The Dislocation defects observed in the images exhibit a hexagon or circle shape. They appear as geometric shapes with six sides (hexagon) or a rounded outline (circle). These defects are characterized by a dark gray or black outline, which contrasts with the surrounding background Fig. 3 depicts the images of each type of defect.



(a) (b) (c)

Fig. 3. Optical images of (a) Particle, (b) Imprint, and (c) Dislocation.

A total of 58 particles were identified as defects caused by foreign substances. Imprint defects, totaling 33 instances, were defined as defects resulting from physical damage, such as the use of tweezers. The remaining 70 instances were categorized as dislocation defects, caused by stress resulting from lattice mismatch. To accurately determine the type of defect in the acquired images, scanning electron microscopy (SEM) imaging was performed. Fig. 4 shows SEM images taken for each type of defect.



(a)

(b)

(c)

Fig. 4. SEM image of (a) Particle, (b) Imprint, and (c) Dislocation

3. Experiment

This paper presents the development of two defect detection models based on machine vision using image processing and deep learning techniques, which are widely used in computer vision. The image processing technique utilizes rule-based algorithms, while deep learning employs learning-based algorithms.

3.1 Image processing based detection algorithm

The image processing algorithm follows a flow chart shown in Fig. 5. The acquired images from the area camera undergo pre-processing steps to eliminate noise and enhance the image quality through binarization and image enhancement techniques. Next, the detection process specific to each type of defect is performed to determine the presence and type of defect. The detected defects are then displayed using Bounding Boxes, as illustrated in Fig. 6. The development of the defect detection algorithm was based on the methods described in references [6-11].

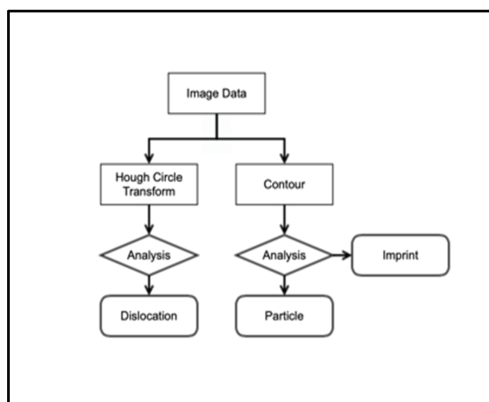
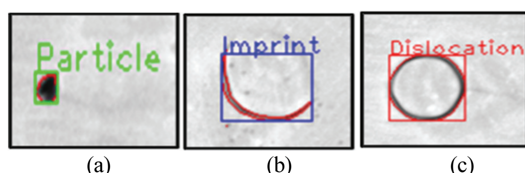


Fig. 5. Algorithm flowchart



(a) (b) (c)

Fig. 6. Bounding boxes for (a) Particle, (b) Imprint, and Dislocation

3.1.1 Particle, Imprint detection algorithm

In the case of Particle and Imprint defects, accurately determining the outline of the defects is crucial. To achieve this, a median weight filter algorithm is applied to the image to remove noise. Subsequently, a threshold value is set, and binarization is performed to separate the background from the defective part more accurately. Using the binarized image, a morphological closure transform is applied to connect objects that may have been fragmented due to blurring and binarization, and additional noise is removed. The preprocessed image is then processed using a contour algorithm to detect the outline of the defects. The length and width of the defect outlines are determined based on this contour detection. If both the length and width exceed a certain threshold value, the defect is classified as a Particle or Imprint. The classification is based on the measurements of length, width, and the ratio between the length and width. The length and width ratio of the contour was calculated using Equation (1).

$$Ratio = 4 \times 3.14 \times Area/Length^2 \qquad (1)$$

A smaller Ratio indicates a shape that is closer to a line, while a value closer to 1 indicates a shape that is closer to a circle. In the case of imprint and line particles, they share a common condition of having a ratio less than 0.1. However, imprints are characterized by being thin lines, while line particles are characterized by being thick lines. Therefore, they are distinguished based on area conditions. In conclusion, if the ratio is greater than 0.1, it is classified as a dot particle. If the ratio is less than 0.1 and the area is greater than or equal to a specific threshold, it is classified as a line particle. If the ratio is less than 0.1 and the area is below the threshold, it is classified as an imprint.

3.1.2 Dislocation detection algorithm

Although dislocations have a hexagonal shape, they appear as circles in the field of view (FOV) and pixel resolution of the captured image. Therefore, an approximation method is used to calculate the shape of the dislocation. Initially, a Gaussian filter is applied to the image to reduce noise while preserving the circular shape. Using the blurred image, the Hough Circle Transform algorithm is applied. The algorithm identifies circles based on a minimum radius condition to avoid misidentifying dot particles as dislocations. If a circle is detected, it is classified as a dislocation.

3.2 Deep learning based detection algorithm

This paper employed a Convolutional Neural Network (CNN) model to detect defects in Sapphire Epi-Wafers used for manufacturing green LEDs. CNN is a powerful deep learning model widely recognized for its exceptional performance in image classification tasks within the field of computer vision. The CNN model consists of two main steps: feature extraction and classification. In the feature extraction step, unique features are extracted from the input data using Kernel Filters. These features capture distinctive patterns and characteristics of the defects. In the classification step, the extracted features are used to classify the type of defect present in the image.

The original dataset used in this study comprised black and white images with dimensions of 2464×2056 pixels. The dataset consisted of three types of defects: 'Dislocation', 'Particle', and 'Imprint', each labeled accordingly. The dataset was divided into training and evaluation sets with a ratio of 8:2, enabling the model to learn from the training data and evaluate its performance on unseen data during the evaluation phase.

In this paper, a convolutional neural network (CNN) model was developed based on the ResNet architecture proposed in reference [12]. The model was implemented using the Keras library in Python. The model takes a single-channel image with dimensions of 213×255 pixels as input. It consists of multiple layers, as depicted in Figure 7. The model starts with an input layer that defines the size and channel of the input image. Subsequently, feature extraction is performed using several convolutional layers and batch normalization layers. The Rectified Linear Unit (ReLU) activation function is applied to introduce nonlinearity in the network. Finally, the output of the convolutional layer is flattened into a 1-dimensional vector, which is then fed into a fully connected layer to produce the final output.

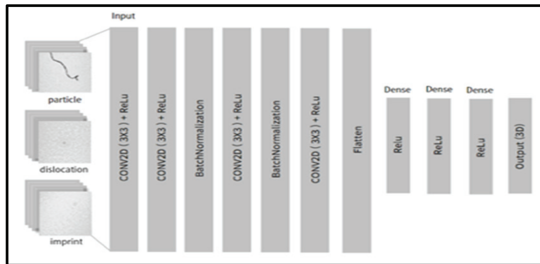


Fig. 7. CNN Model.

4. Results and Discussion

4.1 Performance evaluation of image processing based detection algorithm

The performance evaluation was conducted using a total of 161 images, including 58 Particle, 33 Imprint, and 70 Dislocation images. The comparison between visual inspection and algorithm-based detection results is presented in Table 2. Image processing-based defect detection is commonly used for real-time detection due to its fast processing speed and minimal data requirements for algorithm development. However, it has limitations in recognizing various irregular defects (Fig. 8), resulting in lower detection rates.

Table 2. Image processing based detection algorithm confusion matrix

Predict \ Real	Particle	Imprint	Dislocation
Particle	56	4	2
Imprint	1	27	2
Dislocation	1	2	66

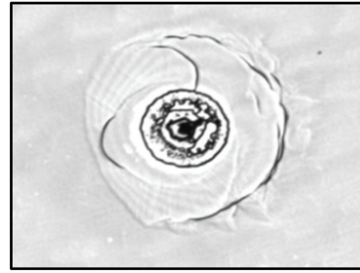


Fig. 8. Irregular defect image.

4.2 Performance evaluation of deep learning based detection algorithm

For performance evaluation, a total of 20% of the images were used from the total of 161 images. The image classification accuracy results using these test images were as follows: Dislocation 100%, Particle 100%, and Imprint 71%. Deep learning has shown high accuracy in both structured and unstructured data, leading to active research in this field. However, solutions based on deep learning require a large amount of data for training and involve heavy computations, making real-time processing challenging. In this study, we also observed relatively lower accuracy in Imprint, which can be attributed to the limited dataset available. To address this, data augmentation techniques were applied to the Imprint images, and additional performance evaluation was conducted, as shown in Table 3. Fig. 9 represents an actual Imprint image misclassified as Dislocation.

Table 3. Deep learning based detection algorithm confusion matrix

Predict \ Real	Particle	Imprint	Dislocation
Particle	12	0	0
Imprint	0	24	0
Dislocation	0	4	14

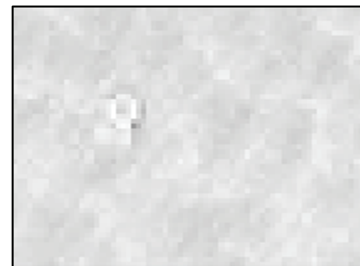


Fig. 9. Irregular Imprint defect image

5. Conclusion

This study conducted research on detecting and classifying defects in Sapphire wafers with GaN-based layers using machine vision. The study compared the performance of two methodologies commonly used in machine vision: rule-based and deep learning.

In this study, the developed rule-based detection algorithm achieved an accuracy of 97% for Particle, 82% for Imprint, and 94% for Dislocation. On the other hand, the learning-based detection algorithm achieved an accuracy of 100% for Particle, 71% for Imprint, and 100% for Dislocation. Additionally, data augmentation techniques were applied, resulting in improved accuracy for Imprint from 71% to 86%, while maintaining 100% accuracy for Dislocation and Particle.

In the semiconductor industry, the choice of methodology depends on various factors such as the complexity of the task, the quantity and quality of the data, and the time and cost considerations. According to the research results, the deep learning algorithm outperformed the rule-based algorithm. Therefore, it can be concluded that for LED semiconductor defect detection, the deep learning algorithm is more suitable if the Imprint dataset can be obtained extensive.

By employing the proposed defect detection methodology in this study, it would be possible to identify which part or line of the sapphire wafer, after Epitaxy, has issues, allowing for further actions such as modifying the manufacturing process recipe. This could potentially lead to improved yield in LED semiconductor production.

Acknowledgement

This study was conducted with the support through the Korea Institute for Advancement of Technology (G02P1880 0005501). We would like to express our gratitude to Nexus1 for the providing research topic, mentoring, and assistance.

References

1. H.K. Cho, J.Y. Lee, G.M. Yang, C.S. Kim, “Formation mechanism of V defects in the InGaN/GaN multiple quantum wells grown on GaN layers with low threading dislocation density,” *Applied Physics Letters*., Vol. 79, No. 2, pp. 215–217, 2001.
2. R. Colby, Z. Liang, I.H. Wildeson, D.A. Ewoldt, T.D. Sands, R.E. García, E.A. Stach, “Dislocation filtering in GaN nanostructures,” *Nano Letter.,* Vol. 10, No. 5, pp. 1568–1573, 2010.
3. William A. Melton, Jacques I, Pankove, “GaN growth on sapphire,” *Journal Of Crystal Growth*., Vol. 178, No. 1, p. 168, 1997.
4. B. Lee, "Optical properties of InGaN/GaN active layer based blue-green light-emitting diodes," Master's thesis, Graduate Schoo of Kangwon National University l, 2020.
5. S.R. Kim, “Non-Referential Defect Detection based on Image Patch Similarity of Semiconductor Scanning Electron Microscope Image,” Master's thesis, Graduate School of Hanyang University, 2017. p. 7
6. Tamás Czimmermann, Gastone Ciuti, Mario Milazzo, Marcello Chiurazzi, Stefano Roccella, Calogero Maria Oddo, Paolo Dario, “Visual-Based Defect Detection and Classification Approaches for Industrial Applications—A SURVEY,” *Sensors*., Vol. 20, No. 5, p.1495, 2020.
7. Yingjie Yin, De Xu, Zhengtao Zhang, Mingran Bai, Feng Zhang, Xian Tao, Xingang Wang, “Surface Defect Detection on Optical Devices Based on Microscopic Dark-Field Scattering Imaging,” *Strojniski Vestnik*., Vol. 61, No. 1, pp. 24-32, 2015.
8. Baik Seung Yeb. “Development of Automatic Precision Inspection System for Defect Detection of Photovoltaic Wafer,” *Journal of the Korean Society of Manufacturing Technology Engineers*., Vol. 20, No. 5, pp.666-672, 2011.
9. Y.J Park, “Development of Bolt Tap Shape Inspection System Using Computer Vision Technology,” *Journal of Digital Convergence.,* Vol. 16, No. 3, pp. 303-309, 2018.
10. N.H Kim, H.J Lee, H.J Jeong, J.G Lee, “Automatic detection system for surface defects of home appliances based on machine vision,” *Smart Media Journal.*, Vol. 11, No. 9, pp. 47-55, 2022.
11. S.H Jeong, S.H Yoo, D.H Joung, H.B Lee, “Development of Vision Inspection system for detecting surface defects of shaft,” *Proceedings of the Autumn Conference and Exhibition of the Korea Society of Automotive Engineers.*, pp. 2196-2200, 2012.
12. HE, Kaiming, et al. “Deep residual learning for image recognition,” *Proceedings of the IEEE conference on computer vision and pattern recognition*., pp. 770-778, 2016.

접수일: 2023년 6월 2일, 심사일: 2023년 6월 14일,
게재확정일: 2023년 6월 21일