AI Image Technology for Fast, Cost-Effective, and Safe Manufacturing Process

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Abstract
This paper describes two artificial intelligence (AI) technologies for generating and analyzing images for OLED display manufacturing. Firstly, many measurement steps are required during fabrication in order to verify TFT patterns, which leads to glass wastage while measurement recipes are generated. We demonstrate that virtual images generated by AI technology can be used to in place of real images of a glass substrate, allowing for fast and cost effective fabrication. Secondly, an automated measurement system utilizing AI is proposed. Precise measurement is required for equipment setup related to delicate processes. Our system employs segmentation AI, followed by image processing for correction, enabling precise measurements automatically. It can reduce human errors and protect engineers from harm when measuring inside equipment. Application of these two technologies has significantly enhanced the efficiency of the display manufacturing process.

Author Keywords
Artificial Intelligence (AI); Generative Adversarial Network (GAN); Critical Dimension Measurement (CDM); Object Detection; Segmentation

1. Introduction
Artificial intelligence (AI) has become an important tool in the manufacturing industry, helping to improve efficiency and productivity. Display manufacturing is no exception, as it actively adopts AI technologies to address specific challenges and enhance operations.

One of the unique aspects of display industry is its reliance on visual inspections to ensure the quality and functionality of its products. To meet these demands, AI is widely used for defect detection and quality control, utilizing advanced image and video analysis techniques [1-2].

Beyond defect inspection, AI is also applied in analyzing process parameter data in order to identify anomalies and facilitate preventive maintenance [3]. Additionally AI helps in optimizing process parameters to improve production quality and efficiency [4]. These uses highlight the importance of AI in ensuring smooth operations and maintaining high standards in manufacturing.

This paper focuses on two specific examples where AI has been applied, both related to dimension measurement during the display manufacturing process. While much attention has been given to defect detection and anomaly analysis, the use of AI image technology in dimension measurement offers unique opportunities to improve efficiency, accuracy and safety. Two main case studies that demonstrate the use of AI in this field are discussed.

Firstly, during fabrication, measuring thin film transistor (TFT) dimensions usually involves matching and identifying specific locations within a designated pattern. This typically requires the capture of real images, which slows the production process. To reduce fabrication time, we have proposed using AI-generated virtual images based on mask layouts instead of real images. Virtual images can reduce processing time and glass wastage. This method and its benefits are explained in detail in Section 2.

Secondly, during the module process, verifying equipment settings has traditionally been manual tasks. Manufacturing engineers would manually measure by rulers and verify whether a piece of equipment was correctly configured or not. This process is time-consuming and prone to human errors. Sometimes it is even dangerous because people have to enter inside the equipment. To solve these issues, we have developed an automated measurement system based on segmentation technology. This approach replaces manual measurements with AI-driven automated measurements, significantly improving both speed and accuracy. The implementation and results of this system are described in Section 3.

2. Virtual Image Generation by AI
Critical dimension measurement (CDM) is a crucial step to accurately measure the dimensions of TFT patterns and verify their compliance with design specifications in the OLED fabrication process. The CDM process is conducted as illustrated in Figure 1. Firstly, the glass substrate after TFT patterning is mounted onto the CDM equipment and a predefined region is magnified using a charge coupled device camera and a single image is captured. Using this we can determine the specific TFT location and registration. Based on this information, a measurement recipe is generated that specifies which patterns to measure in a following step. Next, multiple images are captured across multiple display substrates. Finally, according to the recipe, the images are processed and the line widths of TFTs are determined.

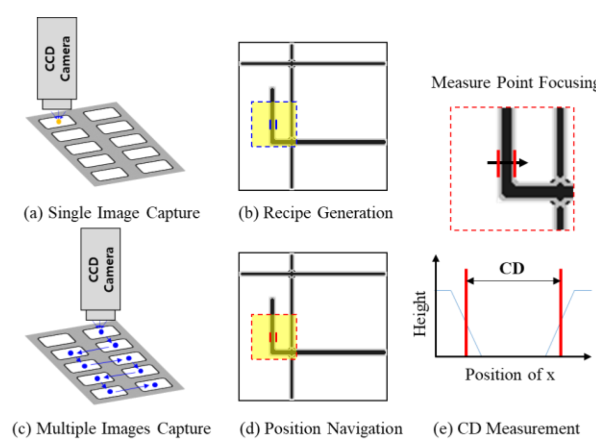

Figure. 1. CDM process

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The measurement recipe is a key factor in ensuring the accuracy of the CDM process. However, since TFT layouts vary for each product, a new measurement recipe must be generated at every process step. This increases the CDM time required and becomes a major cause of delays in the overall production cycle.

To address this issue, a method using realistic virtual images generated from mask layouts, instead of real images, has been proposed. Real images exhibit complex characteristics influenced by various factors such as layer stacking order, interlayer overlap, transmissivity, focus deviation, and material surface quality. Therefore, replacing real images with virtual images in CDM recipe generation requires accurately reflecting these characteristics in the virtual images.

To generate virtual images, a generative adversarial network based neural style transfer algorithm which is commonly used in image synthesis was employed [5]. This deep learning technique combines a content image with the style of another image to create a new image which has a different style from the original content image. Specifically, virtual images were generated by maintaining TFT pattern shapes of mask layouts while transferring the style from real images. However, as the discrepancy between the style and the content of images increases, it becomes more challenging to accurately combine the features of both images. This can result in distorted shapes from the content image or images that fail to adequately reflect the desired style.

To overcome this challenge, a preprocessing step was added to the content images. First, patterns were extracted from each layer of the mask layouts and combined into a single image with weights assigned based on the stacking order. Subsequently, the combined image was colorized by referencing color data from real images of other products with the same process procedure. This approach ensures that, within the same process, the pattern shapes do not affect the color values under identical layer measurement conditions. As a result, while the content image does not fully replicate the texture of real images, it retains a similar overall structure and shading characteristics. By applying style transfer to the preprocessed content image, it is possible to generate images that effectively reflect the style of real images while preserving the TFT patterns.

The effectiveness of the virtual image dataset was evaluated based on the pattern matching rate, which measures the similarity between virtual and real images. The pattern matching rate was determined by defining a region of interest in the virtual image and using pattern matching algorithm based on a gray profile to identify the optimal matching position in the real image (corresponding to the highest matching rate). A comparison across all layers of the OLED revealed that the success rate of measurement recipes generated using virtual images was equivalent to that of recipes generated using real images.

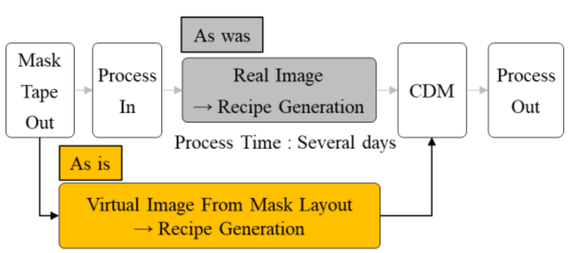

Figure. 2. Newly proposed CDM Setup process

The proposed virtual image-based CDM method significantly improved the efficiency of generating measurement recipes, reducing manufacturing time and enhancing productivity. This new process, visualized in Figure 2, successfully reduced the turn-arround time of the manufacturing process by several days.

3. AI Based Auto Measurement System

During the manufacturing process, equipment settings are adjusted according to products to accommodate a wide range of architecture styles. These adjustments involve not only software but also physical modifications to the equipment itself. In order to prevent disruptions to the manufacturing process, it is essential to verify the accuracy of these settings in advance. Typically, equipment operators stop the machinery and perform manual measurements using, for example, a ruler. However, this approach has a lot of risks, including measurement errors and potential accidents. When operators make measurements deep inside equipments, it poses a risk to safety that they should come into contact with machinery. To manage these risks, an AI-powered automatic measurement software has been developed. This software has been designed with ease of use in mind and has been deployed on mobile devices, enabling straightforward and efficient operation.

The automatic measurement software comprises two main analysis steps, which is shown in Figure 2. The first step is the object detection and segmentation by AI to detect the ojbects which should be measured and to differentiate between the equipment and panel. Subsequently, in the second step, image processing is applied in order to reduce the segmentation noise and to perform perfective transformations. In the object detection and segmentation step, an AI model should be capable of handling a wide range of measurements across a variety of processes, vendors and equipment environments. Since boundary detection algorithm is critical for length measurements, YOLOv8, known for its superior segmentation performance, was utilized [6]. To train the model, approximately 2,000 images from various processes were collected, and multiple constituent components were labelled, for instance the pickers, grippers and panels. By employing similar or identical parts, good accuracy was achieved for a diverse range of processes. After segmentation, we determine the critical components and remove things that are superfluous.

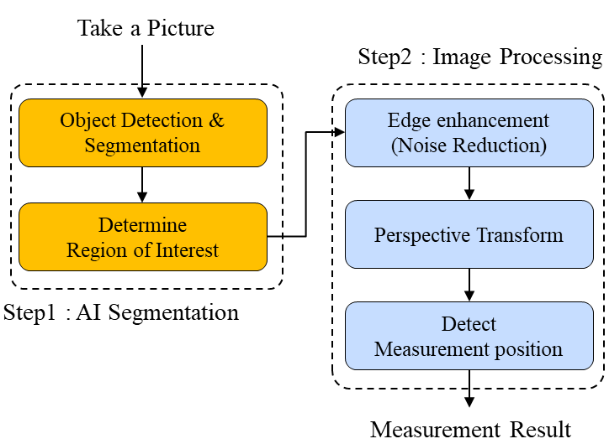

Figure 3. Auto Measurement System Flow

Rough measurement estimates followed by segmentation are possible. However, for precise measurements, additional image processing is required. Initially, segmentation has to delineate object boundaries even which are partially occluded. This process often introduces noise. Thus, post-processing is applied to refine these boundaries.

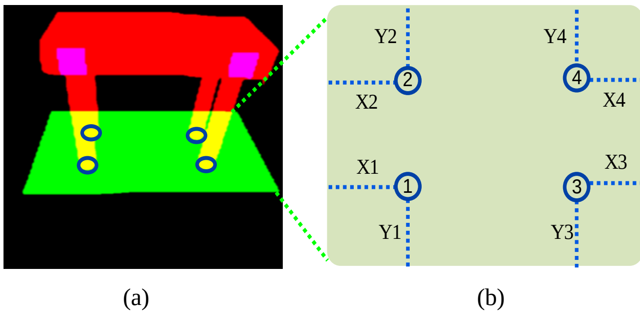

Figure 4. Measurement example (a) Segmentation result. (b) Measured items.

Furthermore, the image processing stage includes algorithms to correct for issues such as panel warping, distortions caused by the camera angle, and errors arising from excessive light. These corrections ensure consistent repeatability, regardless of variations introduced by the operator such as differences in height, field of view, or specific light conditions of equipments.

Once image processing is completed, perspective transformation is applied to convert the image into an orthogonal coordinate system, enabling accurate measurement. Figure 4 illustrates how of the picker's position above the panel is measured. The red and green colors represent the picker of an equipment and the panel respectively in the segmentation result which is shown in Figure 4(a). After image processing, the panel and picker positions are transformed into an orthogonal coordinate system as shown in Figure 4(b). In this case, there are eight measurement results.

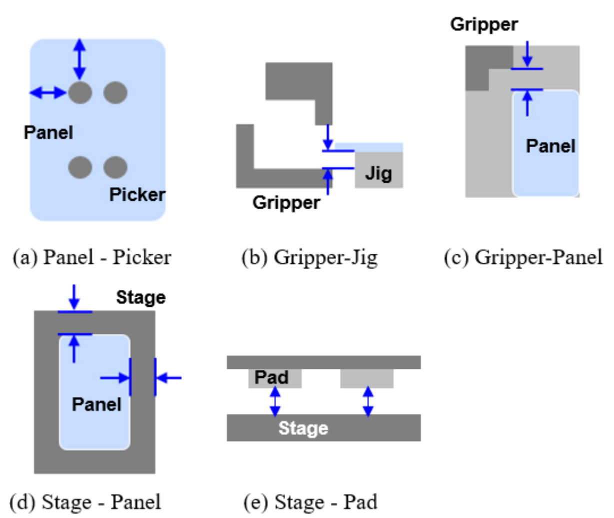

Figure 5. Types of measurements made

The proposed method has been applied to a variety of measurements, including the position of the picker above a panel, the distance between a gripper and a jig or a panel, the position of a panel relative to the stage, and the gap between a stage and a pad. These types of measurements are illustrated in Figure 5.

Introduction of the aforementioned automatic measurement software has reduced measurement times from 2.5 minutes to less than 20 seconds, significantly improving workforce efficiency. Furthermore, by standardization, measurement errors and variability introduced by operators are eliminated. Finally, by eliminating manual measurements that require operators to work inside equipments, workplace safety has also been improved.

Inference is performed directly on the mobile device and results are shared via the internal company network. Only the measurement data itself is transmitted so as to reduce network communication traffic. This software is currently being used within a manufacturing environment. Efforts are ongoing to expand the applicability of the software to other areas where accurate measurements are required.

4. Conclusion

In this study, we proposed two methods to significantly enhance the efficiency of display manufacturing processes with image-based AI technologies.

Virtual Image Generation by AI: By replacing real images with AI-generated virtual images for CDM recipe generation, we have significantly improved the efficiency of the fabrication process. This approach reduces the time spent acquiring real images and ensures accurate recipes from early stages of production, thereby enhancing overall yield.

AI based Auto Measurement System: Segmentation AI (YOLOv8) is utilized for object detection in order to distinguish between equipment and panels. Through image processing techniques, object boundary noise is reduced, and distortions are corrected. As a result, the measurement process has been standardized and automated, yielding more precise measurements.

Through the implementation of these two applications, we have achieved a remarkable reduction in fabrication process time by several days and a 90% decrease in module measurement time. By successfully applying image-based AI to the display manufacturing process, this study has demonstrated the potential for significant improvements in efficiency and productivity.

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