

Automatic Detection and Location for the Fiducial Marks and Reference Fiducial Marks

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Abstract—Automatic detection and location are proposed for the fiducial marks (FM) and reference fiducial marks (RFM) for the LED wafer images in this paper. The LED wafer image has two FMs, where the obvious FM is in the upper layer and the obscure FM is in the lower layer. The upper RFM is automatically detected and the lower RFM is determined after using an image enhancement technique. The automated search FMs of LED wafer images are divided into four steps: rough search, FM matching, fine search and trimming for sub-pixel images. FM matching includes the sum of absolute differences (SAD) and boundary feature matching (BFM). There are two types of experiments on an LED wafer image. In the first type, the upper and lower FMs of an image are circular. In the second type, the upper FM of an image is crossed, while the lower FM of an image is circular. The result shows that if the difference between RFM and FM grey-scale value distributions is small, the SAD matching has good effect. However, if the difference is large, the BFM matching is better. The positioning trimming for sub-pixels has a better effect on low resolution images. To validate the effect of the proposed method, the results are compared with the results of manual image matching in this study. By comparing the experimental results with those of the manual measurement method, we find that there are smaller error levels and a better effect.

Keywords—Fiducial mark, rough search, fine search, LED wafer.

I. INTRODUCTION

WITH the development of manufacturing technology in semiconductor and optoelectronics industries, various types of electronic components are becoming smaller and more precise. The requirement for manufacturing accuracy of the manufacturing industry has become increasingly strict. At present, the positioning of small sized electronic parts depends on manual operation. The parts are aligned visually before they are positioned manually. However, long-term tests have shown that the stability of the positioning mode is relatively poor, and also that the test operation is time-consuming and costly.

The microchips integrated with micromodules and the process' most challenging precision positioning show that the position is very important for industrial precision machinery processes. Many precision components cannot be aligned visually in high resolution image processing. Therefore, the

production automation for industrial precision machinery will depend on future science and technology. The positioning control technology research and development platform is an important part of production automation. This platform system is equipped with one to four industrial cameras (CCD Camera) and positioning feedback control module technology. A CCD alignment system needs to artificially cut out the special fiducial marks (FM), herein called reference fiducial marks (RFM). FMs are used as the standards in searching for the alignment of other images [1]-[6]. Finally, by using the transmission mechanism to compensate for the errors, the purpose of mark alignment can thus be achieved.

Object segmentation is a commonly used method in automatic positioning technology; object segmentation techniques [7]-[17] can accurately differentiating objects and backgrounds of images. Algorithms belonging to the discontinuous method include gradient method [7], Sobel edge detection [7], Canny edge detection [8]-[10], Laplacian edge detection [7], and Laplacian Gaussian edge detection. Algorithms of the similarity method include: Threshold Method [7], Area Growing [11], Region Splitting and Merging [7],[12], and Clustering [11]. The similarity method integrates edge detection and region-based method to improve image segmentation accuracy [13],[14].

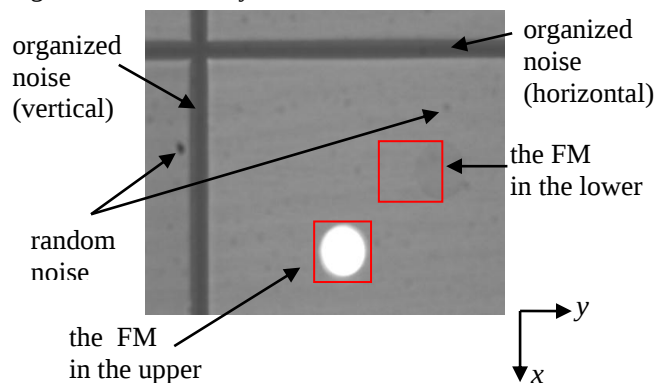


Figure 1 The LED wafer image

After the object segmentation, the FM location is searched according to the FMs. Past studies have focused on the grey-scale energy method [18], fast corner search method [19], and Fast Hough Transform [4]. The previously widely used matching cost computation [20] methods include normalized

cross-correlation (NCC), sum of squared differences (SSD), sum of absolute differences (SAD), Rank and Census.

This study proposes automatic fiducial mark detection and FM search methods for LED wafer mark image, as shown in **Figure 1**. The LED wafer mark image is formed from the upper and lower positioning boards. Each board has an FM. The FM of the upper board in the image is very obvious. The FM of the lower board is blurred. This paper proposes automatic detection of the RFMs, automatic search technique of the FM, and trimming for sub-pixel image, in order to complete the FM location of two positioning boards.

II. THE PROPOSED METHOD

This paper proposes automatic FM detection and FM search methods. The automatic FM detection improves the manually marked FM. The FM search moves from rough search to fine search, and the sub-pixel technology is used for trimming alignment.

A. Image Preprocessing

The LED wafer images have many noises. These noises are divided into organized and random noises as shown in **Figure 1**. The darkest and obvious part is called organized noise, and the others are called random noise. In order to obtain the correct position of the noise, the mean value μ_h of histogram in x or y direction is calculated. Then, $\delta_T = \mu_h + \delta$ is set as the threshold of noise, where δ is the gray-scale value adjustment coefficient. Therefore, if the histogram value in the x or y direction is smaller than δ_T , the noise range is represented by μ_h . According to the experiment on this type of image, the noise can be removed smoothly by setting the gray-scale value adjustment coefficient δ as 45; the experimental results are shown in **Figure 2**.

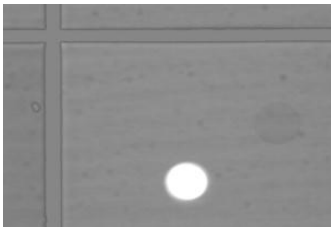


Figure 2 Noise removed result

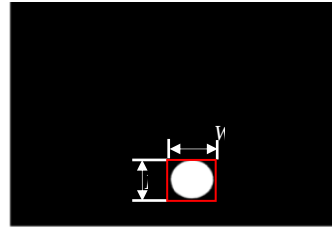


Figure 3 Binary image

B. Automatic Detection of the Reference Fiducial Marks

Regarding the FM image positioning, this study first selected a standard FM known as RFM. The upper FM is auto-detected and the lower FM is manually detected in the LED wafer image.

The automatic fiducial mark detection detects the upper FM. The FM is very obvious, so the intensity threshold of binarization is set as 250; the result is shown in **Figure 3**. These objects are distinguished by component labelling, and each object is segmented in the rectangular region in length H and width W . There may be some small objects after detection, so the minimum area of objects is set as $T_A = 250$ pixels. The

object will be removed if the object area is less than T_A ; the other objects are called RFM.

As the lower FM is very not obvious and is difficult to recognize, the image correlation must be strengthened. In order to avoid the effect of upper FM, the upper FM region is replaced by mean value μ_T , as shown in **Figure 4**. Then, the image contrast is increased by histogram equalization as shown in **Figure 5**. Finally, the lower FRM is obtained manually.

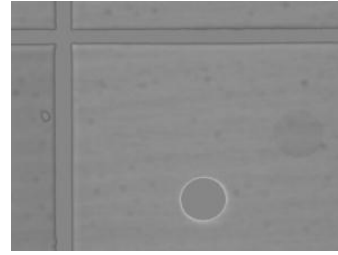


Figure 4
Mark-replaced image

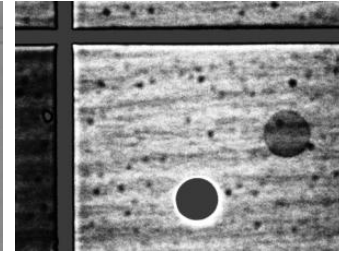


Figure 5
Histogram equalization

C. Automatic Search Technique

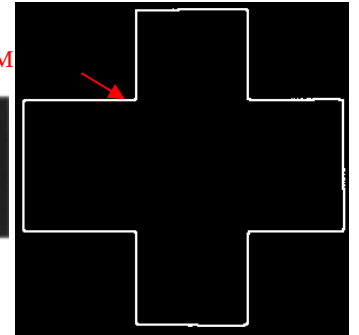
The search for the FM in the image is based on RFM. In this paper, the proposed automatic search techniques are the rough search, the FM matching, and fine search.

Rough search: The image is reduced by Haar Discrete Wavelet Transform. The initial position of FM can be found out earlier, this is called rough search. This paper uses level=3 LL subband images f , f_{LL}^1 , f_{LL}^2 , and f_{LL}^3 for search matching, and the search order is f_{LL}^3 , f_{LL}^2 , f_{LL}^1 , and f .

Fiducial mark matching: The FRM looks for the marks in the image, matching the Sum of Absolute Differences (SAD) and the mark boundary characteristics.



(a) Fiducial mark sample



(b) Boundary information

Figure 6 The fiducial mark sample and boundary information

1. Sum of absolute differences (SAD)

The RFM size is fixed, and then the image is scanned from top to bottom and from left to right, and the SAD [20] of relative positions in the window and the aggregation are calculated as the similarity. In order to increase the speed, the odd line in x direction and the even line in y direction are taken during image scanning. The minimum value of SAD is found out before searching for the SAD values of four neighbouring coordinates.

2. Boundary feature matching (BFM)

The FM boundary is a good matching feature, as the FM must be determined by the object in the image. The object O can be separated easily by Otsu's binarization [21]. The object O is dilated, it is called $\tilde{O}$. The FM boundary B_p is $\tilde{O}$ minus O as shown in **Figure 6(b)**.

The boundary information B for the objects O and $\tilde{O}$ is the intersection $B = B_p \cap B_l$, where B_p is the object boundary of O and B_l is the object boundary of $\tilde{O}$. The similarity value $\sum B$ is summed up. Generally, $\sum B$ decreases with increasing similarity of O and $\tilde{O}$.

Fine search: The images are magnified one by one after rough search, and more accurate FM position is searched for in the neighbouring areas in relation to the initial position till the original image size is searched, this is called fine search. The processing procedure is that the coordinates (x', y') obtained by rough search on the image f_{LL}^3 correspond to the coordinates on the image f_{LL}^2 . The four adjacent pixels at (x', y') are used to calculate the SAD values on all the pixels. The minimum SAD value is used as the object searched. These steps are repeated till the original image f is reduced to.

D. Trimming for Sub-Pixel Image

The accuracy of FM is required to be very high in industrial inspection. The low resolution image has insufficient accuracy. The sub-pixel technique is employed to improve the image accuracy. The accuracy of the located FM will be very low if the resolution is too low, but the search will be accelerated if the resolution is too high.

To increase the image resolution by using image processing technology, the simplest method is to enlarge the image; the interpolation [22] is used most. The high resolution of the image will increase the accuracy of mark positioning, but the computational efficiency of the computer will decrease accordingly. Therefore, this paper will use general nearest neighbor interpolation [22],[23]; this method is the most straightforward method among the interpolation methods.

III. EXPERIMENTAL RESULTS

There are two types of experiments on an LED wafer image, as shown in **TABLE I**. In the first type, the upper and lower FMs of an image are circular. In the second type, the upper FM of an image is crossed and the lower FM of an image is circular. There are three images of each type. The RFM of upper and lower layers in each type is obtained by automatic detection as shown in **TABLE II**. When RFM searches for the FM in an LED wafer image, the SAD and Boundary feature matching and sub-pixel positioning will be used.

A. Performance Evaluation of FM Matching for SAD

The FM is searched for various types of images according to different types of RFM; the positioning difference between the

result of this paper and the manual measurement result is shown in **TABLE III**. The capture mode of the manual positioning measurement is based on the FM region's center point in the image. The result shows that the positioning difference may result from the unobvious FM boundary in the image, so that the central coordinates of FM are unlikely to be captured manually.

TABLE I EXPERIMENTAL IMAGES

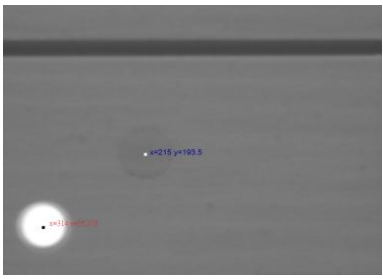
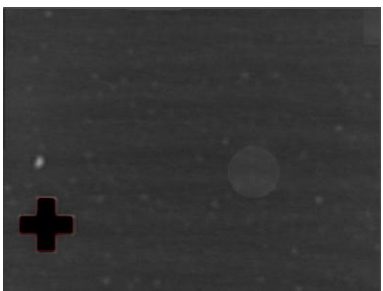
Type	LED Wafer Image	Image number
Type 1		3
Type 2		3

TABLE II RFM OF AN IMAGE IN EACH TYPE

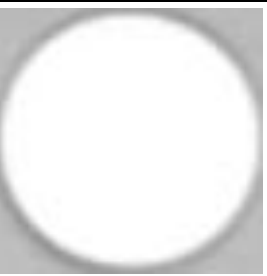
Type	RFM of the upper lay	RFM of the lower lay
Type 1	 (Image size: 61x61)	 (Image size: 70x71)
Type 2	 (Image size: 70x70)	

TABLE III TYPE 1 IMAGE. (IMAGE SIZE: 384×512)

Image number	Upper FM positioning difference (pixels)	Lower FM positioning difference (pixels)
1	(0,2)	(1,2)
2	(3,1)	(3,1)
3	(0,1)	(0,1)

B. Performance Evaluation of FM Matching for BFM

The experiment on BFM uses the LED wafer image of Type 2. The cross FM color is to change the white into black from RFM. However, the experiment on FM search is carried out with fixed RFM; the positioning difference between the result and the manual positioning measurement is shown in TABLE IV. The positioning will fail if SAD matching is used for this experimental image, and precise positioning result can be obtained by using BFM.

TABLE IV TYPE 2 IMAGE (IMAGE SIZE: 384×512)

Image number	Upper FM positioning difference (pixels)	Lower FM positioning difference (pixels)
1	(1,1)	(1,0)
2	(0,0)	(2,1)
3	(0,1)	(1,1)

TABLE V THE FM POSITIONING DIFFERENCE (PIXELS) (IMAGE SIZE: 384×512)

Image number	Type 2 Image	Sub-pixel
1	(0,1)	(1.5,0.625)
2	(0,1)	(1.5,0.375)
3	(0,1)	(0.875,0.375)

C. Performance Evaluation of Trimming for Sub-Pixel Image

The experiment on the trimming for the sub-pixel image used the LED wafer image of Type 2. The positioning difference between the result of this study and manual positioning measurement is shown in TABLE V. The capture mode from manual positioning measurement is based on the centre point of FM. The result shows that the positioning error may result from the unobvious FM contour, so that the FM position is unlikely to be captured manually.

IV. CONCLUSIONS

In this paper, the automatic detection of the RFM can effectively detect the upper FM, and can strengthen the unobvious lower FM in the LED wafer image. The upper RFM

is automatically detected and the lower RFM is determined after using an image enhancement technique. The automated search technique employs rough search, FM matching, fine search and trimming for sub-pixel images. In order to verify the accuracy and efficiency of this method, the experimental results of the SAD and BFM matching methods and position trimming are compared with manual positioning results to determine the positioning difference. The result shows that if the difference between RFM and FM gray-scale value distributions is small, the SAD matching has good effect. However, if the difference is large, the BFM matching is better. The positioning trimming for sub-pixels has better effect on low resolution images. By comparing the experimental results with those of the manual measurement method, we find that smaller error levels and a better effect. Trimming precision of the positioning of sub-pixels has been proved to have good effect for images with lower resolution ratios.

V. FUTURE WORK

The experiments in this paper include extending the various image sets, extending the image number, and how this measure could be used with different methods. These recommendations suggest directions for future work.

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