A study on Practical Defect Detector using Efficient Thresholding Method

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Abstract

Defect detection is one of the most challenging problems in industrial quality control. In this study we developed a vision-based defect detection system for wafer production. To achieve high-accuracy detection, Otsu method was improved so that it can handle both unimodal and bimodal distributions. After thresholding, detected defect regions in the wafer are classified and grouped into user-defined defect categories. The experimental result has proved the efficiency of our system.

1. Introduction

Quality control is an important issue in industry. With the rise of production scale, there is a need of developing a fully automatic method to replace manual defect detection. Especially in semiconductor assembly manufacturing, defect detection in has become increasingly important recently as a mean for quality assurance and controlling contamination sources and process faults, which affects the final products.

A common approach for automatic defect detection is using computer vision. An image of the product is recorded, then the defected regions will be detected by using image processing techniques. Several automated defect detection techniques based on computer vision have been developed by industrial company and institutes. However, most of them are highly application-specific because the model are tuned for specific objects that are expected to appear in the image [4][5][6]. Other methods using template matching or machine learning to deal with various types of defect have been also proposed and developed [4].

Automatic thresholding is a computer vision technique that has been widely used for automated visual inspection of defects. The principle of automatic thresholding is automatically selecting an optimal gray value to separate objects of interest in given image from the background. There are two kinds of automatic thresholding: global thresholding and local thresholding [1][2]. In the former, a single threshold value is automatically selected and applied for the entire image. In local thresholding, gray level information in parts of the image is used to choose multiple threshold values; each value is optimized for corresponding small region in the image. Among global threshold techniques, Otsu method (Otsu, 1979) [1] was regarded as one of the best automatic thresholding methods for general real world images. Otsu method is good for histograms with bimodal or multimodal distribution. However, it fails if the histogram is unimodal or close to unimodal. Because defect regions may vary from small area to large area, the gray level distributions may vary from unimodal to bimodal, which prevents Otsu method from yielding high-accuracy results.

In this research, we proposed and developed a vision-based defect detection system for automatic optical inspection of wafer, which can handle both unimodal and bimodal distributions to increase defect detection efficiency.

2. Wafer Defect Detection System

2.1 Automatic threshold selection

In this section, we briefly review the basic idea of Otsu method and also its drawback. Later, we will present the valley-emphasis method, an improved version of Otsu method for detecting large and small defects.

An image can be represented as an intensity function $f(x,y)$. The value of $f(x,y)$ is the gray value, ranging from 0 to L - 1, where x, y are the coordinates of given pixel in image and L is the number of gray levels. Let the number of pixels with gray value i and the total number of pixels in a given image be n_i and n, respectively, the probability of occurrence of gray value i is defined as:

$$p_i = \frac{n_i}{n} \tag{1}$$

The average gray level of the entire image is computed as:

$$\mu_T = \sum_{i=0}^{L-1} i p_i \tag{2}$$

In case of single threshold, pixels of the image are divided into two classes $C_1 = \{0, 1, \ldots, t\}$ and $C_2 = \{t + 1, t + 2, \ldots, L - 1\}$, where t is the threshold value. C_1 and C_2 are normally corresponding to the foreground (objects of interest) and the background. The probabilities of the two classes are:

$$\omega_1(t) = \sum_{i=0}^{t} p_i \quad and \quad \omega_2(t) = \sum_{i=t+1}^{L-1} p_i \tag{3}$$

The mean gray level of each class can be computed as:

$$\mu_1(t) = \sum_{i=0}^{t} ip_i / \omega_1(t) \; and \; \mu_2(t) = \sum_{i=t+1}^{L-1} ip_i / \omega_2(t) \tag{4}$$

Using discriminant analysis, Otsu (1979) showed that the optimal threshold t^* can be determined by maximizing the between-class variance, that is:

$$t^* = Arg \underset{0 \le t < L-1}{Max} \{ \omega_1(t)\mu_1^2(t) + \omega_2(t)\mu_2^2(t) \} \tag{5}$$

However, Otsu method has a drawback. It fails if the histogram is unimodal or close to unimodal, i.e. the histogram has a single mode. A mode of a probability distribution is a value at which the probability mass function takes its maximum value, in this case the histogram is considered as a probability distribution. In defect detection applications, defects may vary from small area to large area. In some cases the area of defect regions is very small comparing to the background, hence the histogram demonstrates a unimodal distribution. The desired threshold should be the value that separates the small contaminant from the background. Therefore, Otsu method gives the incorrect threshold value and fails to isolate the contaminant.

The valley-emphasis method [2] overcame that drawback. The idea of the valley-emphasis method is selecting a threshold value that has a small probability of occurrence (valley regions in histogram), and also maximize the between group variance, as in original Otsu method. The formula for the valley-emphasis method is:

$$t^* = Arg \underset{0 \le t < L-1}{Max} \{(1 - p_t)(\omega_1(t)\mu_1^2(t) + \omega_2(t)\mu_2^2(t))\} \quad (6)$$

The key of valley-emphasis formula is the appearance of a weight, $1 - p_t$, in the Otsu threshold calculation. The smaller the p_t value is (low probability of occurrence), the larger the weight will be. This weight ensures that the result threshold will always be a value that resides at the valley or bottom rim of the gray level distribution.

2.2 Proposed Method

The inspection system proposed for defect detection in this study is based on Automatic Optical Inspection (AOI) system of LED wafer. As a result of high resolution camera capture, illumination in image varies significantly. To obtain wafer ROI (Region of Interests) easily, low resolution images are generated first to reduce computational complexity. After obtaining low resolution ROI mask, high resolution ROI mask is generated and combined with original high resolution input image to produce final ROI of input image, as shown in Figure 1. In thresholding process, we provide two types of threshold scopes, global and local threshold approaches. For very high resolution input images, we suggest using local threshold approach (in our model, we split the image into 14 local regions) and for other low resolution input cases we used global threshold method.

By using the proposed automatic thresholding methods mentioned above and analyzing the local contrast in each region of the input image, the presence of defects can be reliably detected. After the thresholding step, morphological method and labelling process was implemented to identify defect regions and the number of defects. In the final step, detected defect regions in binary and labelled images are classified into defect categories by using template matching algorithms.

3. Experiments

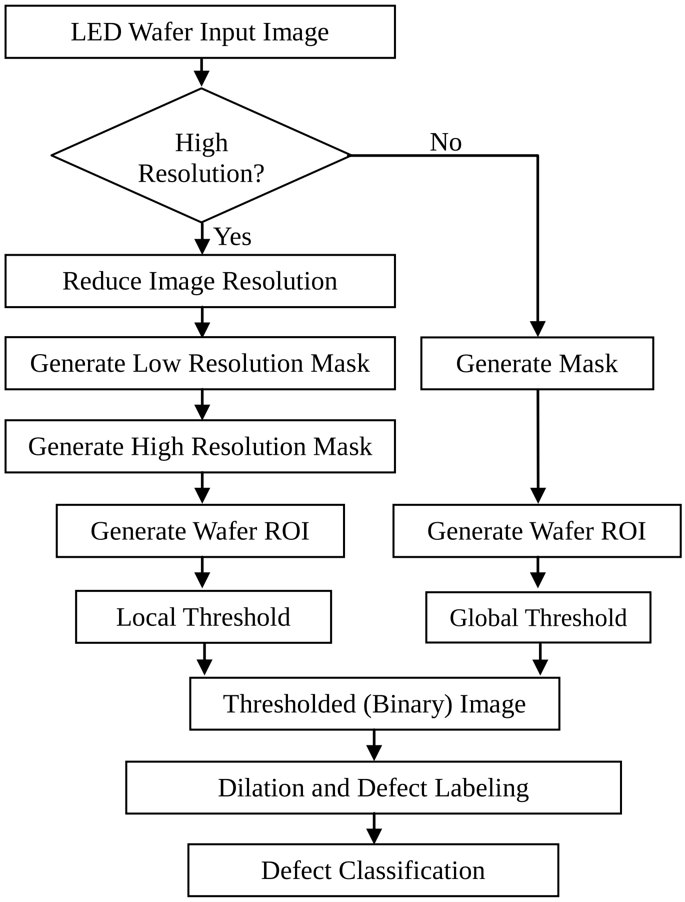
3.1. Threshold Comparison Results

To compare the error rate, the equation is defined in (7) (Yasnoff et al., 1977) [3] and error comparison between Otsu method and Valley Emphasis method is shown in Table 1.

$$\mathrm{Error} = 1 - \frac{|B_O \cap B_T| + |F_O \cap F_T|}{|B_O| + |F_O|} \quad (7)$$

where

- B_O, F_O: number of pixels in ground truth, for background and foreground, respectively.
- B_T, F_T: number of pixels in thresholding result, for background and foreground, respectively.



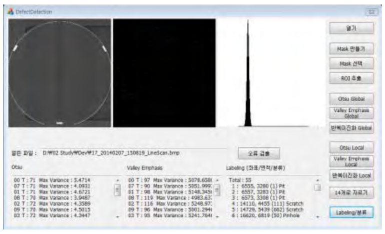
(Figure 1) Flowchart of wafer defect detection process.

<Table 1> Error Rate Comparison between Otsu method and Valley Emphasis method

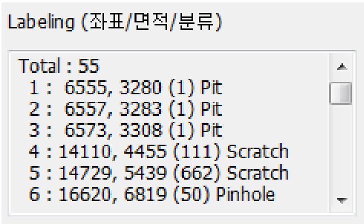
		Otsu	Valley Emphasis
Experiment 1	The # of pixels in difference image	710286	19512
	Error Rate	0.580	0.015
Experiment 2	The # of pixels in difference image	560437	94544
	Error Rate	0.457	0.077

3.2 Performance of Defect Detector

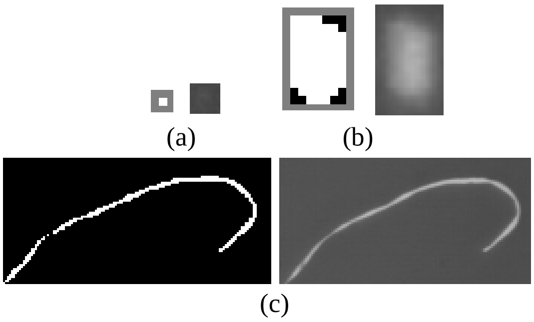
The evaluation of our system is carried out using industrial standard wafer image. Figure 2 shows developed automatic defect detection software which includes several implementation of threshold methods, defect classification methods, labeling methods and a display windows for the input and output images. Figure 3 also represents a result of final localizaton, area estimation and classification of defects for the input images. Table 2 shows the practical example of final classificaton results for the specific wafer. To classify three types of defect (pit, pinhole, scratch), two criteria (the area and the gray value of the center gravity of each defect object) are used and the criteria for the classification is shown in Table 3, the three type of defect images are shown in Figure 4.



(Figure 2) Developed Program GUI



(Figure 3) Detection and Classification Result



(Figure 4) Three type of defect: (a) Pit (1 pixel) (b) Pinhole (67 pixels, white) (c) Scratch (785 pixels, black).

<Table 2> Final Classification Result of Defect

Classification	Number of defects
Pit	11
Scratch	11
Pinhole	33
Total	55

<Table 3> Categories of Defect Classification

Classification	Category1 (Area)	Category2 (Gray Value of Center Gravity)
Pit	1~2 pixel(s)	No corresponding
Scratch	Over 2 pixels	White
Scratch		Black

4. Conclusions

In this study we developed a vision-based defect detection system for the automated optical inspection of wafer. More than 14 industrial-standard test wafers are used for evaluating detection and classification accuracy. The experimental results showed that our method is capable of detecting various types and sizes of defect, yielding high accuracy and reliable results.

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