볼 그리드 배열 기판의 X-ray 영상에서의 새로운 덩어리 검출 필터를 이용한 기포 형태 결함 검출 방법

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Detection of Void Defects in Ball Grid Array X-ray Image Using a New Blob Filter

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Abstract - Due to the advantages of small sizes, more I/O ports, etc., Ball Grid Array (BGA) has been used in the production of printed circuit board (PCB). However, BGA voids can degrade the performance of the board and cause failure. To automatically detect the voids in X-ray image, a novel blob filter that makes use of the local image gradient magnitude is proposed in this paper. The utilization of the local image gradient magnitude magnitude makes the proposed filter invariant to the image brightness, void shape, void position, and component interference. Furthermore, different sizes of box filters are employed to analyze the image in multi-scale, and as a result, the proposed blob filter is robust to void size. Experimental results show that the proposed method can obtain void detection accuracy up to 96.104% while keep low false ratio.

Keywords: BGA, X-ray, Defect detection, Blob detection, Void detection

요약

작은 크기 다양한 입출력 포트 등의 많은 이점으로 PCB 회로기 판에서 볼그리드배열(BGA) 방식의 기판이 사용되고 있다 하지 만 BGA 기판 내부 기포는 기판의 성능을 떨어뜨리고 실패를 야 기한다 자동적으로 X-ray 영상에서 기포를 검출하기 위해서 본 논문에서는 국부 영상 명암 변량 측정 방법을 이용한 새로운 덩 어리 검출기를 제안한다 국부 영상 명암 변량의 활용은 영상의 밝기 기포의 모양, 기포의 위치 및 부품간의 간섭등에도 연산 결 과에 영향이 적은 불변성을 가진다. 또한 박스 필터의 다양한 선 이즈를 적용하여 다양한 크기의 영상을 분석하므로 결과적으로 제안한 덩어리 검출 필터는 기포의 다양한 크기에 도강력하다. 실험 결과는 제안한 기법이 정상 부위를 비정상 부위 로보이는 확률false-ratio)을 낮게 유지하면서 기포 검출률을96.104% 까지 높일 수있음을 보인다.

키워드: BGA, X-ray, 결함 검출, 덩어리 검출, 기포 검출

1. 서 론

BGA voids, which are caused by outgassing flux that gets entrapped in the solder joint during reflow, are defined as cavities formed in the solder joint [1]. Voids in solder joints are one of the most critical defects, since they can affect the solder joint reliability, and the electrical and thermal conducting performance of the solder joint. Therefore, it is very important to develop an automatic void defect detection system for the BGA industry.

There are several challenges to overcome for automatic void detection using image processing techniques: 1) some of the voids have poor contrast, which makes void detection difficult even to the human eye, 2) voids have different sizes and random positions in the ball, 3) due to the various voltage settings in the x-ray machine and the structure characteristics of the ball, BGA images have different non-uniform brightnesses, and 4) there can be interference from the other components on the board.

The motivation of this study is to develop an automatic void detection system that can overcome the mentioned difficulties and precisely detect the voids. In response, a blob filter based on the image gradient magnitude and a multi-scale analysis is presented in this paper. The proposed blob filter makes use of the local image gradient magnitude to overcome the brightness, void position, and component interference problems. In order to detect different sizes of voids, different sized average box filters are employed that set up an image pyramid for multi-scale analysis.

The main contributions of this paper are as follows:

1. Since the proposed blob filter utilizes the image local gradient magnitude, it is invariant to image brightness and it can overcome the random void position, and component interference problems.

2. By employing the multi-scale analysis, the proposed blob filter is invariant to void size. 2. 본 론

2.1 Preprocessing

Since there is noise in the BGA image, the input image noise is reduced by a Gaussian filter (Fig.1). The black regions are then extracted using image binarization (OTSU[2], Fig.2) and a region growing method. The average area of all the black regions is calculated and used to remove the regions whose sizes that are less than 70% of the average area. For each ball, a minimum enclosing rectangle is set to extract the separated balls from the BGA image for the ensuing processing (Fig.3). Since some of the voids have very poor contrast, the histogram stretch method [3] is applied to enhance the contrast of each ball (Fig.4).



<Figure 3> the separated balls <Figure 4> the contrast enhanced balls

2.2 The proposed blob filter

As shown in Fig. 3, the voids in the BGA ball possess blob-like regions. They have the following characteristics: 1) Its shape is blob-like; 2) It is brighter than its background; 3) The voids have different sizes. Therefore, this paper proposes a blob filter to detect the blob-like regions based on the local image gradient magnitude. In this study, we apply the average gray value of a rectangular region to approximately represent a blob region. The average gray value of a rectangular region of the proper size can be applied in order to evaluate the brightness of a blob. As shown in Figure 5, if the center region (0) is a blob, then its brightness is brighter than its neighboring regions (1, 2, 3... 8).

In this paper, we use the brightness differences between a blob region and its neighbors for blob enhancement. Therefore, the gradient magnitude based on the image local regions is defined with respect to four directions: horizontal, vertical, and two diagonal directions. It is denoted as:

$$g_h = r(0) - \max[r(4), r(8)]$$
 (1)

$$g_{v} = r(0) - \max[r(2), r(6)]$$
(2)

$$g_{ld} = r(0) - \max[r(1), r(5)]$$
(3)

$$g_{rd} = r(0) - \max[r(3), r(7)]$$
(4)

where g_{h} , g_{v} , g_{ld} , and g_{rd} represent the gradient magnitudes in the horizontal, vertical, left diagonal, and right diagonal directions, respectively, r(i) denotes the average gray value of the local region *i*. For a blob region, it is obvious that g_{h} , g_{v} , g_{ld} , and g_{rd} are all greater than 0. The brighter the blob is, the greater the value of g_{h} , g_{v} , g_{ld} , g_{rd} will be.

The output of the proposed blob filter is defined as:

$$f(x,y) = (x + y)^* I + (x + y)^* I$$

$$f(x, y) = (g_h + g_v)^* L_1 + (g_{ld} + g_{rd})^* L_2$$
(5)

where $(g_h + g_v)$ and $(g_{ld} + g_{rd})$ are the gradient magnitude information of a local region. L_1 and L_2 are the likelihood of a blob, defined as:

$$L_{1} = \frac{\min(|g_{h}|, |g_{v}|)}{\max(|g_{h}|, |g_{v}|)}, \quad L_{2} = \frac{\min(|g_{ld}|, |g_{rd}|)}{\max(|g_{ld}|, |g_{rd}|)}$$
(6)

For a blob region, L_1 and L_2 are closely equal to 1 whereas for a line, one of the values is closely equal to 0. In order to detect the different sizes of voids, the blob filter needs to be scale invariant. Hence, different sized average box filters are employed to set up an image pyramid in order to detect the different sizes of voids. Applying the average box filter to an input image is a smoothing process, which calculates the average gray values of the pixels inside a box region. Therefore, the integral image technique [4] is applied to speed up the computation process when a mass of region based summation is required [5].

The process of generating the final blob image using the proposed method is shown in Fig.6. As we can see, the input image is first transformed into an integral image. Different sizes of average box filters are then performed on the integral image, which generates an image pyramid including the different smoothed images. For each smoothed image, the local image gradient magnitude is calculated and a blob image is generated using (5). Finally, the final blob image is generated by selecting the maximal points of the blob images (blob image 1, 2, 3... N).



<Figure 5> a blob region <Figure 7> The void detection process



2.1 The void detection

After generating the final blob image, a threshold is set in order to obtain a binary image. Region growing is applied again to obtain the candidate void regions. In order to locate the voids, a defined outer rectangle of the candidate region is used to capture a local region from the original image (Fig.7(a)). The contrast of the region is enhanced by the histogram stretch method (Fig. 7(b)). The contrast enhanced region is then binarized by a threshold (Fig. 7(c)). Finally, the void region is obtained through region growing and the true voids are determined according to the roundness of the region.

3 Experimental results

In order to evaluate the performance of the proposed method, 355 BGA images were captured by a CT machine provided by *TechValley Ltd.* [6]. The performance of the proposed method is evaluated according to the detection accuracy and the false ratio, which are defined as:

$$Accuracy = \frac{TP}{VN} \times 100\%$$
(7)

$$False Ratio = \frac{FP}{VN} \times 100\%$$
(8)

In (7) and (8), TP (true positive) denotes the number of voids that are correctly detected. FP (false positive) is the number of normal regions that are incorrectly detected as void regions. VN is number of true voids.

Tables 1 shows the detection results of the proposed method. As we can see, the proposed method achieved high detection accuracy up to 93.504% while maintained a low false ratio.

<Table 1> The image information and the Void Detection Results

Image information				
Size	Format	Image number		Gray level
1024*768	BMP	355		256
Detection results				
VN	ТР	FP	Accuracy	False ratio
10253	9587	757	93.504%	7.383%

4. 결 론

Automatic void detection is critical in the production of BGA boards. In this work, an automatic void detection system is presented based on the proposed blob filter. A novel blob filter is proposed to enhance the BGA voids by taking advantage of the image local gradient magnitude. The utilization of the local image gradient magnitude makes the proposed filter invariant to the image brightness, void shape, void position, and component interference. Different sizes of box filters are employed to analyze the image in multi-scale, and as a result, the proposed blob filter is robust to void size.

Acknowledgement

본 연구는 교육과학기술부 산학연협력우수연구실사업의 핵심애로기술 개발지원사업 연구비지원(2010년)에 의해 수행되었습니다.

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