A rotation-invariant and nonreferential approach for Ball Grid Array (BGA) substrate conduct paths inspection

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Abstract

The aim of this paper is to locate and classify boundary defects such as open, short, mousebite, and spur on Ball Grid Array (BGA) substrate conduct paths using machine vision. Boundary defects are detected by a boundary-based corner detection method using covariance matrix eigenvalues. Detected defects are then classified by discrimination rules derived from variation patterns of eigenvalues and the geometrical shape of each defect type. Real BGA substrates with both synthetic and real boundary defects are used as test samples to evaluate the performance of the proposed method. Experimental results show that the proposed method achieves 100% correct identification for BGA substrate boundary defects under a sufficient image resolution. The proposed method is invariant with respect to the orientation of the BGA substrates, and it does not require pre-stored templates for matching. This method is suitable for various types of BGA substrates in small batch production because precise positioning of BGA substrates and the prestored templates are not necessary.

Keywords: BGA substrate conduct path; Defect detection; Defect classification; Covariance matrix; Discrimination rules; Rotation-invariant

1. Introduction

In recent years, electrical components have tended to be smaller in size but to require more functionality and better quality performance. Therefore, the Printed Circuit Board (PCB) has evolved to provide more conduct paths and finer specification in a much smaller layout area [1]. One advanced type of PCB called the Ball Grid Array (BGA) substrate, as illustrated in Fig. 1, has been extensively used to connect the solder ball array on Integrated Circuits (ICs) for electrical conductivity in Surface Mount Technology (SMT) [2]. As linewidths and linespacings on BGA substrates become smaller, defects are hard to detect and they could seriously disable conductivity.

Generally, the existing PCB inspection algorithms using machine vision can be classified into three categories [3]: referential approaches [4-6], non-referential approaches [7-9], and hybrid approaches [10, 11]. Referential approaches are the earliest developed PCB inspection algorithms. They compare the test board image with the defect-free board stored in the image database in a pixel-by-pixel or window-by-window (i.e., a region composed by a pixel matrix) scheme to detect the defective areas. They are also known as template-matching techniques. In recent research, the primitives (including circular pad, single horizontal line, double vertical lines, single slant lines, etc.) on PCBs are off-line trained. Then, they are incorporated with template-matching techniques for further classification using neural fuzzy [12, 13] or statistical classifiers [14]. Referential approaches generally work well in identifying large size defects. However, they suffer from angular errors produced by board distortion during the fabrication process and rotational misalignment to the fiducial points on defect-free PCBs. Considerable shifts in the X-Y coordinates will result from minor angular errors. Furthermore, referential approaches are time-consuming for matching operations, sensitive to noise, and require large amounts of data storage for template images [6, 13].

Nonreferential approaches use design specification knowledge to verify small or medium size defects. They perform successfully only for certain types of defects (such as line widths, spacing violations, etc.). However, a serious defect such as the circuit short could be falsely treated as the conduct path [13]. Nonreferential approaches are also error prone when rotational error is incurred [6].

Hybrid methods combine referential approaches and nonreferential approaches to acquire all the benefits for detecting various defect types in different sizes. Since both approaches can complement each other, hybrid methods generally achieve better identification results among the existing inspection systems [13]. However, greater computation efforts are expected with hybrid methods. Hybrid methods also inherently suffer from rotational error and noise effects.

In geometrical aspect, the boundary of BGA substrate conduct paths can be considered as the combination of lines, arcs, and joints. The tangent directions of boundary points are constant on the lines, change smoothly on the arcs, and vary rapidly on the joints. Since a joint and a boundary defect can be considered respectively as single corner and multiple jag corners in this study, a corner detection approach based on the eigenvalue from the covariance matrix of the boundary points over a small region of support is implemented to localize the boundary defects. The eigenvalue patterns and the geometrical information of defective segments are collected to establish discrimination rules for the classification of defect types.

In this study, four serious and common boundary defect types including open, short, mousebite, and spur (see Fig. 2) on BGA substrate conduct paths are detected and classified. The proposed BGA substrate inspection algorithm does not require prestored templates, predefined primitives, and training process. Furthermore, the proposed approach is rotation-invariant since it is based on a rotation-invariant corner detection scheme. It reduces the sensitivity of angular error, compared with conventional PCB inspection algorithms. The proposed approach is particularly suitable for various BGA substrate types in small batch production because it does not require prestored templates and precise alignment of the BGA substrates under inspection.



Fig. 1. Real BGA substrate conduct paths (bottom side). (a) Original image with a 25mm x 18mm field of view and 640 x 480 pixels resolution. (b) Binary image of the BGA substrate shown in (a).



Fig. 2. Four serious and common boundary defects on BGA substrate: (a) Open. (b) Short. (c) Mousebite.(d) Spur.

This paper is organized as follows: In section 2, the eigenvalues of the covariance matrix from a boundary segment are presented to detect corners and locate potential defects. The process for filtering noise on conduct path boundaries is also explained in this section. Then, the discrimination rules used for classifying four defect types (e.g. open, short, mousebite and spur) are described in section 3. Experimental verification of the proposed method is shown in section 4. Finally, the conclusion is given in section 5.

2. Defect Detection

2.1 Eigenvalues of covariance matrices

Since common defects such as open, short, mousebite and spur can be treated as multiple jag corners on BGA substrate conduct path boundary, an effective corner detection algorithm derived from the eigenvalue of the covariance matrix from a digital boundary segment is employed to locate joints and defects. This corner detection scheme has been validated to be faster, more precise, rotation-invariant, and scale-invariant with respect to other corner detection methods [15]. The binary image of a BGA substrate is pre-processed by boundary following [16] to extract the X-Y coordinates of each boundary point along the conduct paths. Let the sequential n digital points describe a boundary P,

 $P = \{p_i = (x_i, y_i), i = 1, 2, 3, ..., n\}$

where p_{i+1} is adjacent to p_i on **P**. Further, let $N_s(p_i)$ denote a small boundary segment

centering on point p_i over the region of support between points p_{i-s} and p_{i+s} for

some integer s, i.e.,

$$N_{s}(p_{i}) = \{p_{j} \mid i \cdot s \qquad j \qquad i + s\}$$

Therefore, the covariance matrix M of a boundary segment $N_s(p_i)$ is given by

$$\boldsymbol{M} = \begin{bmatrix} \boldsymbol{m}_{11} & \boldsymbol{m}_{12} \\ \boldsymbol{m}_{21} & \boldsymbol{m}_{22} \end{bmatrix}$$

where

$$\boldsymbol{m}_{11} = \left[\frac{1}{2s+1} \sum_{j=i-s}^{i+s} x_j^2\right] - \overline{x_i}^2$$
$$\boldsymbol{m}_{22} = \left[\frac{1}{2s+1} \sum_{j=i-s}^{i+s} y_j^2\right] - \overline{y_i}^2$$
$$\boldsymbol{m}_{12} = \boldsymbol{m}_{21} = \left[\frac{1}{2s+1} \sum_{j=i-s}^{i+s} x_j y_j\right] - \overline{x_i} \overline{y_i}$$
$$\overline{x_i} = \frac{1}{2s+1} \sum_{j=i-s}^{i+s} x_j$$
$$\overline{y_i} = \frac{1}{2s+1} \sum_{j=i-s}^{i+s} y_j$$

 \overline{x}_i and \overline{y}_i are the geometrical center of $N_s(p_i)$. The covariance matrix M is a 2 x 2, symmetric, and positive semidefinite matrix. The eigenvalues λ_L and λ_S of matrix M are obtained from following equations:

$$\lambda_{L} = (\boldsymbol{m}_{11} + \boldsymbol{m}_{22} + \sqrt{(\boldsymbol{m}_{11} - \boldsymbol{m}_{22})^{2} + 4\boldsymbol{m}_{12}^{2}})$$

$$\lambda_{S} = (\boldsymbol{m}_{11} + \boldsymbol{m}_{22} - \sqrt{(\boldsymbol{m}_{11} - \boldsymbol{m}_{22})^{2} + 4\boldsymbol{m}_{12}^{2}})$$

The curvature information about a curve can be extracted from the smaller eigenvalue λ_s . For an ellipse object, the square root of λ_L and λ_s are the semi-major and semi-minor axial lengths of the ellipse, respectively. The λ_s value is approximate to

zero when a point p_i is on a straight line or on a flat curve. The smaller the radius of a circle, the larger the λ_s value obtained. Likewise, the sharper the corner, the larger the λ_s value that results. The λ_s value of a corner point on the boundary segment is a local maximum. Away from the corner, the λ_s values of the boundary points decrease gradually. Since the boundary defects of short, open, mousebite, and spur are constructed by multiple jag corners, each of them should ideally result in multiple peaks in 1-D λ_s diagram. Therefore, the 1-D λ_s waveform pattern is utilized to locate the joint or defect on the boundary of BGA substrate conduct paths. Fig. 3(a) shows a portion of BGA substrate conduct paths with synthetic boundary defects. The numbers shown in Fig. 3(a) represent the boundary number p_i . The corresponding λ_s values as a function of the boundary points are illustrated in Fig. 3(b). In Fig. 3(b), consecutive zero or near-zero λ_s values are respectively generated for the points on straight lines and circular arcs. The peaks in 1-D λ_s waveforms in Fig. 3(b) result from joints, boundary noise, and defects. For example, a mousebite is constructed between boundary points 133-152 in Fig. 3(a) and its corresponding jag waveform can be located in Fig. 3(b).)

2.2 Filtering boundary noise and locating defect candidates

Owing to the effect of digital quantization and lighting, noisy boundary points may result in significant non-zero λ_s values. In this section, a specific λ_s value is

selected as a threshold to distinguish the noisy segments and joints on the boundary of BGA substrate conduct paths. Noisy boundary points could result in false alarms during inspections. They can be filtered out if their λ_s values are less than a specified threshold. Generally, the λ_s values of joints are ensured to exceed this specified threshold.

To find the λ_s threshold, the *intraset-interset* distance cluster algorithm [17] is employed to divide the noisy segments and joints on the boundary of BGA substrate conduct paths into two separate groups. The boundary points connecting the line and circular pad may result in consecutive non-zero λ_s values (e.g. points 84-95 and 376-388 in Fig. 3(b)). These intersection points perform similarly with the noisy segments in terms of the magnitude of λ_s . Therefore, the intersection points are also treated as boundary noise for convenience. A defect-free BGA substrate is utilized to collect the λ_s data of the joints and boundary points for clustering. A joint is represented as the waveform with a single peak and the noisy boundary segment could have more than one peak in the 1-D λ_s waveform. In order to locate each waveform of joint and noisy segment, the λ_{S} of a boundary point p_{i} is assigned to zero if the λ_s values of three consecutive points p_{i-1} , p_i and p_{i+1} are all less than $(\mu_{\lambda}+0.5\sigma_{\lambda})$. In this manner, the λ_{s} values of boundary points between the waveforms of joints and noisy segments are zero. The mean (μ_{λ}) and standard deviation (σ_{λ}) for the λ_s values of all points on the defect-free BGA substrate image are first computed. Then, the maximum λ_s value in the *i*th waveform of noise segment or joint is extracted and denoted by $\lambda_s^*(i)$. If there are totally N joints and noisy boundary segments on BGA substrate conduct paths, the $\lambda_s^*(i)$ (e.g. i = 1, 2, ..., N) values are initially sorted in ascending order. That is,

$$\lambda_{\mathcal{S}}^{*}(1) \leq \lambda_{\mathcal{S}}^{*}(2) \leq \lambda_{\mathcal{S}}^{*}(3) \leq \ldots \leq \lambda_{\mathcal{S}}^{*}(N)$$

By the *intraset-interset* distance cluster algorithm, given a cluster with K samples, the mean square distance from sample i to the other samples in the cluster $(D(x^i))$ is defined as:

$$\boldsymbol{D}(\boldsymbol{x}^{i}) = \frac{1}{\boldsymbol{K}} \sum_{j=1}^{\boldsymbol{K}} \boldsymbol{d}^{2}(\boldsymbol{x}^{i}, \boldsymbol{x}^{j})$$

Where $d^2(x^i, x^j)$ is a distance measure, defined as $(x^i - x^j)^2$ in this study.

Thus, the *intraset* distance within the noise cluster ($D^{I}_{intraset}$) and the joint cluster ($D^{2}_{intraset}$) on the defect-free BGA substrate with N noisy segments and joints are:

$$\boldsymbol{D}^{I}_{intraset} = \frac{1}{N_{I}(N_{I}-1)} \sum_{i=1}^{N_{I}} \sum_{j=1}^{N_{I}} d^{2} \left(\boldsymbol{\lambda}_{S}^{*}(i), \boldsymbol{\lambda}_{S}^{*}(j)\right)$$
$$\boldsymbol{D}^{2}_{intraset} = \frac{1}{N_{2}(N_{2}-1)} \sum_{i=N_{I}+1}^{N} \sum_{j=1}^{N} d^{2} \left(\boldsymbol{\lambda}_{S}^{*}(i), \boldsymbol{\lambda}_{S}^{*}(j)\right)$$

where N_I is the number such that $\lambda_S^*(N_I)$ gives the specified threshold ($2 \le N_I \le N-2$) and $N_2 = N - N_I$.

The *interset* distance ($D_{interset}$) between the noise cluster and the joint cluster is defined similarly:

$$\boldsymbol{D}_{interset} = \frac{1}{N_I N_2} \sum_{i=1}^{N_I} \sum_{j=N_I+1}^{N} \boldsymbol{d}^2 \left(\boldsymbol{\lambda}_{\boldsymbol{S}}^{*}(i), \boldsymbol{\lambda}_{\boldsymbol{S}}^{*}(j) \right)$$

The measure of $Q(\lambda_s^*(N_I))$ is computed as:

$$\boldsymbol{Q}\left(\boldsymbol{\lambda_{\mathcal{S}}}^{*}(N_{I})\right) = \frac{\boldsymbol{D}^{I}_{intraset} + \boldsymbol{D}^{2}_{intraset}}{\boldsymbol{D}_{interset}}$$

Therefore, the $\lambda_s^*(N_I)$ reaches the minimum of $Q(\lambda_s^*(N_I))$ and is defined as the best threshold to distinguish between the boundary noise and joints on the BGA substrate conduct paths. The determined threshold $\lambda_s^*(N_I)$ is abbreviated as T_{λ} . Since a boundary defect is constructed by multiple corners, the following conditions for BGA substrate conduct paths $\left\{ \begin{array}{c} \text{are concluded.} \\ \text{are concluded.} \end{array} \right.$

a noisy segment, if its $\lambda_s^* \leq T_\lambda$ a joint or a defect, if its $\lambda_s^* > T_\lambda$ A 1-D λ_s waveform represents

The λ_s of a boundary point p_i in Fig. 3(a) is assigned to zero if the λ_s values of p_{i-1} , p_i and p_{i+1} are all less than $(\mu_{\lambda}+0.5\sigma_{\lambda})$. The Fig. 3(b) is therefore updated to Fig. 3(c). In Fig. 3(c), every defect candidate can be located easily if the λ_s^* value in its waveform is greater than T_{λ} . The defect candidates are labeled by character "A" as shown in Fig. 3(c). Then, we can concentrate on these defect candidates for further classification.



Fig. 3. (a) A portion of BGA substrate conduct paths with synthetic defects. (b) The corresponding 1-D λ_s diagram with the region of support s=5 (c) Every Defect candidate labeled by char. "A" is located by its λ_s^* value and threshold T_{λ} .



(Fig. 3. Continued)

3. Discrimination Rules for Defect Classification

Potential defects can be effectively detected using the corner detection scheme described in the previous section. However, it's not easy to classify these defect candidates into joint, open, short, mousebite, or spur in one single approach. The attributes regarding the λ_s waveform, the λ_s^* value, geometrical property, and gray value information of a defect candidate are extracted for classification purposes. The joints on BGA substrate conduct paths give single-peak waveform (see Fig. 4(a)), whereas defects such as short, mousebite, and spur are represented by multiple-peaks waveforms in the 1-D λ_s diagram (see Fig. 4(c)-4(d)). Ideally, an open defect usually has two corners close to each other. It is possibly represented by a single-peak waveform with extremely large λ_s^* value (Fig. 4(e)) if the width of conduct paths is relatively too small with respect to the image resolution. Likewise, boundary defects such as mousebite, short, and spur may also give single-peak waveforms due to insufficient image resolution or inappropriate regions of support. For instance, a wide-shallow mousebite shown in Fig. 5(a) may resemble two separate joints. In Fig. 5(b), a long bridge (long distance short) may be considered as two closely sharp joints. A high-steep spur illustrated in Fig. 5(c) could be detected as a single sharp joint. Although the above problems indicated in Fig. 5(a)-5(c) can be solved by using larger



Fig. 4. The number of peak(s) in 1-D λ_s waveform, the dividing points (p_b and p_t), vectors a and b, and midpoint location for each feature type: (a) Joint. (b) Open. (c) Short. (d) Mousebite. (e) Spur. (The features in Fig. 4(a)-4(e) are extracted from Fig. 3(a).)



Fig. 5. (a) Shallow-wide mousebite. (b) A short with long bridge. (c) High-steep spur. (d) Huge mousebite on circular conduct path.

regions of support (i.e. larger *s* values) to merge two false joints or by using larger image resolution (image magnification), false alarms may occur on non-defective regions simultaneously. Therefore, the defect type can not be identified simply by depending on the peak counts in its waveform. Three additional attributes are acquired for robust classification.

First of all, by statistical quality control, defects such as open and short involve distinctly sharp corners, and their λ_s^* values (local maximum in a waveform) will be greater than the upper control limit (e.g. $\mu_A + 3\sigma_A$). Further, since mousebite and spur involve at least two jag corners, the first two largest λ_s values (e.g. 1st λ_s^* and the 2nd λ_s^* shown in Fig 4(d)-4(c)) from their peaks on the waveform must be greater than the selected threshold T_A .

Secondly, if the waveform of a defect candidate is composed by a set of sequential points starting from p_b and terminating at p_t , this boundary segment is denoted as **FS** and defined as follows:

$$FS = \{p_i \mid p_i > (\mu_{\lambda} + 0.5 \sigma_{\lambda}), \forall p_i = p_b, p_{b+1}, \dots, p_{t-1}, p_t\}$$

The boundary points p_b and p_t are called dividing points for this defect candidate (see Fig. 4(a)-4(e)). In Fig. 4(a)-4(e), two vectors \mathbf{a} and \mathbf{b} are used to describe the boundary-following directions around a joint or a defect. The terminal point of vector \mathbf{a} is p_b and the initial point of \mathbf{a} is p_{b-s} , which is s points away from p_b in the backward boundary-following direction. Vector \mathbf{b} starts at point p_t and terminates at p_{t+s} , which is a distance of s points away from p_t along the forward boundary-following direction. The angle between \mathbf{a} and \mathbf{b} is denoted by $\boldsymbol{\theta}$, and it is computed as follows:

$$\theta = \cos^{-1} \frac{\mathbf{a} \cdot \mathbf{b}}{|\mathbf{a}||\mathbf{b}|}$$

where $\mathbf{a} = [x_b - x_{b-s}, y_b - y_{b-s}], \quad \mathbf{b} = [x_{t+s} - x_t, y_{t+s} - y_t]$ $p_b = (x_b, y_b), \quad p_{b-s} = (x_{b-s}, y_{b-s}), \quad p_t = (x_t, y_t), \quad p_{t+s} = (x_{t+s}, y_{t+s})$ s = the region of support.

The angle θ is greater than $3\pi/4$ for the defects open and short. Conversely, it will be less than $3\pi/4$ for the defects mousebite and spur. However, as shown in Fig. 5(d), the angle θ for a huge mousebite or spur on a circular conduct path may be greater than $3\pi/4$. If the angle θ of a defect is greater than $3\pi/4$, points p_b and p_t must be redefined to eliminate the ambiguity. Therefore, by tracing forward from the original p_b , the new starting point p_b is selected to be the first position at which λ_s is greater than $\mu_{\lambda}+3\sigma_{\lambda}$. If no such point is met, the new p_b is s points apart from the original p_b in the forward direction. The new termination point p_t is located in a similar way as p_b but in the backward direction. The original p_b and p_t will be replaced by the new p_b and p_t to define the directional vectors \mathbf{a}^{f} and \mathbf{b}^{f} . Then, the angle $\boldsymbol{\theta}$ is recalculated and used as one of the attributes for describing this defect candidate.

Finally, the midpoint on the line segment connecting p_b and p_t will fall on the background (which has a gray value of 255 in 8-bits intensity) if the defect is open (see Fig. 4(b)). In case it is a short (see Fig. 4(c)), the midpoint on the line segment connecting p_b and p_t will fall on the conduct path (which has a gray value of 0). Defects such as mousebite and spur can be distinguished with the same practice (see Fig. 4(d) and 4(e)). The gray value of midpoint can be either 0 or 255 for a joint.

Thus, the number of peaks in the waveform, the largest λ_s value(s), the angle θ , and the gray value of the midpoint for defect candidates are collected for establishing the discrimination rules to classify them into joint, open, short, mousebite, and spur. The aforementioned discrimination rules are summarized in Table 1. Each defect type is classified by a specific set of discrimination rules. The detailed classification procedure is expressed as a flow diagram illustrated in Fig. 6. The proposed classification procedure does not rely on the pre-stored templates and training process to accomplish the classification task. A brief description for locating and classifying BGA substrate boundary defects is summarized in Fig. 7.

Item	Discrimination rule
A	The number of peaks = 1 and $\lambda_{S}^{*} > T_{\lambda}$
В	The number of peaks ≥ 2 and $1^{\text{st}} \lambda_s^* > T_\lambda$ and $2^{\text{nd}} \lambda_s^* > T_\lambda$
С	$T_{\lambda} < \lambda_{S}^{*} < (\mu_{\lambda} + 3\sigma_{\lambda})$ (for single-peak waveform)
D	$\lambda_{s}^{*} \geq (\mu_{\lambda} + 3\sigma_{\lambda})$ (for single-peak waveform)
Ε	Both $1^{\text{st}} \lambda_{s}^{*}$ and $2^{\text{nd}} \lambda_{s}^{*} \ge (\mu_{\lambda} + 3\sigma_{\lambda})$
F	Angle θ between $a_{\rm p}$ and $b_{\rm p} \ge 3\pi/4$
G	Angle $\boldsymbol{\theta}$ between \mathbf{a} and $\mathbf{b} < 3\pi/4$
Н	Gray value of the midpoint $= 0$
Ι	Gray value of the midpoint $= 255$

Table 1. The discrimination rules for defect classification



Fig. 6. The procedure for classifying the defect candidates into joint, open, short, mousebite, and spur.









4. Experimental Results

Two experiments are conducted in this study. One evaluates the performance of the proposed defect detection and classification method, and the other one verifies its rotation-invariant property. A LED ring lighting source, 25mm lens, and 12mm extension ring are used to increase the visibility of the BGA substrate conduct path. The defect detection and classification program is edited in the C language and executed on the vision package software named "Optimas" using a personal computer.

In the first experiment, the upper side, the bottom side, and the left-bottom side of a real BGA substrate shown in Fig. 1(a) are captured as test image samples to evaluate the defect detection capabilities of the proposed algorithms. Each sample image is captured in a 25mm x 20mm field of view, which corresponds to 850 x 640 pixels in image. In Figs. 8(a)–8(c), one hundred synthetic boundary defects are created on every sample. Each sample contains 20 opens, 20 shorts, 30 mousebites, and 30 spurs. Both simple and complicated shape defects are included to fit the real inspection environment. The detection errors come from three sources: 1) False alarm (i.e., a normal region is detected as a defect), 2) Fail to alarm (i.e., failure to alarm a true defect), and 3) True alarm with wrong defect types (i.e., a true defect is detected but the type is misclassified.).



Fig. 8. BGA substrate test sample images. (a) Top side – sample 1. (b) Bottom side – sample 2. (c) Left-bottom side – sample 3.

In real BGA components inspections, image magnification is the first and most important step to obtain accurate measurement [18]. Initially, the image of 850 x 640 pixels contains a 25x20mm² physical region so that better resolution is obtained for describing the detail of conduct paths. Furthermore, different regions of support may affect the structure of λ_8 waveforms. Various *s* values must be incorporated to realize the effect on this experiment. The predefined threshold T_{λ} , the mean μ_{λ} , and the standard deviation σ_{λ} of a defect-free BGA substrate in a given resolution are calculated off-line. The resulting number of detection errors for each sample images by different *s* value (*s* = 5, 6, 7, 8, 9, 10) is shown in Table 2.

In Table 2, the number of detection errors is 10 and no false alarm is generated out of a total of 300 synthetic defects in three sample images if *s* is set to 7. This reaches a 96.66% correct identification. More specifically, 9 of the 10 detection errors are "fail to alarm," which are all shallow-wide mousebites as shown in Figs. 9(a)–9(c). The other detection error is "true alarm with wrong defect types," which is a mousebite right on the circular pad joint (Fig. 9(d)). These detection errors appear repeatedly in other *s* values. To achieve 100% correct identification, the resolution for these subtle defects should be enlarged. Therefore, we magnify the test images up to 1.1X, 1.15X, and 1.25X and perform the same detection procedure. The parameters such as T_{λ} , μ_{λ} and σ_{λ} will vary since different resolutions are involved. In Table 3, a 100% correct identification

Region of support	11 (s=5)		13 (<i>s</i> =6)			15 (<i>s</i> =7)			17 (<i>s</i> =8)			19 (<i>s</i> =9)			21 (<i>s</i> =10))	
μ_{λ}	0.000197			0.00024			0.000289			0.000362			0.000405			0.00048		
σ_{λ}	0.000218			C	.0003	05	0.0004			0.000603			0.000623			0.00075		
T_{λ}	0.000503		0.000666			0.000839			0.000982			0.00116			0.00136		6	
Detection error*	I	п	ш	I	II	ш	Ι	п	ш	I	II	ш	Ι	II	III	Ι	п	III
Sample1 (Fig. 8(a))	2	2	2	0	2	0	0	2	0	0	2	3	2	4	6	3	6	4
Sample2 (Fig. 8(b))	4	5	0	0	5	1	0	3	1	0	6	2	1	7	2	2	14	1
Sample3 (Fig. 8(c))	3	5	1	0	6	0	0	4	0	1	8	3	1	10	6	3	10	8
Total		24			14			10			25			39			51	

Table 2. Defect detection and classification results from each sample image by different *s* values.

Detection error * I: false alarm, II: fail to alarm, and III: true alarm with wrong defect types



Fig. 9. (a) One "fail to alarm" error from sample 1. (b) Four "fail to alarm" errors from sample 2. (c) Four "fail to alarm" errors from sample 3. (d) One "true alarm with wrong defect type" error from sample 2.

Table 3.	Defect	detection	and	classificatio	n results	from	each	sample	image
(1.25X m	agnifica	tion) by di	ffere	ent <i>s</i> values.					
		11	1	2 15		17	1(21

Region of support	11 (s =5)				13 (s =6)	15 (s =7)			17 (<i>s</i> =8)			19 (<i>s</i> =9)))	
μ_{λ}	0.000326			0.00038			0.00043			0.000485			0.000547			0	15	
σ_{λ}	0.000267		0.000334			0.00042			0.000524			0.000639			0	61		
T_{λ}	0.000753		0.000914			0.000839			0.00127			0.00144			0.0016			
Detection error*	I	п	ш	I	II	ш	I	Π	III	I	II	III	I	Π	III	I	п	III
Sample1 (Fig. 8(a))	1	0	1	0	0	0	0	0	0	0	0	1	0	1	3	0	2	3
Sample2 (Fig. 8(b))	1	2	0	0	1	0	0	0	0	0	2	1	0	2	0	1	7	0
Sample3 (Fig. 8(c))	1	1	0	0	1	0	0	0	0	0	2	1	0	4	2	0	4	3
Total	7 2			0 7					12			17						

Detection error * I: false alarm, II: fail to alarm, and III: true alarm with wrong defect types

is accomplished in 1.25X magnification with the s value of 7. The performances of other s values are also improved significantly in the 1.25X images.

In the second experiment, various angled images including 0°, 1°, 2°, 3°, 4°, 5°, 10°, 15°, 25°, 45°, 90°, and 135° of a BGA substrate are used to verify the rotational effect. The 0° binary image involves 40 synthetic defects, containing 10 opens, 10 shorts, 10 mousebites, and 10 spurs (see Fig. 10(a)). The images in 5°, 15°, 25°, 45°, 90°, and 135° rotations with respect to the original 0° image in Fig. 10(a) are shown in Figs. 10(b)-10(g), respectively. The required parameters of T_{λ} , μ_{λ} , and σ_{λ} for each rotated image are the same as the first experiment for a given region of support (e.g. *s* = 7). The defect detection results from the images in various orientations are illustrated in Table 4.

It can be seen from Table 4 that the proposed method in this study is rotation-invariant in the range of 1°-15°, in which no detection errors are generated. In practice, rotational errors exceeding 15° may not exist in the real BGA substrate inspection. In Fig. 11(a), a mousebite and a spur are identified successfully on the 0° image. However, for images in larger rotational angles, the mousebite and the spur are undetected due to the digital quantization effect. More specifically, the mousebite becomes shallower to incur the "fail to alarm" error, the sharp spur becomes smoother and is misclassified as a mousebite on the 25° image (see Fig. 11(b)). The detection errors



Fig. 10. BGA substrate binary images in varying orientations for verifying the rotational effect (a) 0° , (b) 5° , (c) 15° , (d) 25° , (e) 45° , (f) 90° , (g) 135° .

Rotational	Detection								
angle]								
	Ι								
0°	0	0	0						
1°	0	0	0						
2°	0	0	0						
3°	0	0	0						
4°	0	0	0						
5°	0	0	0						
10°	0	0	0						
15°	0	0	0						
25°	0	1	1						
45°	0	1	0						
90°	0	0	0						
135°	0	1	1						

Table 4. Detection error incurred by varyingrotational angles on BGA substrate.

Detection error * I: false alarm, II: fail to alarm	I,
and III: true alarm but wrong defect types	



Fig.11. (a) A mousebite (left) and a spur (right) are identified correctly on the 0° image. (b) The "fail to alarm" error on the mousebite (left) and the "true alarm with wrong defect type" error on the spur (right) in 25° image. (c) The "fail to alarm" error on the mousebite in 45° image. (d) The "fail to alarm" error on the mousebite (left) and the "true alarm with wrong defect type" error on the spur (right) in 135° image.

respectively occur on the same defective regions for 45° and 135° images (see Figs. 11(c)-11(d)). Following the same practice as the first experiment, we magnify the images of larger rotational angles up to 1.25X and repeat the detection procedure. The resulting detection errors from 1°-135° images are completely eliminated. Thus, we have validated this proposed approach to be a rotation-invariant one in BGA substrate inspection under the circumstance of sufficient image resolution.

Two real defective BGA substrates shown in Fig. 12(a) and Fig. 13(a) are used to demonstrate the proposed approach in the real inspection environment. The images in 45° and 90° orientations for Fig. 12(a) are respectively illustrated in Fig. 12(c) and Fig. 12(d). The short defects and the spur defects are reliably detected. They are respectively marked by white squares and triangles dotted lines. Each cross sign points out the position with the largest λ_8 value on each defect. The orientations of 45° and 90° are also executed for BGA substrate shown in 13(a). The open defects are encircled by white dotted lines in Fig. 13(a), Fig. 13(c), and Fig. 13(d), respectively. The results reveal that all defects are reliably identified and well localized.



Fig. 12. (a) Real defective BGA substrate with a short and a spur. (b) The gray level image of Fig. 12(a). (c) The image of Fig. 12(a) in 45° orientation. (d) The image of Fig.12(a) in 90° orientation. (The short and spur defects are respectively marked by white squares and triangles dotted lines.)



Fig. 13. (a) Real defective BGA substrate with open defects. (b) The gray level image of Fig. 13(a). (c) The image of Fig. 13(a) in 45° orientation. (d) The image of Fig.13(a) in 90° orientation. (The open defects are encircled by white dotted lines)

5. Conclusion

In this study, the BGA substrate conduct path boundary defects of open, short, mousebite, and spur have been initially located by eigenvalues λ_s derived from the covariance matrix of the boundary points over a small region. Then, every boundary defect is classified by the discrimination rules, which are based on the λ_s waveform pattern and geometrical attributes of each defect type. The proposed approach avoids inspection errors resulting from board distortion and misalignment. It requires no pre-stored templates, no template-matching procedure, and no training process. Therefore, computational time and data storage can be significantly reduced. The experimental results shows that the proposed method is rotation-invariant and can achieve 100% correct identification for BGA substrates conduct paths inspection if the region of support is set to 7 under image resolution of approximately 40 pixels/mm.

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