A Rotation-Invariant and Non-Referential Approach for Ball Grid Array (BGA) Substrate Conducting Path Inspection

C.-H. Yeh and D.-M. Tsai
Department of Industrial Engineering, Yuan-Ze University, Taiwan

The aim of this paper is to locate and classify boundary defects such as open and short circuits, mousebites, and spurs on ball grid array (BGA) substrate conducting 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 prestored templates for matching. This method is suitable for various types of BGA substrate in small-batch production because precise positioning of BGA substrates and the prestored templates are not necessary.

Keywords: BGA substrate conduct path; Covariance matrix; Defect classification; Defect detection; 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 conducting paths and a finer specification in a much smaller layout area [1]. One advanced type of PCB called the ball grid array (BGA) substrate, 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 harder to detect and can 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]. Hybrid approaches [10,11].

Referential approaches were 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 of a pixel matrix) scheme to detect the defective areas. They are also known as template-matching techniques. In recent works, 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 defects. However, they suffer from angular errors produced by board distortion during the fabrication process and rotational misalignment of 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, are sensitive to noise, and require large amounts of data storage for template images [6,13].

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

Hybrid methods combine referential approaches and non-referential approaches to acquire all the benefits when 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 effort is expected by hybrid methods. Hybrid methods also suffer inherently from rotational error and noise effects.

From a geometrical aspect, the boundary of BGA substrate conducting paths can be considered as a combination of lines,
corner detection scheme. It reduces the sensitivity to 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 pre-stored templates and precise alignment of the BGA substrates under inspection.

This paper is organised 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 conducting path boundaries is also explained in this section. Then, the discrimination rules used for classifying four defect types (e.g. open circuit, short circuit, mousebite’ and spur) are described in Section 3. Experimental verification of the proposed method is shown in Section 4. Finally, the conclusions are given in section 5.

2. Defect Detection

2.1 Eigenvalues of Covariance Matrices

Since common defects such as open and short circuits, mousebites’ and spurs can be treated as multiple jag corners on BGA substrate conducting path boundary, an effective corner detection algorithm derived from the eigenvalue of the covariance matrix from a digital boundary segment is used to locate joints and defects. This corner detection scheme has been shown to be faster, more precise, rotation-invariant, and scale-invariant than 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 conducting paths. Let the sequential n digital points describe a boundary P,

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

where \( p_{i+1} \) is adjacent to \( p_i \) on \( P \). Further, let \( N_s(p_i) \) denote a small boundary segment centring on point \( p_i \) over the region of support between points \( p_{i-s} \) and \( p_{i+s} \) for some integer \( s \), i.e.

\[ N_s(p_i) = \{ p_j | i-s \leq j \leq i+s \} \]

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

\[
M = \begin{bmatrix}
m_{11} & m_{12} \\
m_{21} & m_{22}
\end{bmatrix}
\]

where

\[
m_{11} = \frac{1}{2s + 1} \sum_{j=-s}^{s} x_j^2 - \bar{x}_i^2
\]

\[
m_{22} = \frac{1}{2s + 1} \sum_{j=-s}^{s} y_j^2 - \bar{y}_i^2
\]

\[
m_{12} = m_{21} = \frac{1}{2s + 1} \sum_{j=-s}^{s} x_j y_j - \bar{x}_i \bar{y}_i
\]

\[
\bar{x}_i = \frac{1}{2s + 1} \sum_{j=-s}^{s} x_j
\]

\[
\bar{y}_i = \frac{1}{2s + 1} \sum_{j=-s}^{s} y_j
\]