Automatic visual position and inspection of printed circuit boards using E-M algorithm

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Abstract. In the PCB manufacturing, position accuracy is very important for automatic assembly and defect inspection. In this paper we present a machine vision scheme for printed circuit board (PCB) positioning and inspection based on the Expectation-Maximization (E-M) algorithm. It can be well tolerated with deformation and incomplete shape of the template object in the PCB. The proposed method starts with edge detection to extract edge points in the image. For an edge point in one image, the E-step in the E-M algorithm uses a fast spiral search to find its corresponding edge point with the shortest distance in the compared image. The weight of the point is then inversely proportional to the distance. In the M-step, the center, directional angle and size of the object are calculated from the weighted edge points. The estimated geometric parameter values are then used to transform the test object. It then loops back to the E-step to update the weights of individual edge points. The E-M algorithm is generally converged very fast. At the end of the E-M process, the shift, rotational angle and size scale between the template and the instance in the test image is used to adjust the position of the test PCB. With the proposed E-M template matching, the windows in both template and test images can be fixed at the same regions. It is not required to slide the window pixel by pixel throughout a search region and, thus, is computationally very efficient. The performance of the proposed method is demonstrated with the position accuracy of fiducial marks in PCBs, and defect detection of PCBs by simple image subtraction.

Keywords: Machine vision; Template matching; PCB positioning; PCB inspection; E-M algorithm

1. INTRODUCTION

Precision positioning is very important for automatic assembly and inspection for products with or without fiducial marks in the manufacturing process. In printed-circuit board (PCB) manufacturing, the alignment of the PCB ensures the correct insertion of electronic components on the board in the DIP (Dual Inline Package), VCD (Variable Centered Distance) or SMT (Surface Mount Technology) assembly process. The automatic visual inspection of bared and assembled PCBs also relies on precise alignment between the defect-free template and the test board.

The most commonly-used template matching methods in industrial applications are either the simple image subtraction or the normalized cross correlation (NCC) to meet the real-time inspection requirements of a very large image. Both methods must evaluate all possible translations in a search region, and are very sensitive to rotation changes of the inspection object. In this paper, we propose a fast image alignment method using the Expectation-Maximization (E-M) algorithm. The proposed algorithms are especially applied to positioning and defect inspection of printed circuit boards (PCBs). They can well handle deformed or incomplete object shapes with translation, rotation and scale changes.

There are two main approaches for image alignment: region-based registration and feature-based registration. The image registration methods have been reviewed in references [1*, 2*]. In the region-based approach, the pixel values defined in a small window are used to calculate the similarity between the template and the test image. The NCC [3*] is a popular measure for template matching. It is evaluated by shifting the window pixel-by-pixel between two compared images. The phase correlation [5*] in the Fourier domain is also used for image registration. It detects the peak of the normalized cross power spectrum to find the shift of two compared images.

For feature-based approach, the edges are typical representation of an object. [8*], used Fourier descriptors for object and image alignment. It needs to detect object edges in the image and then links edges into object contours. The Hausdorff distance [9*] has been used to evaluate the similarity between two edge-point sets. It measures the extent to which each edge point of a template object lies near some edge point of the scene image, and vice versa. It is scale- and rotation-dependent, and thus computationally very expensive. keypoints of edges are an alternative to represent object structures. The keypoint-based methods find a set of dominant points such as corners from two compared images. The scale invariant feature transform (SIFT) descriptor proposed by Lowe [14*] is the most popular keypoint-based method for object matching and image registration.

For region-based image alignment techniques used in electronic industry applications, [15*] applied the NCC to align images and then used the simple subtraction to inspect chip components in PCBs. The direct measure of sum of absolute difference (SAD) or mean squared error (MSE) between pixel pairs in two compared images are also popularly used to estimate the geometric transformation parameters. [16* and 17*] used the simple image subtraction to align and inspect defects on bare PCBs. [18*] studied the image alignment of PCBs by evaluating the minimum SAD using the genetic algorithm. [20*] proposed the use of MSE and NCC for PCB image registration. [23*] used the mutual information criterion to find geometrical transformation parameters and solved the optimization problem by the genetic algorithm. [24*] applied the phase correlation to align the bare PCBs, and then used the image subtraction to locate defect areas.

For feature-based image alignment for electronic industry applications, [27*] used Fourier descriptors to align images for automatic defect inspection. The method relies on good linkage of object contours, and can only be applied best for simple electronic objects in isolated regions. [28*] used the Hausdorff distance for PCB inspection. The image is first represented by object edges. The alignment of PCB is carried out by minimizing the associated Hausdorff distance using the simplex search algorithm. [29*] evaluated the SIFT descriptors for the inspection of printed characters in PCB electronic components.

The currently available image alignment methods generally need specific fiducial marks in a clear background for automatic positioning and inspection in manufacturing. The meta-heuristic optimization approach with similarity criterion of NCC, SAD, MSE or mutual information is computationally expensive to search for the parameter values in an extremely wide solution space.

In this study, we propose a feature-based Expectation-Maximization (E-M) algorithm for automatic positioning and inspection, with emphasis on bare and assembled PCBs. It can be applied to objects with deformed or partially occluded shapes for accurate estimation of geometrical transformation. The proposed method starts with edge detection to extract edge points in the image. For an edge point in one image, the E-step in the E-M algorithm uses a fast spiral search to find its corresponding edge point with the shortest distance in the other image. The spiral search can be carried out by a pre-determined look-up-table and, thus, is very efficient to find the closest neighboring point. The weight of an edge point is then inversely proportional to the distance. In the M-step, the centroid, orientation and size of the object are calculated from the weighted edge points. The translation, rotation angle and scale change are thus obtained from the differences of the geometrical parameter values of the two compared images. The estimated translation, rotation and scale are then used to transform the test image. The E-step and M-step proceed recursively to update weights of edge points and transformation parameter values. The E-M algorithm generally converges very fast. At the end of the E-M process, the location shift, rotation angle and size scale between the template and the corresponding instance in the test image are used to position the test object for assembly, or align the whole test image for inspection.

The paper is organized as follows: Section 2 presents the E-M algorithm for the estimation of geometrical transformation parameters. Section 3 presents the experimental results on PCBs. The estimation accuracy of geometrical parameters is analyzed. The defect detection for PCBs is then reported. This paper is concluded in Section 4.

2. The proposed method

The proposed method in this study for image alignment is feature-based. In this study, the Canny edge detector [33*] is applied to extract fine object edges in the image. Denote by $E_T(x_T, y_T)$ and $E_I(x_I, y_I)$ the Canny edge maps for the template T and the test image I, with the value of 1 for edge points and 0 for non-edge points (background).

2.1 E-step for updating weights of edge point

Before we present the E-step of the E-M algorithm, the spiral search process is described first. It can find the shortest distance from an edge point in one image to tis corresponding point in another image. The weighting factor of the edge point is then inversely proportional to the distance. A spiral is a curve that emanates from the origin with the increasing angle of rotation, i.e., $r = a \cdot \theta$, where θ is the polar angle measure in radians, and a is a constant that controls the spacing between successive turnings of the spiral. Let the spiral center be the origin with coordinates (0, 0). A point p with polar angle θ_p on the spiral can be defined in the Cartesian coordinates of a digital image by ($x(p)$, $y(p)$), where

$$x(p) = Int[a \cdot \theta_p \cdot \cos\theta_p] \tag{1a}$$

$$y(p) = Int[a \cdot \theta_p \cdot \sin\theta_p] \tag{1b}$$

In the digital image, the spacing between two successive turnings is 1 pixel and, thus, the constant a must be less than $1/2\pi$. By carefully selecting the turning constant a (with a < $1/2\pi$) and the increment of polar angle θ_p, the digital spiral in the 2D discrete image can be constructed off-line. The Look-Up-Table (LUT) of the digital spiral then contains the coordinates ($x(p)$, $y(p)$) and distance $d(p)$ with p as the index.

Denote by $P_T = \{(x_{T,i}, y_{T,i}), i = 1,2,...,n_T\}$ a set of n_T edge points with $E_T(x_{T,i}, y_{T,i}) = 1$ for the template image *T*, and $P_I = \{(x_{I,j}, y_{I,j}), j = 1,2,...,n_I\}$ a set of n_I edge points with $E_I(x_{I,j}, y_{I,j}) = 1$ for the test image *I*. The spiral search of the shortest distance from an edge point $(x_{T,i}, y_{T,i})$ in the template *T* to its corresponding edge point in the test image I proceeds as follows. First, the edge point $(x_{T,i}, y_{T,i})$ is taken as the spiral center in the test image. It then emanates from the center by evaluating $(x_{T,i} + x(p), y_{T,i} + y(p))$ in the test image using the spiral LUT. The smallest index number p^* with $E_I(x_{T,i} + x(p^*), y_{T,i} + y(p^*)) = 1$ gives the shortest distance $d(p^*)$ from the edge point $(x_{T,i}, y_{T,i})$ in the template *T* to the edge point $(x_{T,i} + x(p^*), y_{T,i} + y(p^*))$ in the test image *I*. That is,

$$p^* = Min\{p \mid E_I(x_{T,i} + x(p), y_{T,i} + y(p)) = 1, p < p_{\max}\} \tag{2}$$

$p_{\max}$ in eq. (2) is the maximum number of the spiral sequence. Note that $x(p)$, $y(p)$, and $d(p^*)$ are directly obtained from the spiral LUT. The search simply increases the spiral index *p* by 1 at a time until an edge point is found. No geometrical computation and complicated search and sorting are required. The weight $w_{T,i}$ of the edge point $(x_{T,i}, y_{T,i})$ in the template image *T* is given by $1/\max\{d(p^*),1\}$. Likewise, the weight $w_{I,j}$ of an edge point $(x_{I,j}, y_{I,j})$ in the test image I can be obtained using the same spiral search above. To prevent false correspondence, we calculate the overall edge direction in a small window for edge points in both compared images. If the edge directions of edge points in two images do not meet the direction constraint, the spiral search will continue until the closest neighboring point with coherent direction is found.

2.2 M-step updating geometrical transformation parameter

In this study, the position of the object in the image is defined by the weighted centroid, i.e. the position $(\bar{x}_T, \bar{y}_T)$ of the template object is given by

$$\bar{x}_T = \sum_{i=1}^{nT} x_{T,i} \cdot w_{T,i} \quad \text{and} \quad \bar{y}_T = \sum_{i=1}^{nT} y_{T,i} \cdot w_{T,i} \tag{3}$$

and the weights are further normalized to unity

The orientation of the template object is evaluated from the weighted PCA (Principal Component Analysis). The weighted covariance matrix of the x- and y-coordinates for the template *T* is given by

$$M_T = \begin{bmatrix} m_{xx} & m_{xy} \\ m_{yx} & m_{yy} \end{bmatrix} \tag{4}$$

where $$m_{xx} = \sum_{i=1}^{n_T} x_{T,i}^2 \cdot w_{T,i} - \bar{x}_T^2$$

$$m_{yy} = \sum_{i=1}^{n_T} y_{T,i}^2 \cdot w_{T,i} - \bar{y}_T^2$$

$$m_{xy} = m_{yx} = \sum_{i=1}^{n_T} x_{T,i} \cdot y_{T,i} \cdot w_{T,i} - \bar{x}_T \cdot \bar{y}_T$$

The square root of the major eigenvalue λ_1 of the covariance matrix M_T gives the length of the major axis and is used to represent the size scale of the object. The directional angle of the major eigenvector e_1 is used to define the object orientation. They are calculated as follows:

$$\lambda_1 = (m_{xx} + m_{yy} + \sqrt{(m_{xx} - m_{yy})^2 + 4m_{xy}^2})/2 \tag{5}$$

$$e_1 = [e_{1x} \; e_{1y}]^T \tag{6}$$

where $e_{1x} = m_{xy} / \sqrt{(\lambda_1 - m_{xx})^2 + m_{xy}^2})$

$e_{1y} = (\lambda_1 - m_{xx}) / \sqrt{(\lambda_1 - m_{xx})^2 + m_{xy}^2})$

The orientation of the template $\theta_T = \tan^{-1}(e_{1y} / e_{1x}) \cdot 180 / \pi$.

Similarly, the position $(\bar{x}_I, \bar{y}_I)$ and orientation θ_I for the object in the test image I can also calculated from the centroid and PCA of edge points $P_I = \{(x_{I,j}, y_{I,j}), j = 1,2,...,n_I\}$ using the weights $w_{I,j}$. The translation $(\Delta x, \Delta y)$ and rotation angle $\Delta\theta$ between the template and the corresponding object in the test image are thus given by

$$(\Delta x, \Delta y) = (\bar{x}_I - \bar{x}_T, \bar{y}_I - \bar{y}_T) \qquad (7)$$
$$\Delta\theta = \theta_I - \theta_T$$

The estimated parameters $(\Delta x, \Delta y, \Delta\theta)$ are used to transform the edge points in the test image. The newly transformed test image is then used to update the weights $w_{T,i}$ and $w_{I,j}$. in both compared images until convergence.

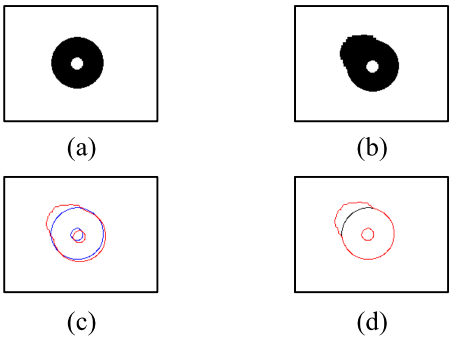

Figure1. E-M position on circular fiducials in PCB (a) t emplate (b) test fiducial; (c) alignment with equal weight s(initial solution); (d) E-M alignment result.

Figure 1 demonstrates a circular fiducial, where (a) is the template and (b) is the test object with partial intrusion due to over-etching. Figure 1(c) and (d) presents the transformation results by superimposing the test object on the template, where (c) is the result from all edge points with equal weights and (d) is the result from the proposed E-M positioning algorithm. It shows that the proposed method can precisely align the fiducial with incomplete shape in the test image.

3. Experimental result

In this section, we present the experimental results of PCB positioning and inspection. The maximum spiral radius used for spiral search is 10 pixels. In our implementation, all algorithms are coded in the C++ language and are executed on a personal computer with an Intel Core i7-3770 3.40GHz processor.

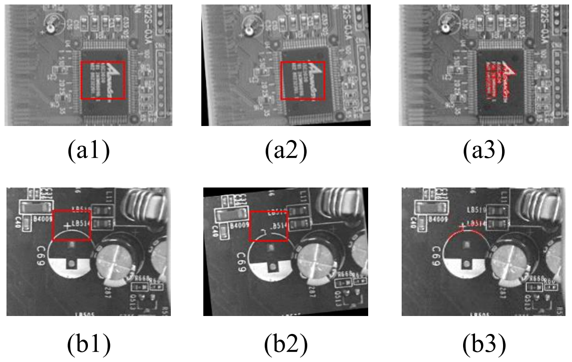

Figure2. Performance evaluation of the proposed method for PCB translation and rotation errors; (a1),(b1) Templat e images; (a2),(b2) test images; (a3),(b3) alignment result s.

Figure 2(a1)-(b1) presents two different PCB images with arbitrary templates of size 60×50 pixels. Figure 2(a2)-(b2) are the test PCB images with varying translations and rotations. The alignment results are illustrated in Figure 2(a3)-(b3) by superimposing the transformed edge points in the test images on the template images. The superimposing results show that the two test images are well aligned. Table 1 summarizes the actual and estimated geometrical parameter values of the two PCB test images in Figure 2. It shows that the proposed E-M positioning algorithm can yield a translation error less than 1 pixel in either x- or y-axis, and a rotation error less than 1°. The computation times of the two test images are about 0.2 seconds, as shown in Table 1.

The proposed E-M positioning algorithm can align the PCB image from one single template with high shift and rotation accuracy. Therefore, it can be well applied for defect detection in PCB using the simple image subtraction. Denote by $f_T(x, y)$ the defect-free template image of a PCB, and $\hat{f}_I(x, y)$ the aligned PCB to be inspected. The image difference is given by

$$\Delta f(x, y) = | f_T(x, y) - \hat{f}_I(x, y) | \qquad (8)$$

Table 1. Positioning accuracy and computation time of test images in Figure2

Test image	Actual translation	Estimated translation	Translation error	Actual rotation	Estimated rotation	Rotation error	Computation time
Figure 2(a)	(5,1)	(4.35,0.57)	0.78	-4°	-3.66°	0.34°	0.15
Figure 2(b)	(5,3)	(5.20,3.39)	0.44	-6°	-5.64°	0.36°	0.25

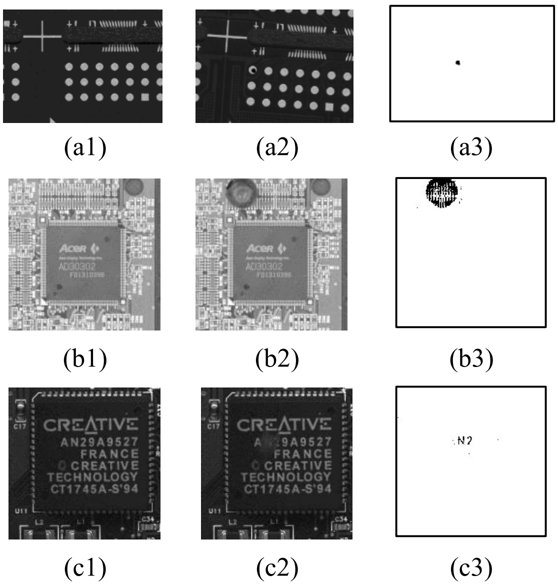

Figure 3. E-M position and image subtraction for PCB d efect detection: (a1)-(c1) PCB templates; (a2)-(c2) test P CBs; (a3)-(c3) defect detection results.

A significantly large $\Delta f(x, y)$ indicates a defect point at coordinates (x, y). Figure 3 displays the PCB images for the test, where Figures 3(a1)-(c1) are the templates. Figure 3(a2) contains a pinhole defect in the bare PCB. Figure 3(b1) presents a defective component in the assembled PCB, and Figure 3(c) shows that some printed characters on the IC are blurred. Figures 3(a3)-(d3) are the binarized results of image subtraction between the templates and the aligned test images. All defects are well detected. The detection results reveal that the proposed E-M positioning algorithm can accurately transform the test images to align with the template image. It makes the simple and fast image subtraction operation applicable for real-time defect detection in the manufacturing process.

4. Conclutions

In this paper, we have proposed an Expectation-Maximization algorithm for image alignment and applied to positioning and inspection of PCBs. In the Expectation step, the weight of an edge point in one image is updated based on the distance to its neighboring point in another image. The pre-constructed spiral look-up-table is applied for fast access of the neighboring point with minimum distance. In the Maximization step, all edge points with their updated weights in each individual image are used to calculate the geometrical transformation parameters. The recursive E- and M-steps can be converged in a few iterations and generate accurate estimation of the geometrical parameters.

Because the weights of individual edge points are updated by the neighboring distances, they can well represent the similarity of two compared objects with incomplete edge information or deformation. The proposed E-M positioning algorithm needs only to fix the window of the test object at the same location as the template in the image. It is especially suited for PCB positioning, where the PCB can by physically aligned by fixtures and presents only a few translation and rotation changes. Experimental results have shown that the proposed method can achieve translation error less than 1 pixel and rotation error less than 1 degree. For template alignment in a very complicated background, we need an effective correspondence constraint or criterion to eliminate false match of edge points. It is worth investigating in the future to further improve the weights of edge points.

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