Vision-Based Printed Circuit Board Inspection

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Abstract

Printed circuit boards are used in electronic devices such as digital cameras, computers, etc. With time, many components are being added to the printed circuit board, and hence the density of members and the manufacturing tolerance is also increasing. This has resulted in the increased demand for inspection techniques as well. One such requirement is 100% inspection. The inspection technique should be quick and complete the inspection process as fast as possible. The main objective of inspecting the printed circuit board is to assess defects, cracks, missing components, etc. An attempt has been made in the present research work to set printed circuit boards using a vision system. The method not only does the classification of PCB into known defect classes but also locates the position of the defect and measures the associated dimensions. The method is quick and finds application in the 100% inspection of printed circuit boards.

Keywords: Printed circuit board inspection, non-contact inspection, Machine vision, Computer vision

1. Introduction

With the demand for refrigerators, computers, digital cameras, washing machines, and other products increasing, it necessitates the production of quality printed circuit boards. Inspection of printed circuit boards is becoming very challenging. The number of components present on the printed circuit board increases and the tolerance of the various parts grows. In addition, PCB manufacturers have to deliver quality printed circuit boards in a short lead time. This aspect also places the need for the design and development of quick, non-contact, accurate, and robust inspection techniques suitable for online and 100% inspection of printed circuit boards. The significance of printed circuit board inspection is that the board will function satisfactorily when put into service. Many researchers have been working in PCB inspection (Oguz et al. 1991, Moganti et al. 1996, Sasai et al. 2000, Mashohor 2004, Greenberg et al. 2006). PCB inspection technique in which the actual image is compared with the standard image for identifying defects is known as the referential method. In the non-referential process, the actual image is assessed by referring to the design specifications. Some inspection techniques use both referential and non-referential methods (Mashohor 2004). A printed circuit board may consist of various defects such as fractures, cuts, scratches, cracks, pinholes, spurs/ or protrusions, variations between printed lines, etc. Many of these defects can be broadly classified into fatal and non-fatal classes. Many researchers have proposed methods for PCB inspection not with complete success (Capson 1988, Nakagawa 1982). If a printed circuit board is deployed without assessment may lead to board failure and a short circuit. This shows the importance of PCB inspection. In this research work, an attempt is made to design and develop a vision-based inspection procedure for printed circuit boards.

2. Methods

The method proposed in the current research work uses a vision system to acquire printed circuit boards. The technique uses a charge-coupled device (CCD) camera having a resolution of 1600x1236 pixels. The camera is connected to a server fitted with a dual monitor system. The specimen (printed circuit board) is mounted on the mount table and illuminated by diffused lighting during the experiment. The image of the specimen is stored on the server's hard disk. The above procedure is repeated, taking one specimen at a time. Thus, all the images of various specimens are captured and stored for further analysis. During image capture, there can be multiple types of noise affecting the quality of the image. Hence, the captured images are subjected to pre-processing.

2.1 Image acquisition and camera calibration

Figure 1 shows an image of a printed circuit board captured using a CCD camera. Table 1 shows the digital image of a specimen (PCB). Camera calibration helps in correcting for lens distortion if any. For example, there can be radial distortion and tangential distortion. The camera calibration is performed using calibration context, which holds the required settings. Camera calibration would help in measuring objects in real-world units.

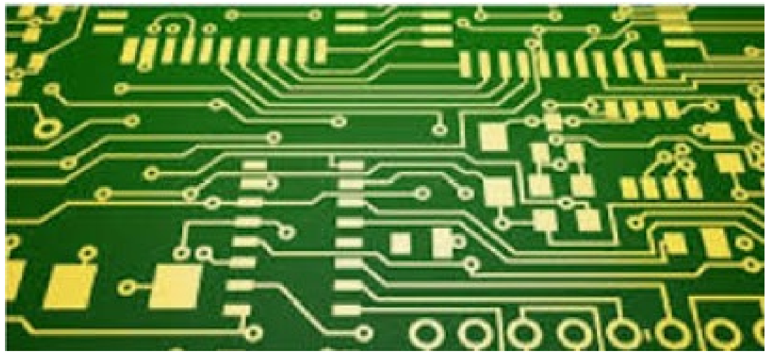

Figure 1. Printed circuit board

Table 1. Digital image of a PCB

149	187	188	177	148
143	141	180	198	146
165	148	147	195	182
143	147	146	196	185
140	180	144	180	182
145	186	186	144	186
166	185	190	145	142
177	190	198	191	149
178	192	175	198	146
157	195	166	194	182
173	175	156	146	185
180	184	155	140	192
185	186	189	174	196
186	185	183	185	192

2.2 Image pre-processing

Figure 2 shows the (a) processed image and (b) binary image. The image acquired may have noise, and hence the raw image is processed using a Laplacian filter (Figure 2 b). The image pre-processing step also ensures correcting the input image against different types of image distortions. Figure 2 (a) Shows the smoothened image. Laplacian filter is applied to the smoothened image for extracting edges. This would help the subsequent steps for identifying defects. Figure 2(b) shows the binary image. The binary image would help in quickly classifying images into good or defective.

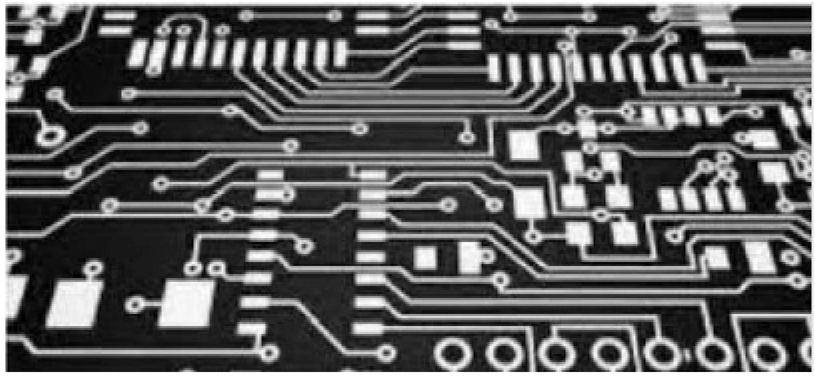

Figure 2 (a). Processed image.

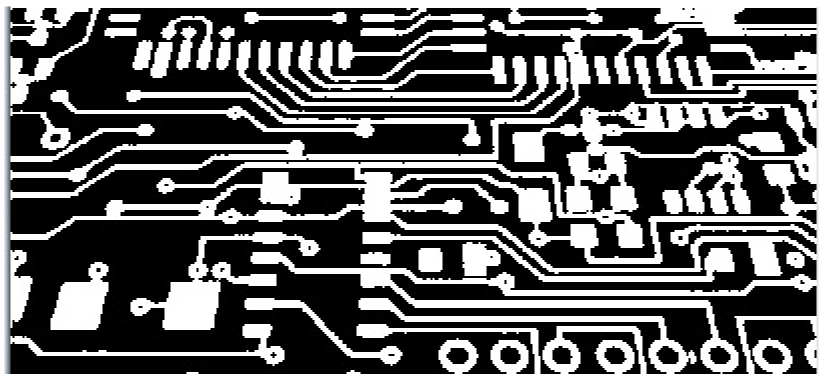

Figure 2 (b). Binary image.

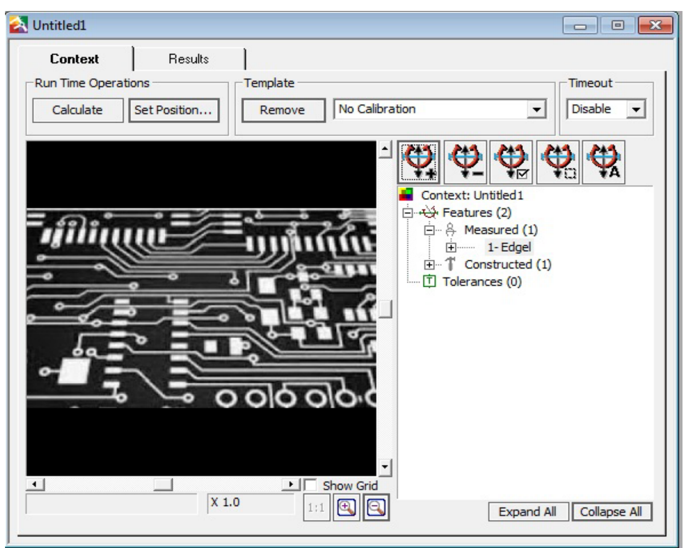

Figure 3. Intermediate step in defect identification

1.1 Texture feature extraction: The processed image is used for extracting texture features as in Table 3. In Table 2, specimen numbers are shown as 1-10, whereas I-XII represents various texture features extracted through Grey level co-occurrence matrix-GLCM ([a]Kiran 2021; [b]Kiran 2021; [c]Kiran 2021; [d]Kiran 2021). GLCM is calculated using the digital image. The feature vectors would extract different aspects of texture. The in-house software was developed (Figure 3 and Figure 4) using C++ classifies the printed circuit board into different categories such as Good, Fracture, Cuts, Scratches, Pinholes, Distance Variation, and Protrusions. The software developed inhouse computes the Euclidean distance between the test class and the different classes. The software would assign the test image to the class when the Euclidean distance is minimum. MATROX Imaging library is used for performing the processing of images. As can be seen from Figure 3 and Figure 4, different types of measurements are possible.

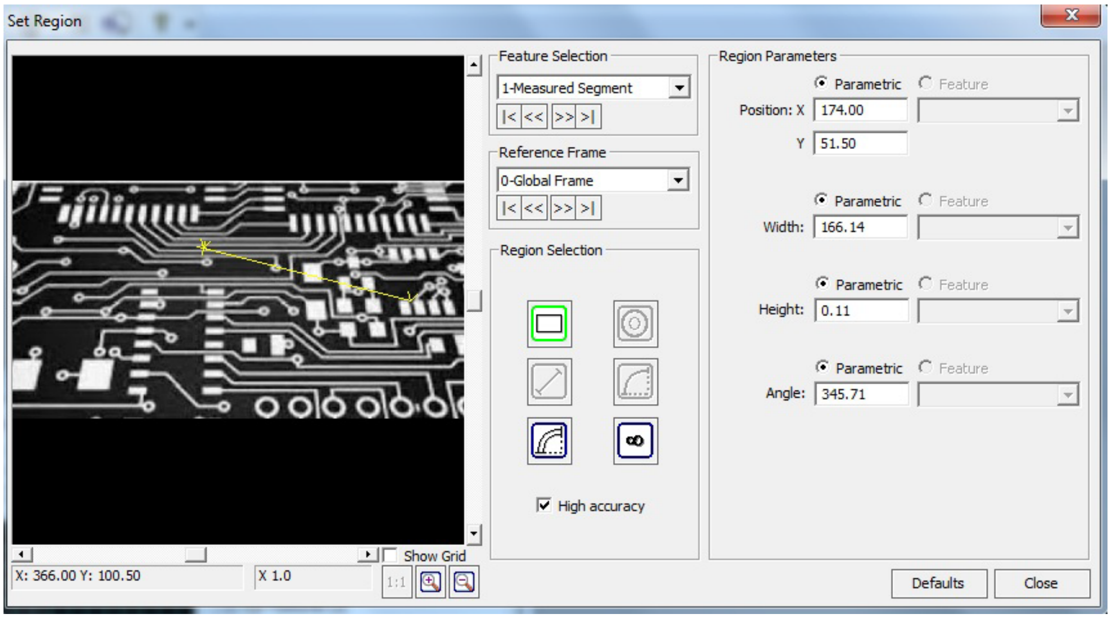

Figure 4. Defect identification

Table 2. Classification Experiment

(a) Training Step

Training							Classified as
G	**F**	**C**	**S**	**P**	**PT**	**DV**	
150							**G**
	150						**F**
		150					**C**
			150				**S**
				150			**P**
					150		**PT**
						150	**DV**

(b) Testing step

Testing							Classified as
G	**F**	**C**	**S**	**P**	**PT**	**DV**	
141	**2**	**2**	**4**	**1**			**G**
	140	**2**	**3**	**2**	**2**	**1**	**F**
		142	**2**	**1**	**5**		**C**
			143	**5**	**2**		**S**
			1	**142**	**4**	**3**	**P**
					144	**6**	**PT**
				2	**5**	**143**	**DV**

Note: Good (G), Fracture (F), Cuts (C), Scratches (S), Pinholes (P), Distance Variation (DV), and Protrusions (PT)

From Table 2, it is clear the software was trained using 150 sample images belonging to different categories. After training, the model's efficiency was tested using images from the test classes.

Table 3. Texture Feature values for various PCB specimens

Feature/ No.	1	2	3	4	5	6	7	8	9	10
I	2.93	2.67	2.97	2.86	2.86	2.97	2.97	2.97	2.82	2.97
II	0.11	0.08	0.08	0.34	0.38	0.14	0.15	0.15	0.07	0.16
III	0.84	0.59	0.77	1.05	1.09	0.94	0.96	0.98	0.96	1.06
IV	2.01	2.14	2.78	1.87	2.38	2.36	2.74	2.64	2.58	2.58
V	0.56	0.55	0.57	0.46	0.46	0.56	0.46	0.53	0.57	0.59
VI	1.06	1.04	1.63	0.94	0.94	0.97	1.08	1.06	1.04	0.97
VII	1.37	1.46	1.36	0.98	0.93	1.38	1.63	1.47	1.34	1.37
VIII	55.4	53.8	51.7	58.6	57.2	54.3	51.4	51.4	51.6	53.6
IX	1.35	1.45	0.86	1.37	1.37	0.94	1.35	0.98	0.98	1.34
X	5.55	5.24	4.27	5.78	5.78	5.82	4.87	4.24	5.69	5.78
XI	0.06	0.06	0.07	0.27	0.18	0.05	0.24	0.27	0.27	0.49
XII	0.67	0.57	0.56	0.64	0.68	0.64	0.55	0.59	0.57	0.69

Out of 150 sample images of class 'Good,' 141 images were classified as belonging to the category 'Good.' In contrast, '2' images were classified as belonging to the 'Fracture' class, and 2' images belonged to the class 'Cuts,' '4' images were classified as belonging to the 'Scratches' class, and '1' image belonged to the class 'Pinholes. Thus, the classification accuracy was 93.33%.

Out of 150 sample images of class 'Fracture,' 140 images were classified as belonging to the category 'Fracture.' In contrast, '2' images were classified as belonging to the 'Cuts' class, '3' images belonged to the class Scratches, '2' images were classified as belonging to the 'Pinholes' class, '2' images belonged to the class 'Protrusions,' and '1' image belonged to the class 'Distance Variation.' Thus, the classification accuracy was 94%.

Out of 150 sample images of class 'Cuts,' 142 images were classified as belonging to the category 'Cuts.' In contrast, '2' images were classified as belonging to the 'Scratches' class, '1' image belonged to the class 'Pinholes,' and '5' images were classified as belonging to the 'Protrusions' class. Thus, the classification accuracy was 93.33%.

Out of 150 sample images of class 'Scratches,' '143' images were classified as belonging to the category 'Scratches.' In contrast, '5' images were classified as belonging to the 'Pinholes' class, and '2' images belonged to the class 'Protrusions.' Thus, the classification accuracy was 95.33%.

Out of 150 sample images of class 'Pinholes,' 142 images were classified as belonging to the category 'Pinholes.' In contrast, '1' images were classified as belonging to the 'Scratches' class, '4' images belonged to the class 'Protrusions,' and '3' images were classified as belonging to the 'Distance Variation' class. Thus, the classification accuracy was 93.33%.

Out of 150 sample images of class 'Protrusions,' '144' images were classified as belonging to the category 'Protrusions.' In contrast, '6' images were classified as belonging to the 'Distance Variation' class. Thus, the classification accuracy was 96%.

Out of 150 sample images of class ‘Distance Variation,’ 143 images were classified as belonging to the category ‘Distance Variation.’ In contrast, ‘2’ images were classified as belonging to the ‘Pinholes’ class, and ‘5’ images belonged to the class ‘Protrusions.’ Thus, the classification accuracy was 95.33%.

3. Conclusion

The method proposed in the current research uses a Vision system for identifying defects in the PCB images. The technique identifies various defects in the printed circuit board, such as fractures, cuts, scratches, cracks, pinholes, spurs/ or protrusions, and variations between printed lines. The method is quick and finds application in the online inspection of the printed circuit boards. The technique can also identify defects with the given tolerance, and the method’s accuracy is very high in identifying deficiencies in subpixel accuracy. The technique is also robust in terms of providing consistent results. The meth identifies the various types of defects and locates the defect's position, and measures the associated dimensions.

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Biography

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