PCB Defect Classification Using Logical Combination of Segmented Copper and Non-Copper Part

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Abstract. In this paper, a new model for defect classification of PCB, inspired from bottom-up processing model of perception, is proposed. The proposed model is a non-referential based approach because sometimes aligning test and reference image may be difficult. In order to minimize learning complexity at each level, defect image is segmented into copper and non-copper part. Hough Circle based circular features with variations compromisation is extracted as features from copper part, which is further learned by 1vR type SVM. For non-copper part, color histogram with variable block dimensions depending on amount of correlation among defect types over RGB dimension is extracted as feature which is further learned by SVM with polynomial kernel. Discoloration is analyzed independently from copper part, because it is color defect and in copper part classification edge based features are extracted. Final defect class is predicted by logical combination of defect classes of Copper and Non-Copper part. The effectiveness of this model is evaluated on real data from PCB manufacturing industry and accuracy is compared with previously proposed non-referential approaches.

Keywords: PCB, AVI, Copper Part, Non-Copper Part, SVM

1 Introduction

Inception of Electronic Industry marked an era in digital revolution. Nowadays, electronic goods are everywhere in our lives. The new technology Internet of Things (IoT) plans to bring electronics even closer to our lives. The main basic component of Electronic Industry is Printed Circuit Board (PCB), on which ICs are mounted. Any alteration in PCB correctness may result in different circuit behaviour which is undesirable. Conventionally, industries employed human to identify and classify defects in PCB but this is very slow, painful and unreliable. With the developments in Computer Vision, Automatic Visual Systems (AVI) were proposed for PCB inspection which are very fast and reliable.

AVI models can broadly be divided into three classes: Referential Approach, Non-Referential Approach, Hybrid Approach. In referential approach, defect area is detected by subtracting test image with corresponding reference image and then defect area is classified. But, perfect alignment between test and reference image is difficult also it is sometimes difficult to get reference image. Non-referential approach involves extracting features from whole image based on truth establishment or properties. But, it is difficult to characterize every defect type. Hybrid approach uses models from both referential and non-referential approach.

Defect types include Open, Short, Deficit, Foreign, Discoloration, Dust etc as shown in Figure 1. Some of these are true defects like Short, Deficit and some are pseudo defects, which can be removed easily and PCB can be used for good, like Dust. In this model types of defects covered are Deficit, No Defect, Foreign, Dust, Discoloration. Open, Short could not be covered due to unavailability of data.

Owing to the difficulties in referential approach, in this paper a non-referential model is proposed. As human vision model dictates, first low level abstract extraction then combining these to go upward pyramidical, thus interpretation. That is what we have tried to model. To make complexity less, segmentation into copper and non-copper part is done. Identifying deviation independently in copper and non-copper part and then combining these deviations to predict final fault is the goal of this paper.

2 Related Work

Many previous approaches has been proposed in all the three classes of solution model Referential Approach, Non-Referential Approach and Hybrid Approach. Inoue. *et al.* [1] proposed a non-referential method using Bag of Keypoints (BoK) and SVM as classifier. They formed Visual Word dictionary (VWD) of Root-SIFT features from whole image using BoK. Then BoK Histogram features are used for SVM learning and classification. Ibrahim *et al.* [2] proposed a new method to enhance performance of image difference operation, used to extract defect region in referential based approach, in terms of computation time using wavelet transform. Second level Haar wavelet is used for wavelet transform. They compute wavelet transform of both test and reference image and then perform the image difference operation. Heriansyah *et al.* [3] proposed a technique that adopts referential based approach and classifies the defects using neural network. The algorithm segments the image into basic primitive patterns, enclosing the primitive patterns; pattern assignment, pattern normalization, and classification were developed using binary morphological image processing and Learning Vector Quantization (LVQ) Neural Network. For performance comparison, a pixel-based approach developed by Wu *et al.* was used. West *et al.* [4, 5] implemented a boundary analysis technique to detect small faults by using Freeman Chain Coding [6] to describe the boundaries. Small faults are easily distinguishable features from normal electronic board. Freeman Chain Coding

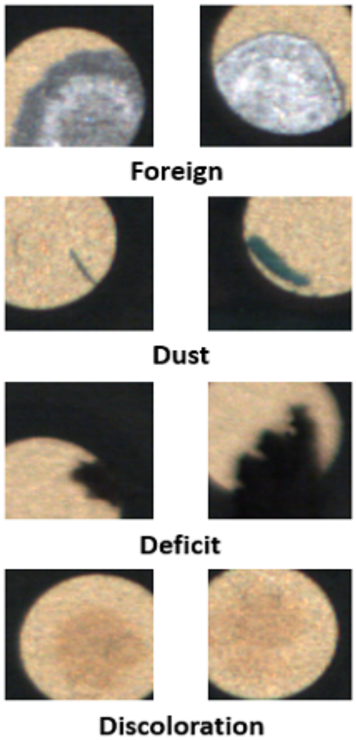

Fig. 1. Defect Classes

translates boundary into polygonal approximation which eliminates thresholding noise. In this method first Euclidean distance and boundary distance of two boundary points are compared which are at constant number of chain segments apart. In Hybrid Approach, Tsai *et al.* [7] proposed a Case Based Reasoning (CBR) approach to classify defects. First indexing of past cases is done using k-means clustering and then on arriving at new cases similar cases are extracted from the database using indexes and then defect type is predicted.

3 Defect Classification by Logical Combination

3.1 Outline of Proposed Approach

In the new proposed non-referential approach, test image is segmented into copper and non-copper part at first in order to reduce the feature learning complexity from the whole image. Segmentation is based on true color segmentation.

1. For the Copper part, center of outlined copper circle is detected using Hough Circle transform with specified range of radius depending upon magnification

or distance of scanner from the PCB, which can be considered constant for particular system, thus constant radius is assumed here. Using the center coordinate obtained LHS (Left Hand Side) circular equation: $(x-h)^2 + (y-k)^2 = r^2$ is extracted, which for a connected circle should be around r^2. Trained SVM classifier, with Linear Kernel, on previous training copper part images is used to predict defect classes.
2. For the non-copper part, 3D non-uniform color histogram is extracted. Dimensions of non-uniform intensity blocks are decided based on measure of correlation or uncorrelation of non-copper images of different defect types over different intensity block region. Trained SVM classifier, with polynomial kernel of degree 4, on previous training non-copper part images is used to predict defect classes.
3. Discoloration Classification is done separately because of different features requirement from copper part. Histogram of RGB channel is deduced and classified using trained SVM classifier with polynomial type kernel of degree 4.
4. Logical combination of defect classes of copper and non-copper part is done, as shown in Table 1, to predict final defect class. Statistical error minimization is avoided as not to include extra error.

Outline of proposed approach is shown in Figure 2.

3.2 Segmentation into Copper and Non-Copper part

PCB images taken from rear acute angle, as used in most of the systems, tend to reflect particular color with a little variation. Since, this color is retained in all of the copper part, so true color based segmentation is used to avoid computational complexity. Copper patches in Figure 2 are extracted with range of colors from test images. Discolored copper is also extracted as a part of copper due to its saturation similarity. Pixels in test images are classified as copper pixels if they are within thresholding boundaries of RGB intensity levels of copper patches. Threshold are decided empirically but inspired from different sensitivity of human visual system towards different color like Green is more perceptible than Red. Figure 3 shows copper and non-copper part of the test image.

3.3 Copper Part Feature and Classification

Copper part can be either good or chunked up from inside, losing connectivity, or from boundary, losing circularity, thus two defect classes for copper part: Deficit or No Defect. In this case, edges can totally provide difference between circular outline and deviations from it. Keeping this in mind, Canny Edges are extracted using suitable minimum and maximum threshold values for hysteresis thresholding. Assuming circular joint points in PCB, if AVI system is taking images with M magnification then

$$r^{'} = \sqrt{M}r \tag{1}$$

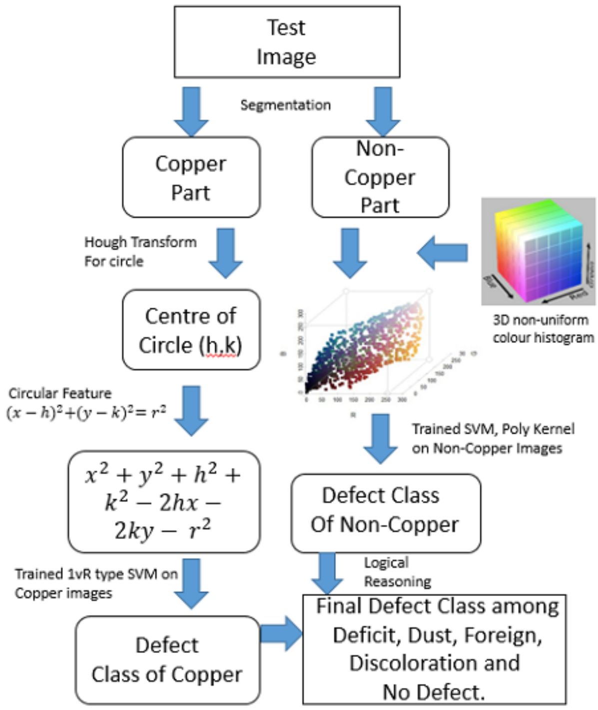

Fig. 2. Outline of Proposed Approach

thus new radius can be made known from original radius. Hough Circle transform [9] is used with restricted range of radius, bounded by Magnification M, to detect center of copper edges (h,k) returned by Canny Edge Detector. Number of intersection criteria, as stored in accumulation array, is kept low considering the fact that fair part of original circle of copper cluster may be distorted owing to defects. Center of detected circle with the closest radius to the new determined radius from M is the center of copper edges. It diminish the the possibility of detecting another circle, because of low number of intersection criteria in center space, formed by chunk off part violating connectivity criteria of copper or by boundary deterioration. Now, mathematical measure of circularity is detected for each of the edge pixel. Equation of circle with radius r, center (h,k) is

$$(x-h)^2 + (y-k)^2 - r^2 = 0 \tag{2}$$

Considering randomness caused by sampling, quantization in (x,y) and (h,k) and also by Canny Edge Detector to be small, magnitude wise, the LHS of a general circle equation should be close to 0 for No Defect Copper edges in every dimension, considering LHS value at each pixel in different dimension. Owing to the method of sampling and quantization, distribution of these variables can be

Fig. 3. Defect Image, Copper Part, Non-Copper part

safely assumed to be uniform, thus expectation of LHS becomes

$$E[LHS] = 0 \tag{3}$$

which means that there exist a cylinder with some radius $r1$ such that in 2D

$$|(x-h)^2 + (y-k)^2 - r^2| < r1^2 \tag{4}$$

where $|.|$ is modulus. Since, no defect copper edges LHS values are shown to be bounded, so a tight or somewhat loose wrapper around the feature vector of no defect copper can be found. Also, any further distortion should cause LHS value to go outside wrapper, thus separating feature vectors of Deficit and No Defect in copper part. 1vR type SVM is used for classification which does exactly what needed here. First, 1vR SVM type is trained on available data to obtain needed Support Vectors. Enough iterations, determined empirically, are provided to obtain good support vectors. The trained SVM is used for classification.

3.4 Non-Copper part Feature and Classification

Uniqueness of information for each type of defects lies in distribution and blending of color. This feature can be attributed by 3D color histogram in RGB space [10]. Starting with the uniform bins, but non-copper part of defect classes like Foreign, Dust etc differ only in some intensity ranges of RGB color space. To reduce computation time as well as to increase performance RGB color space can be divided into non-uniform bins. Bins intensity ranges in each color dimension can be decided by similarity or dissimilarity in histogram of any channel dimension. RGB channel histogram of non-copper defect images is compared based on their correlation coefficients. To compare two histograms H_1 and H_2, a metric d(H_1,H_2) is computed, where

$$d(H_1, H_2) = \frac{\sum_I (H_1(I) - \bar{H_1})(H_2(I) - \bar{H_2})}{\sqrt{\sum_I (H_1(I) - \bar{H_1})^2 (H_2(I) - \bar{H_2})^2}} \tag{5}$$

and

$$\bar{H_k} = \frac{1}{N} \sum\nolimits_J H_k(J) \tag{6}$$

and N is the total number of histogram bins, here used 256. Intensity ranges where d(H_1,H_2) is fairly large in all of defect images can have large bin size in that dimension of color in which this comparison is done. This divides the RGB space into non-uniform bins adaptive to color differences in non-copper part of defect types. This 3D non Uniform histogram is then extracted as feature vector. SVM with polynomial kernel of degree 4 is used for training and classification. Kernel can be written as

$$K(x, y) = (\mathbf{x}^T\mathbf{y} + c)^4 \tag{7}$$

where **x** and **y** are feature vectors in input space.

3.5 Discoloration

Discoloration can be considered as color defect in copper part. For copper classification, defect classes deficit or no defect are classified using attributes of copper edges, extracting canny edges then circular features, but Discoloration is a true color defect. So, edge features cannot satisfy the purpose. To account for color features, histogram of RGB channel separately is extracted with number if bins are 256 and intensity range are 0 to 255. Histograms are the simplest color representation of an image and provide a very good global color representation of an image. Final feature dimension is RGB channel histogram of 256 bins pushed back, thus 256*3=768. For this very high dimensional feature vector SVM with polynomial kernel of degree 4 is used for training and classification. Termination criteria of SVM is selected to be iteration count but enough to find optimal Support Vectors. Accuracy obtained is 100%.

3.6 Logical Combination of Copper and Non-Copper Defect Classes

In order to reduce learning complexity, defect image is segmented to learn independent characteristics from copper and non-copper part. The same conclusion can be made by focusing on different unique bunch of information posed by the individual part, where defect may be in copper or surroundings. Stochastic or probabilistic approach is not adopted because it will introduce errors, inadvertently because of limitations in hyperspace parameters optimization. Also, it is computationally expensive which might not be a good choice for a real time system.

The final defect class of defect can be easily broken down in terms of defects classes of the copper and non-copper part. The same analogy can be given for the logical combination reasons, suppose p be the number of defect classes of copper part and q be the number of defect classes of non-copper part, where p,q $\in \mathbb{N}$, then total number n of combinations.

$$n = pq \tag{8}$$

So, total number of final possible defect classes are finite and can be assumed to be fairly small, like order of 10, but also, final defect classes are Foreign, Dust, Discoloration, Deficit, No Defect, so there may possibly be many repetitions. After combining all the classes of copper and non-copper part and ruling out repetitions, Table 1 is prepared.

Table 1. Logical Combination Table

COPPER DEFECT CLASS	NON-COPPER DEFECT CLASS	FINAL DEFECT CLASS
No Defect	No Defect	No Defect
Deficit	No Defect + Deficit	Deficit
No Defect + Deficit	Foreign	Foreign
No Defect + Deficit	Dust	Dust
Discoloration	Any Class	Discoloration

So, final defect class is predicted from the classes obtained in copper and non-copper part using Table 1. It may be noticed that all the variations, local or global, in copper and non-copper part are captured by this table and obtained classes.

4 Results

Accuracy obtained from proposed method and paper [8] and paper [9] is compared. Defect types are divided into True Defects, Deficit, Foreign, Discoloration and Pseudo Defects, Dust.

Result of accuracy is shown in Table 2.

Table 2. Accuracy

Model	True Defect		Pseudo Defect		Accuracy(%)
	Correct	Incor.	Correct	Incor.	
Paper[8]	496	104	452	148	79.0
Paper[1]	532	68	572	28	92.0
Proposed	711	48	309	7	94.88

In copper part, accuracy of deficit is slightly less, the cause may be the assumption of smaller magnitude of random error in coordinates. Also, large chunk off near original boundary of copper might have caused unpredictable results.

5 Conclusion

This paper proposed a non-referential model for PCB Defect classification. The accuracy can be seen to better than other non-referential methods proposed in literature. This paper classifies only one defect per image which may not be true in all cases, so using maximum likelihood approximation methods to give confidences per defect class can be future prospect of research and also to maximize performance. Deep Learning Architectures like CNN can be also explored in extension of this research.

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References

1. Inoue, H., Iwahori, Y., Kijsirikul, B., Bhuyan, M. K.: SVM Based Defect Classification of Electronic Board Using Bag of Keypoints. ITC-CSCC 2015, 31-34 (2015)
2. Ibrahim, Z., Al-Attas, S. A, R., Aspar, Z.: Model-based PCB Inspection Technique Using Wavelet Transform. 4th Asian Control Conference, September 25-27 (2002)
3. Heriansyah, R., Al-Attas, S. A. R., Zabidi, M. M.: Neural Network Paradigm for Classification of Defects on PCB. Master Thesis, University Teknologi Malaysia (2004)
4. West, G. A. W., Norton-Wayne, L., Hill, W. J.: The Automatic Visual Inspection of Printed Circuit Boards. Circuit World, Vol.8, No.2, 50-56 (1982)
5. West, G. A. W.: A System for the Automatic Visual Inspection of BarePrinted Circuit Boards. IEEE Transactions of Systems, Man and Cybernetics, Vol.SMC-14, No.5, 767-773, September/October (1984)
6. Freeman, H.: Computer Processing of Line-Drawing Images. ACM Computing Surveys, Vol.6, No.1,57-97, (1974)
7. Tsai, C.-Y., Chiu, C.-C., Chen, J. S.: A case-based reasoning system for PCB defect prediction. Elsevier Expert Systems with Applications (2005)
8. Inoue, H., Hagi, H., Iwahori, Y.: Defect Classification of Electronic Board Using RealAdaBoost SVR in AVI. Tokai Section Joint Conference on Electrical, Electronics, Information and Related Engineering, H1-2 (2014)
9. Ioannou, D., Huda, W., Laine, A. F.: Circle recognition through a 2D Hough Transform and radius histogramming. Elsevier Image and Vision Computing, Vol.17, 15-26 (1999)
10. Jones, M. J., Rehg, J. M.: Statistical Color Models with Application to Skin Detection. International Journal of Computer Vision, Vol.46, No.1, 81-96 (2002)