Defect classification of electronic circuit board using SVM based on random sampling

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Abstract

This paper proposes a new approach to improve the classification accuracy of true defect and pseudo defect of electronic circuit board. The proposed approach introduces the defect detection which corresponds to the color image and concept of random sampling using multiple SVMs. The approach first detects the defect candidate region with high accuracy based on the difference between test image and reference image, then extracts the features to recognize true or pseudo defect. Data and features for multiple subsets based on random sampling and feature selection is applied to find the effective combination of features. Selected combination of features are used for the recognition by each SVM and weighted voting process is applied to determine the final discrimination. Computer experiments were demonstrated and the usefulness of the proposed approach is evaluated with the accuracy of defect classification.

1. Introduction

Basically, electronic circuit board is used for the various purposes in computer, display or the precision devices. The portion of electronic circuit board that is not needed are etched off, leaving circuits which connects the components. It is used to mechanically support and electrically connect electronic components using conductive pathways, or traces, etched from copper sheets and laminated onto a non-conductive substrate. Electronic circuit board is rugged, inexpensive and highly reliable and so it is used in virtually all but the simplest commercially produced electronic devices.

In recent years, the demand of electronic devices with more compact design and more sophisticated functions has forced the electronic circuit boards to become smaller and denser with circuits and components. As it is crucial part

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of electronic device it needs to be properly inspected before get launched. Automatic inspection systems are used for this purpose but due to more complexity in circuits, electronic circuit board inspections are now more problematic. This problem leads to new challenges in developing advanced inspection systems in electronic circuit board.

Automatic Optical Inspection (AOI) has been commonly used to inspect defects in Printed circuit board during the manufacturing process. An AOI system generally uses methods which detect the defects by scanning the electronic circuit board and analyzing it. AOI uses methods like Local Feature matching, image Skeletonization and morphological image comparison to detect defects and has been very successful in detecting defects in most of the cases but production problems like oxidation, dust, contamination and poor reflecting materials leads to most inevitable false alarms. To reduce the false alarms is the concern of this paper.

There are previous approaches for detecting defects of electronic circuit board such as 1,2,3. Paper 1 uses infrared light image to detect the defect by testing electrically, while 2 extracts the global features using the interest point and its surrounding points and detects the defect using Mahalanobis distance. Paper 3 uses two images one of which is testing image including defect and the other of which does not include defect as a reference image, and its difference image and logical AND operation extracts the defect candidate region. This also tries to reduce misdetection with morphology processings.

Other papers such as 4,5,6 propose for defect discrimination and classification. Paper 4 proposes shape based classification, while paper 5 performs classification using neural network. Both approaches treats only the true defect and does not treat pseudo defect such as dust. Other problems include the local minimum problem where the optimized solution depends on the initial values of the weighted vector.

Paper 6 proposes two class classification of true and pseudo defects using Support Vector Machine (SVM)7. Paper 6 uses a single SVM and the discrimination margin may be affected by the noise included in the learning data. This approach corresponds to monochrome gray scale image and threshold is determined for each kind of defects to detect the defect region. To improve the accuracy of defect recognition and to obtain the better performance the results in the previous approaches, this paper further extends the previous approaches using color images and performs the better accuracy of classification between true defects and pseudo defects. Original approach proposed in this paper is based on random sampling based SVM for a defect detection with high accuracy and defect classification. The original difference of this paper includes introducing random sampling with color information to classify the defect based on SVM. The proposed approach is evaluated through the real example data set provided from the inspection cooperation and it is confirmed that the defect is detected with high accuracy and defect is classified with high performance using random sampling based SVM.

2. Kinds of defect of electronic circuit board

Two kinds of defect exist in the electronic circuit board, one of which is the true defect and the other of which is the pseudo defect. Further, each of them can be classified into multiple kinds of defects based on the shape of defect. True defects are classified into Disconnection (Fig.1(a)), Connection (Fig.1(b)), Projection (Fig.1(c)) and Crack (Fig.1(d)). These defects has the features that shape of lead line changes.

![Fig. 1. Example of true defects](image)

Pseudo defects are classified into Oxidation (Fig.2(a)) and Dust (Fig.2(b)). These defects has color change and do not have feature for shape of the lead line or that of the base part does not change.
3. Proposed approach

3.1. Detection of defect candidate region

Position calibration is necessary to reduce the positioning error under the condition between test image and reference image. This approach fits the position by estimating the amount of movement using Phase Only Correlation (POC) for test image and reference image as shown in Fig.3.

Difference between test image (Fig.4(a)) and reference image (Fig.4(b)) is extracted and its difference image (Fig.4(c)) is generated. For each of RGB components of the difference image, discriminant analysis method is applied and its threshold value is determined. Using those threshold values, binary image (Fig.4(d) to (f)) are generated. Logical AND (Fig.4(g)) of three images are taken and noise is removed (Fig.4(h)). Thus the defect candidate region is detected as shown in Fig.4(i).

3.2. Feature extraction

Features are extracted from the defect candidate region. Color information and shape information are extracted as features and extracted features are used for learning and classification by SVM.
3.3. Color information


3.4. Shape information


3.5. Classifier

Subset is made using random sampling from the learning data set and each classifier for each subset is constructed. Introducing random sampling based learning aims robust learning to the noise. Features with any number of dimension are randomly selected to be used for classifier. Feed forward selection is applied to the selected features and SVM learning is done using the effective features selected for the discrimination. Test data are input to the classifier which has been constructed for each subset. The corresponding output from each classifier is voted and the final classification is determined with weighted majority voting processing. Constructed Classifiers are shown in Fig. 5.
3.5.1. Making subsets

It is noted that subset is made carefully because data are selected depending on the class with large number of data if number of learning data in each class has some difference. As a result, classifier is learned based on the class with a large number of data and there is a problem that correct classification is difficult for the class with small number of data. So, the following processing is applied to balance the learning data between classes in making the subset.

Step1. Class is randomly selected
Step2. Data which belongs to the selected class is randomly selected and it is added to the learning data.

The above processing is repeated until the number of learning data becomes the number of settings.

3.5.2. Weights

The following two weights are used for each subset.

- Weights based on LOO-bound $w_1$
- Weights obtained by Maximum likelihood estimation $w_2$

LOO-bound is the upper limit of expected value of error when Leave-One-Out is applied for SVM as one of the cross validations. LOO is represented by Eq.(1) as it is applied with number of learning data.

$$E = \frac{1}{M} \sum_{m=1}^{M} \frac{SV_m}{M-1}$$

where $E$ represents upper limit of error, $SV_m$ represents the number of support vectors, and $M$ represents the number of data. LOO-bound represents the reliability of the classifier and corresponds to the error ratio of SVM. The reliability becomes higher when $E$ takes smaller value, inversely the reliability becomes lower when $E$ takes larger value. Weights $w_1$ of subset is given by Eq.(2) since LOO-bound is the error ratio of SVM.

$$w_1 = 1 - E$$

The coefficient $w_2$ which minimizes the following likelihood function $\mathcal{L}$ represented by Eq.(3) is used.

$$\mathcal{L}(w_2) = \prod_{i=1}^{l} \frac{1}{1 + \exp (-2y_i w_2 f(x_i))}$$
where \( l \) represents the number of whole data, \( x_i \) represents whole data set, \( y_i \) represents the correct label, \( f \) represents the discriminative function of subset. Here the objective function \( J \) represented by Eq.(4) is minimized for the variable \( w_2 \) and Nelder-Mead Simplex method\(^{12} \) is applied for this minimization.

\[
J(w_2) = -\ln L(w_2)
\]  

(4)

4. Experiments

4.1. Detection of defect candidate region

Comparison between the proposed approach and paper\(^6 \) about the detection of defect candidate region is shown in Fig.6 to Fig.11.

![Fig. 6. Disconnection](image)

(a) Paper\(^6 \)  (b) Proposed Approach

![Fig. 7. Connection](image)

(a) Paper\(^6 \)  (b) Proposed Approach

![Fig. 8. Projection](image)

(a) Paper\(^6 \)  (b) Proposed Approach

![Fig. 9. Crack](image)

(a) Paper\(^6 \)  (b) Proposed Approach

![Fig. 10. Oxidation](image)

(a) Paper\(^6 \)  (b) Proposed Approach

![Fig. 11. Dust](image)

(a) Paper\(^6 \)  (b) Proposed Approach

It is confirmed that both of previous approach and proposed approach can detect the defect with high accuracy for samples with large change of color such as disconnection (Fig.6) and oxidation (Fig.10). However it is also confirmed that the proposed approach can detect the pseudo defect of dust with small change of color as shown in Fig.11 in comparison with the previous approach. This confirms that the proposed approach has effectiveness for automatic determination of threshold on detecting defect and introducing color images.
4.2. Defect classification

Experiments were done for comparison with paper\(^6\), proposed approach and the case where a single SVM was used in the proposed approach.

Data set includes a total of 634 defects which are 203 true defects, 431 pseudo defects, and the evaluation used is 10-fold cross validation. RBF kernel was used as kernel function of SVM. Each approach was tested with both of gray scale images and color images. The previous approach is corresponded to the color image by taking intensity value with RGB values and 14 kinds of features were used. The previous approach and a single SVM used a feed forward feature selection and the parameter \(C\) of SVM and the parameter \(\sigma\) of RBF kernel were determined by the grid search. \(C = 4, \sigma = 1.0\) were taken for the gray scale image in the previous approach, while \(C = 2, \sigma = 0.9\) were taken for the color image in the previous approach. A single SVM approach took \(C = 2, \sigma = 1.0\) for the gray scale image, and \(C = 16, \sigma = 0.9\) for the color images. The proposed approach used 250 learning data of subset, square root of number of whole features as randomly selected features. That is, 4 kinds of randomly selected features for gray scale image, 17 kinds of randomly selected features for color images are used, while number of subset was 50. Parameter \(C\) was taken 1 to 100 and \(\sigma\) was taken from 0 up to 1, these parameters were randomly taken and used for each subset.

Correct and incorrect number and its correct ratio for true and pseudo defects by each approach are shown in Table 1.

Table 1. Classification result

<table>
<thead>
<tr>
<th></th>
<th>True Defect</th>
<th>Pseudo Defect</th>
<th>Correct Ratio [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Correct</td>
<td>Incorrect</td>
<td>Correct</td>
</tr>
<tr>
<td>Paper(^6)(Gray Scale)</td>
<td>164</td>
<td>39</td>
<td>358</td>
</tr>
<tr>
<td>Single SVM (Gray Scale)</td>
<td>162</td>
<td>41</td>
<td>388</td>
</tr>
<tr>
<td>Proposed (Gray Scale)</td>
<td>172.8</td>
<td>30.2</td>
<td>362.3</td>
</tr>
<tr>
<td>Paper(^6)(RGB)</td>
<td>169</td>
<td>34</td>
<td>400</td>
</tr>
<tr>
<td>Single SVM (Color)</td>
<td>162</td>
<td>41</td>
<td>423</td>
</tr>
<tr>
<td>Proposed (Color)</td>
<td>184.8</td>
<td>18.2</td>
<td>407.7</td>
</tr>
</tbody>
</table>

Table 1 suggests that the correct ratio is improved in all approaches when color images are used rather than the case when gray scale images are used. That is, the effectiveness of color images is confirmed in defect classification and feature combinations are selected from multiple color representation systems which consist of (1) Ratio and Kurtosis of lead line and defect candidate region with R in RGB, (2) Entropy of B in RGB, (3) Ratio and Variance of lead line and defect candidate region of S in HSV, (4) Mode (5) Kurtosis of L* in L*a*b*, Ratio and Entropy of base part and defect classification region of base part of X in XYZ, (6) Correlation between test image and reference image of Y in XYZ. Thus, the result suggests that combination of color representation system is effective for the defect classification.

It is also shown that the proposed approach improves the correct ratios in both cases of gray scale images and color images in comparison with the previous approach. The result suggests that the proposed approach improves the correct ratio for color images in comparison with a single SVM based approach although the correct ratio for gray scale image gives the lower value. As the reason why the correct ratio gives the lower value for the gray scale images, number of features used in each subset is 4 and this is small. The classification result is shown in Table 2 when proposed approach is executed 10 times.

Table 2 suggests that the correct ratio in the worst classification accuracy is lower than that of previous approach but the number of incorrect classification of true defects is lower than that with a single SVM. If the true defect is misclassified into the pseudo defect, that may give the risk for the market. In this sense, it is important and useful that the proposed approach gives lower misclassification of true defect.

To confirm the effect of the weighted majority voting, performance of proposed approach was compared with 1) majority voting without weighting for the output of subset, 2) weight based on LOO-bound with weighted majority voting using only weight \(w_1\), 3) weight based on maximum likelihood estimation with weighted majority voting using
only weight $w_2$, 4) weights using $w_1$ and $w_2$. Correct number, incorrect number and the correct ratio are shown in Table 3.

Table 3. Classification Result of Weigted Majority Voting

<table>
<thead>
<tr>
<th></th>
<th>True Defect</th>
<th>Pseudo Defect</th>
<th>Correct Ratio [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Majority Voting</td>
<td>Correct: 186.9</td>
<td>Incorrect: 16.1</td>
<td>93.20</td>
</tr>
<tr>
<td></td>
<td>Correct: 404.0</td>
<td>Incorrect: 27.0</td>
<td></td>
</tr>
<tr>
<td>Weight based on LOO-bound</td>
<td>Correct: 184.4</td>
<td>Incorrect: 18.6</td>
<td>93.19</td>
</tr>
<tr>
<td></td>
<td>Correct: 406.4</td>
<td>Incorrect: 24.6</td>
<td></td>
</tr>
<tr>
<td>Weight based on Maximum likelihood estimation</td>
<td>Correct: 184.3</td>
<td>Incorrect: 18.7</td>
<td>92.70</td>
</tr>
<tr>
<td></td>
<td>Correct: 403.4</td>
<td>Incorrect: 27.6</td>
<td></td>
</tr>
<tr>
<td>Proposed Approach</td>
<td>Correct: 184.8</td>
<td>Incorrect: 18.2</td>
<td>93.45</td>
</tr>
<tr>
<td></td>
<td>Correct: 407.7</td>
<td>Incorrect: 23.3</td>
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Table 3 suggests that the cases with weight based on LOO-bound or Maximum likelihood estimation gives the lower correct ratio than simple majority voting, while the proposed approach with two weights gives the higher correct ratio than simple majority voting. This shows that using weights gives the efficient improvement of classification accuracy rather than simple majority voting.

5. Conclusion

This paper proposed a new approach using color images for the defect detection and classification of electronic circuit board. The approach consists of the defect detection with high accuracy and classification using SVM with random sampling. The approach was evaluated with real image data of electronic circuit board via experiments. The proposed approach was compared with the previous approach and gave the better performance to discriminate true defect and pseudo defect. Previous approach determined the threshold for each kind of defect for detection and used gray scale images, where the problem is the classification does not work well when noise data are selected as support vector using a single SVM. The proposed approach detects the defect using each component of RGB of color image and improved the accuracy for detection and classification by increasing information with converting multiple color systems. It was also shown that using multiple SVM selected with random sampling from the learning data gave the better classification accuracy with weighted majority voting to the outputs.
Acknowledgment

Iwahori’s research is supported by JSPS Grant-in-Aid for Scientific Research (C) (26330210) and a Chubu University Grant. The authors would like thank useful discussions with Takuya Nakagawa and other lab member of Chubu University.

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