Defect Classification of Electronic Board Using Multiple Classifiers and Grid Search of SVM Parameters

Takuya Nakagawa, Yuji Iwahori, and M.K. Bhuyan

Abstract. This paper proposes a new method to improve the classification accuracy by multiple classes classification using multiple SVM. The proposed approach classifies the true and pseudo defects by adding features to decrease the incorrect classification. This approach consists of two steps. First, the features are extracted from the defect candidate region after extracting the difference between the test image and the reference image. Here, candidate extraction is carefully extracted with high accuracy and the useful combination of features is determined using the feature selection. Second, selected features are learned with multiple SVM and classified into the class. When the result has the multiple same voting counts to the same class, the judgment is treated as the difficult class for the classification. It is shown that the proposed approach gives efficient classification with the higher classification accuracy than the previous approaches through the real experiment.

Keywords: Support Vector Machine, Multiple Class Classification, Extraction of Defect Candidate, Defect Classification, Grid Search.

1 Introduction

Basically, Printed Circuit Board (PCB) is a piece of phenolic or glass epoxy board with copper clad on one or both sides. The portion of copper that are not needed are etched off, leaving 'printed' 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

Takuya Nakagawa · Yuji Iwahori
Graduate School of Engineering, Chubu University, 1200 Matsumoto-cho,
Kasugai 487-8501, Japan
e-mail: tnakagwa@cvl.cs.chubu.ac.jp, iwahori@cs.chubu.ac.jp

M.K. Bhuyan
Dept. of Electronics & Electrical Engg. IIT Guwahati, Guwahati - 781039, India
e-mail: mkb@iitg.ernet.in

R. Lee (Ed.): *Computer and Information Science*, SCI 493, pp. 115–127.
DOI: 10.1007/978-3-319-00804-2_9

non-conductive substrate. PCBs are rugged, inexpensive and highly reliable and so it is used in virtually all but the simplest commercially produced electronic devices.

It has become one of the basic components of electronic devices. It provides the electrical connections between the electronic or IC components mounted on it. In recent years, the demand of electronic devices with more compact design and more sophisticated functions has forced the PCBs to become smaller and denser with circuits and components. As it is crucial part of electronic device it needs to be properly investigated before get launched. Automatic inspection systems are used for this purpose but due to more complexity in circuits, PCB inspections are now more problematic. This problem leads to new challenges in developing advanced automatic visual inspection systems for PCB.

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 detects the defects by scanning the PCB 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.

Previous approach Tanaka *et al.* [1] classifies the defects using neural network and Rau *et al.* [2] proposes a method to classify the defects using the intensity at the pixels around the defects region. These approaches classify the defect under the condition that kinds of the defects are previously known. There are some defects whose recognitions are difficult even with the visual inspection. These defects cause the problem. The problem includes the case of misjudgment where a true defect is recognized as a pseudo defect and it is included in the products as a result. Kondo *et al.* [3] has been proposed for the distinction of defect classification by determining the features at random. Kondo *et al.* [3] classifies the kinds of defect with selecting the appropriate features with classifiers, but there are still incorrect classification cases where a true defect is classified into a pseudo defect.

Approaches to extract the defect candidate region are proposed in [4, 5, 6]. Onishi *et al.* [4] prepares two images of test image and reference image of mask pattern and takes difference image by logical AND. Maeda *et al.* [5] and Numada *et al.* [6] propose IR image matching and Mahalanobis distance, respectively.

Kondo *et al.* [7] selects features at random and determines the combination of features with bagging process to classify the defects. Other classification approaches include Wakabayashi *et al.* [8] using PCA, Ishii *et al.* [9] using variance inside and outside classes, Amabe *et al.* [10] using Genetic Algorithm, Roh *et al.* [11] using Neural Network. Another approach to remove incorrect classification of true defect is proposed in Iwahori *et al.* [12, 13], where histogram for each defect and evaluating equation are introduced.

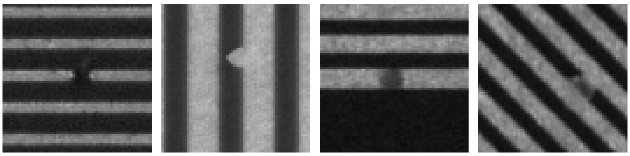
The approach discriminates the true defect and pseudo defect and improves the accuracy of classification by introducing multiple classes for the real defect dataset. Experiments give the usefulness of the approach through the evaluation of defect classification.

2 Defect Classification Using Multiple Classifiers and Grid Search of Parameters

Defect candidate region is extracted from both test image and reference image. The features are extracted from the defect candidate region and the useful combination of features are determined using feature selection. This procedure is applied to each classifier of multiple classifiers. SVM is used to learn the selected features and the discrimination of true defect and pseudo defect is done based on the results of each SVM.

2.1 Definition of Class in Defect of Electronic Board

Iwahori *et al.* [12] classifies into two classes of true and psuedo defects, while this paper considers an approach to classify into more than three classes. The number of classes is assumed to be three. Class 1 condists of true defects which include lack (Fig.1(a)) and connection, class 2 consists of projection (Fig.1(b)) and wear rust which has the similar intensity as that of lead line, while class 3 includes pseudo defects. True defect is not allowed for the market while pseudo defect is still allowed with cleaning before forwarding to the market. While pseudo defects consists of weak rust (Fig.1(c)) which has the low intensity and dust (Fig.1(d)) which has the high intensity. A defect which is similar to both of true defect and pseudo defect is treated as that in the difficult discrimination class. Not only shape but also intensity are used to classify a defect into each of three classes. When only shape is used, more number of classes should be used but the accuracy for discrimination decreases. This is the reason three classes are introduced in the paper.



(a) Lack (b) Projection (c) Weak Rust (d) Dust

Fig. 1 Defect of Each Class

2.2 Detection of Defect Candidate Region

Defect candidate is first generated using an inspection image and a reference image respectively. The difference image is generated using an inspection image and a reference image as shown in Fig.4. The reference image is shifted with every one pixel within $\pm$ 5 pixels and the minimum point of the shift is determined from the sum of the absolute differences of each image. This process is applied to two reference images. That is, two difference images are generated using two reference images for one inspection image.

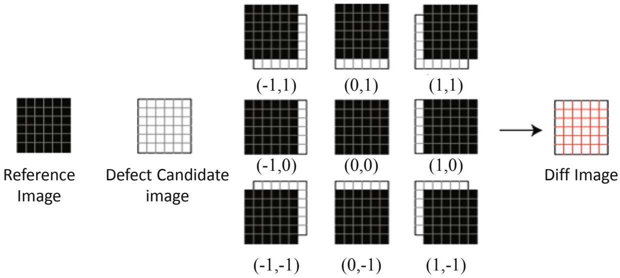
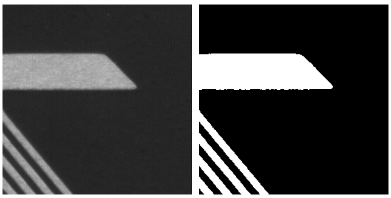


Fig. 2 Obtaining Difference Image

Iwahori *et al.* [12] determines the threshold value empirically for each class of true and pseudo defect, however there is a problem that an appropriate threshold value becomes different based on the condition that the defect is on the lead line or on the base region. The same threshold value also the problem that detected accuracy becomes different. In this situation, this paper proposes a different approach to extract the defect candidate region with higher accuracy.

Discrimination analysis is applied as shown in Fig.3.



(a) Original Image (b) Binary Image

Fig. 3 Result of Discrimination Analysis

Since the intensity of the board may become different for the same location of the board and the intensity has some range (as shown in Fig.4), the range of intensity taken in the board is used for the threshold value.

Let the maximum intensity of the lead line part be L_h and the minimum intensity be L_l. then the threshold value T_L for the lead line part is represented as Eq.(1).

$$T_L = L_h - L_l \tag{1}$$

Let the maximum intensity of the base part be B_h and the minimum intensity be B_l, then the threshold value T_B is represented as Eq.(2).

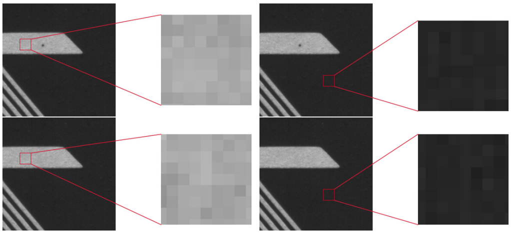


Fig. 4 Difference of Intensity in Each Part of Board

$$T_B = B_h - B_l \quad (2)$$

Defect candidate region is extractd from pixels which has the difference greater than the threshold T_L in the lead line part and that greater than T_B in the base part. This gives the higher accuracy for extracting the candidate region.

2.3 Feature Extraction and Selection

Features are extracted from the defect candidate region. The features include (1) Mean of Intensity, (2) Maximum Intensity, (3) Minimum Intensity, (4) Proportion of High Intensity, (5) Circularity, (6) Aspect Ratio, (7) Variance, (8) Intensity ratio of candidate region and lead line, (9) Intensity ratio of candidate region and base part, (10) Area, (11) Size of x-direction, (12) Size of y-direction, (13) Perimeter, (14) Diagonal Length, (15) Difference between center of gravity of intensity and maximum intensity, where these features are used in Iwahori *et al.* [12]. Further features used are (16) Complexity, (17) Smoothness, (18) Contrast, (19) Correlation, (20) Angular Second Moment, (21) Inverse Difference Moment, (22) Mode, (23) Skewness, (24) Kurtosis. Thus, a total of 24 features are used. Nine added features of (16) to (24) are used as new features including (18) to (21) in co-occurrence matrix as the statistical features.

2.4 Co-occurrence Matrix

GLCM (Co-occurrence Matrix) uses the relation of relative location of some direction shown in Fig.5 The matrix represents the counts so that the corresponding pair of the pixels (x_1,y_1) and (x_2,y_2) becomes (i,j).

The definitions of features such as contrast, correlation, angular second moment, inverse difference moment obtained from Fig.6 are represented below. $P_x(i)$, $P_y(j)$, μ_x, μ_y, σ_x, σ_y are defined as follows.

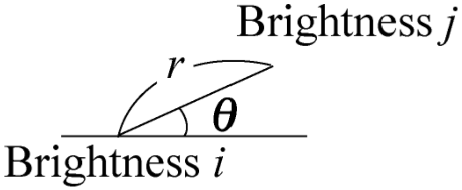


Fig. 5 Pair of Pixels

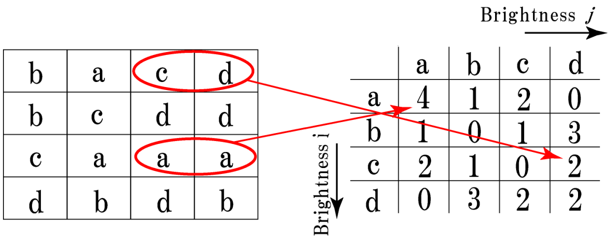


Fig. 6 Co-ocurrence Matrix

$$P_x(i) = \sum_{j=0}^{n-1} P_\delta(i,j) \qquad P_y(j) = \Sigma_{i=0}^{n-1} P_\delta(i,j)$$

$$\mu_x = \sum_{i=0}^{n-1} iP_x(i) \qquad \mu_y = \Sigma_{j=0}^{n-1} jP_y(j)$$

$$\sigma_x^2 = \sum_{i=0}^{n-1} (i-\mu_x)^2 P_x(i) \ \ \sigma_y^2 = \Sigma_{j=0}^{n-1} (j-\mu_y)^2 P_y(j)$$

Angular Second Moment (ASM)

$$ASM = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} (P_\delta(i,j))^2 \tag{3}$$

Contrast (CON)

$$CON = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} P_\delta(i,j) \tag{4}$$

Correlation (COR)

$$COR = \frac{\Sigma_{i=0}^{n-1} \Sigma_{j=0}^{n-1} ijP_\delta(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{5}$$

Inverse Difference Moment (IDM)

$$IDM = \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} \frac{1}{1-(i-j)^2} P_\delta(i,j) \tag{6}$$

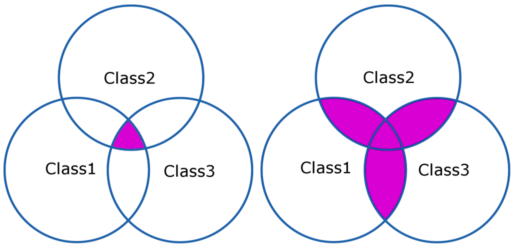
Here, let quantization level be n, and let probability of point which is $\delta = (\mathrm{r}, \theta)$ apart from the point of interests with the gray level i be $P_\delta(i,j)$.

2.5 Classification into Multiple Classes

Classification into multiple class determines the class with the distance of hyper plane or at random in general, but this paper treats the defect with difficult discrimination when the final class cannot be determined to one class. This enables to prevent the incorrect classification by keeping the status of difficult discrimination for unknown data which does not belong to one class.

2.5.1 Region of Multiple Classifier

As the representative approaches, there are one-versus-the-rest (1-v-R) and one-versus-one (1-v-1). These approaches cannot determine the final result when the voting number of output becomes the same. This paper proposes a method to improve the problem in Iwahori *et al.* [12]. These two approaches take different region which is used as the difficult classification class. 1-v-1 cannot represent the fuzzy defect for each class. The difference of region is shown in Fig.7.



(a)1-v-1 (b)1-v-R

Fig. 7 Region of Same Voting Count for Multiple Classes

2.5.2 Construction of Classifiers

1-v-R used here is shown in Fig.8. 1-v-R constructs M-SVMs $(i = 1, 2, ..., M)$ to learn the data in M classes and judges the belonged class via integrating its results. Actually there is a case that the same voting count is output to the same class with M classifiers. The approach treats the difficult discrimination to prevent the incorrect classification by keeping the status of difficult discrimination for unknown data which do not belong to one class based on Iwahori *et al.* [12]. In Fig.8, Class 1 represents the true defect which is similar to the intensity of the base part, class 2

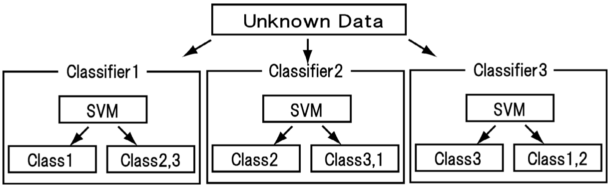


Fig. 8 Construction of Classifier Using 1-v-R

represents the true defect which has the similar intensity to that of the lead line, and class 3 represents the pseudo defect.

2.6 Grid Search

Necessary parameters for SVM are C and σ. Grid search is introduced to determine the combinations of parameters. The method starts the search for wide range of parameters and coarse to fine search is applied to the high precision search with smaller step. Near optimized combination of parameters is determined and the classification can be done with high accuracy as a result.

Here parameter C represents the allowance parameter for incorrect learning. When C takes large value, SVM does not accept the error. Thus the soft margin SVM is introduced with parameter C.

Parameter σ represents the kernel parameter and width of Gaussian kernel. When σ takes large value, region of class becomes wider.

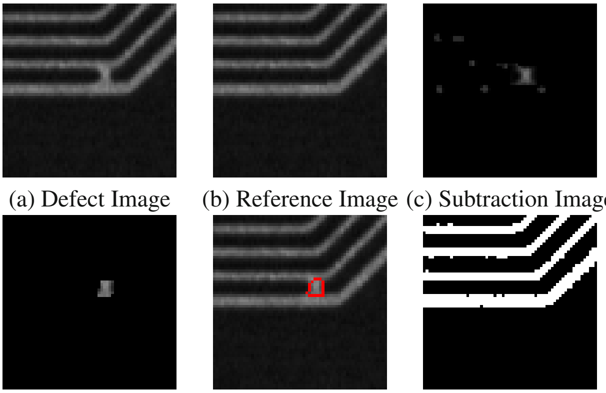
3 Experiment

The proposed approach was compared with the approach Iwahori *et al.* [12]. The approach was also compared with another construction of multiple class classification. The comparison consists of detection of defect candidate region and result of defect classification.

3.1 Extraction of Defect Candidate Region

Result of detection of defect region is shown in (Fig.9 (a)) as an example. The detected image size is 64×64 and the defect candidate region is extracted from the subtraction image (Fig.9 (c)) between an image including defect candidate and a reference image. Discrimination analysis is applied to the reference image to make a binary image (Fig.9 (d)). The threshold values are set for each of lead line part and base part and final defect region (Fig.9 (e)) is extracted from the subtraction image with the determined threshold value. Thus, defect candidate region was extracted with high accuracy (Fig,9 (f)).

Defect candidate region was extracted from a total of four images which consist of two dust images and two weak rust images. Defect candidate region obtained by

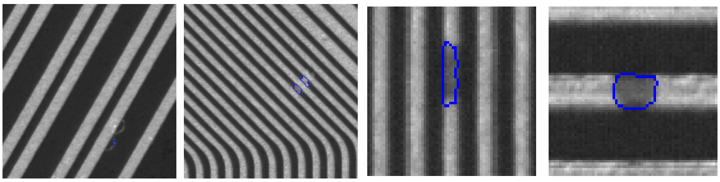


(a) Defect Image (b) Reference Image (c) Subtraction Image

(d) Binary Image (e) Defect Image (f) Detection Image

Fig. 9 Detection Result of [12]

Iwahori *et al.* [12] is shown in Fig.10, while that by the proposed approach is shown in Fig.11. It is observed that Iwahori *et al.* [12] has the cases that the defect candidate region is not always the precise as shown in Fig.10 (a) (b), or over-detection including non-defect region is seen in Fig.10 (c). While it is confirmed that the proposed approach has the higher precision for the detection of defect candidate region.



(a) Dust 1 (b) Dust 2 (c) Rust 1 (d) Rust 2

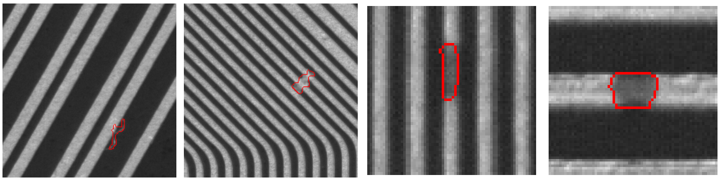
Fig. 10 Extraction by [12]

Other extraction result for other kind of defects except dust and weak rust is shown in Fig.10.

It is shown that other defects are also extracted with high accuracy like dust or weak rust in Fig.12. This result suggests the effectiveness of the automatic determination of threshold value to extract the defect candidate region.

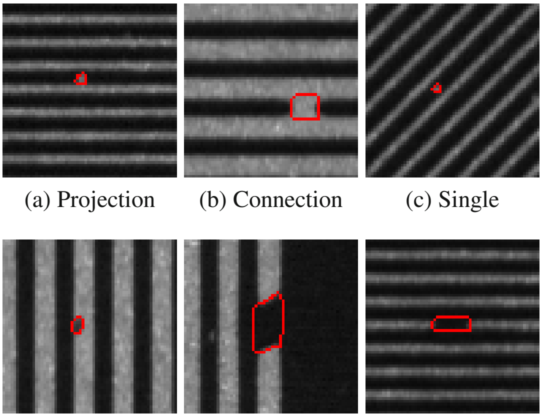
3.2 Classification Result

Dataset used consist of 120 images for each of learning data and test data. Features consist of 24 kinds and correct ratio was calculated using feed forward selection for



(a) Dust 1 (b) Dust 2 (c) Weak Rust 1 (d) Weak Rust 2

Fig. 11 Extraction by Proposed Approach



(a) Projection (b) Connection (c) Single

(d) Lack (e) Disconnection (f) Wear Rust

Fig. 12 Extraction of Each Defect

the learned SVM with RBF kernel. The purpose is to reduce the incorrect classification of true and pseudo defects. When the output is defect similar to the intensity of lead line or that similar to the intensity of base part, it is judged as true defect. While when there are multiple same voting counts, it is judged as a defect with difficult discrimination and the rest is treated as pseudo defect.

Correct ratio is defined as Eq.(7) and correct ratio for positive and negative samples is calculated by Eq.(8) for the evaluation. Further, Iwahori *et al.* [13] considers the incorrect classification for the true defect rather than the incorrect classification for the pseudo defect, and this was evaluated by Eq.(9). Here, let the number of classification of true defect correctly classified be TP, let the number of its incorrect classification be TN, let the number of its difficult classification be TD, let the number of correct classification of pseudo defect be FP, the number of its incorrect classification be FN, the number of its difficult classification be FD.

$$Accuracy = \frac{TP+FP}{TP+TN+FP+FN} \times 100 \quad [\%] \tag{7}$$

$$ErrorateAccuracy = \frac{TP+TN+FP+FN}{AllData} \times 100 \quad [\%] \tag{8}$$

$$Performance = \frac{AllData - TN}{TP+TN+FP+TD+FD} \times 100 \quad [\%] \tag{9}$$

The classification accuracy of each classifier is shown in Table I. The result of each classifier in the proposed approach is shown in Table I and the result of classification of unknown data using proposed approach and Iwahori *et al.* [12] is shown in Table II. The accuracy is calculated from correct classification and incorrect classification except difficult judgment class. represents the portion of data which was not classified to the difficult class. The value of parameter C was 1 and the values of σ were 0.5 for classifier 1, 0.15 for classifier 2, and 0.39 for classifier 3 from the result of grid search.

Table 1 suggests that the efficient feature selection has been done for each classifier based on the different combination of features used in each classifier. Added features selected are contrast(18)Ccorrelation(19), and inverse difference moment(21) and these features are effective to the defect classification of electronic board.

Table 2 gives comparison between the proposed approach and Iwahori *et al.* [12] shows that 6.6% is improved for the accuracy, 43% is improved for the correct ratio for positive and negative samples, and 5.2% is improved for the performance with

Table 1 Result of Each Classifier

		Classifier1	Classifier2	Classifier3
Feature		7.8.9.19	8.9	8.9.18.21
First Class	True	96	91	88
	False	4	9	12
Second Class	True	195	194	188
	False	5	6	12
Accuracy		97.0%	95.0%	92.0%
Performance		98.6%	96.9%	95.8%

Table 2 Comparison between Proposed Approach and [12]

		Proposed Method	1-v-1 Mehod	Reference[11]
True Defect	True	183	184	89
	False	3	14	9
	Difficult	14	2	102
Pseudo Defect	True	86	85	45
	False	5	15	5
	Difficult	9	0	50
Accuracy		97.1%	89.9%	90.5%
Errorate Accuracy		92.3%	99.3%	49.3%
Performance		98.9%	95.1%	93.7%

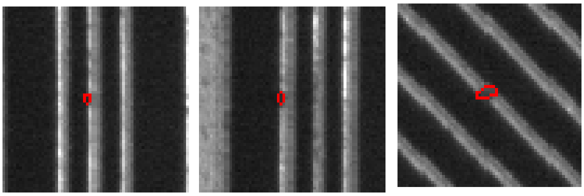
the decrease of the incorrect classification. This is based on defining one class from the result of multiple class classification not treating one class for the margin region.

Comparison between the proposed approach and 1-v-1 approach, 1-v-R gave 8 incorrect samples but 1-v-1 gave 29 incorrect samples based on the reason without covering the region over the classes.

The proposed approach introduced a class for a defect with difficult sidcrimination in order to reduce the error rate for the true defects. The effect is confirmed from the evaluation result.

3.3 Incorrect Classification

Incorrect classification of true defect is a problem rather than that of pseudo defect in the defect classification of electronic board. Sample images in the incorrect classification of true defect to pseudo defect is shown in Fig.13.



(a) Difficulty 1 (b) Difficulty 2 (c) Difficulty 3

Fig. 13 Incorrect Classification of True Defect

Fig.13(a) or Fig.13(b) are the lack of true defect and its width depends on the shape of the defect. It tends to be misclassified for the defect which has the small area of defect candidate region. The defect obtained from the defect candidate region is not necessarily misclassified and single defect is not misclassified. In case that there are similar data, the classification tends to be succeeded. Fig.13(c) shows the connected defect of true and pseudo defects which have the similar intensity values. This defect was treated as one defect and this caused misclassification.

4 Conclusion

This paper proposed a new approach to improve the classification accuracy of defect of electronic board by introducing classification with multiple classes, reducing the number of misclassified samples with adding features and determining parameters of SVM.

The usefulness of the approach was shown through the comparison with the previous approach with the experiments for true defect, pseudo defect and difficult judgment of classification. Parameters of SVM were determined by discrimination analysis and grid search. The evaluation of the proposed approach provided 97%

accuracy with the dataset. Reducing the number of misclassification and recognition percentage of true defect to the pseudo defect are necessary and this is further subject.

Acknowledgment. Iwahori's research is supported by JSPS Grant-in-Aid for Scientific Research (C) (23500228) and Chubu University Grant.

References

1. Tanaka, T., Hotta, S., Iga, T., Nakamura, T.: Automatic Image Filter Creation System: To Use for a Defect Classification System. IEICE Technical Report 106(448), 195–198 (2007)
2. Rau, H., Wu, C.-H.: Automatic Optical Inspection for Detecting Defects on Printed Circuit Board Inner Layers. The International Journal of Advanced Manufacturing Technology 25(9-10), 940–946 (2005)
3. Kondo, K., et al.: Defect Classification Using Random Feature Selection and Bagging. The Journal of the Institute of Image Electronics Engineers of Japan 38(1), 9–15 (2009) (in Japanese)
4. Onishi, H., Sasa, Y., Nagai, K., Tatsumi, S.: A Pattern Defect Inspection Method by Grayscale Image Comparison without Precise Image Alignment. J. IEICE, D-II J86-D-I I(11), 1531–1545 (2003)
5. Maeda, S., Ono, M., Kubota, H., Nakatani, M.: Precise Detection of Short Circuit Defect on TFT Substrate by Infrared Image Matching. J. IEICE D-II J80-D-II(9), 2333–2344 (1997)
6. Numada, M., Koshimizu, H.: A Method for Detecting Globally Distributed Defects by Using Learning with Mahalanobis Distance. In: ViEW 2007, pp. 9–13 (2007)
7. Kondo, K., Kikuchi, K., Hotta, S., Shibuya, H., Maeda, S.: Defect Classification Using Random Feature Selection and Bagging. IIEEJ 38(1), 9–15 (2009)
8. Wakabayashi, T., Tsuruoka, S., Kimura, F., Miyake, Y.: Study on Feature Selection in Handwritten Numeral Recognition. IEICE J78-D-II(11), 1627–1638 (1995)
9. Ishii, K., Ueda, N., Maeda, E., Murase, Y.: Descriptive Pattern Recognition. Ohmsha (1998)
10. Amabe, H., Nagao, T.: A Support Vector Machine Approach to Defect Classification by Selecting Image Characteristics. In: FIT 2006, vol. I-033, pp. 79–80 (2006)
11. Roh, B., Yoon, C., Ryu, Y., Oh, C.: A Neural Network Approach to Defect Classification on Printed Circuit Boards. JSPE 67(10), 1621–1626 (2001)
12. Iwahori, Y., Futamura, K., Adachi, Y.: Discrimination of True Defect and Indefinite Defect with Visual Inspection Using SVM. In: König, A., Dengel, A., Hinkelmann, K., Kise, K., Howlett, R.J., Jain, L.C. (eds.) KES 2011, Part IV. LNCS, vol. 6884, pp. 117–125. Springer, Heidelberg (2011)
13. Iwahori, Y., Kumar, D., Nakagawa, T., Bhuyan, M.K.: Improved Defect Classification of Printed Circuit Board Using SVM. In: KES IDT 2012, pp. 1–10 (2012)