SVM Based Defect Classification of Electronic Board Using Bag of Keypoints

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Abstract

This paper proposes a new approach for the defect classification of electronic board using Bag of Keypoints and SVM. The main purpose of this paper is not to use the reference image which can be used to extract the difference region of defect. The approach represents histogram features of Bag of keypoints based on extracting features from data set images. Feature vectors are used for SVM learning and classification. The effectiveness of the approach is evaluated with accuracy of defect classification for images with actual defects in comparison with the previously proposed approaches.

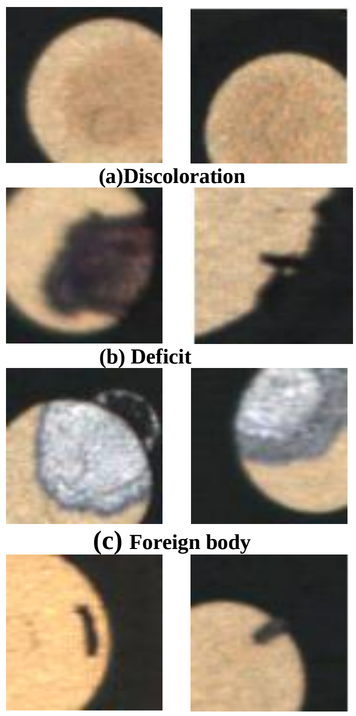
Keywords: SVM, Bag of Keypoints, Defect Classification

1. Introduction

In the final stage of inspection in manufacturing of electronic board, AVI (Automatic Visual Inspection) is introduced in general. AVI is processed to the lamination or coating of board which intermediate inspection has been passed. Final goal is to reduce the human's "verify check" as much as possible and automatic inspection with high accuracy is desired to solve this problem in the manufacture industries.

Previous approaches [1] [2] [3] have been proposed to detect defects of electronic board. Paper [1] detects defect based on the position of heat on IR image using the property of generated heat of electric leakage current of the electronic board. Paper [2] tried the global defect detection by learning using the Mahalanobis distance. Paper [3] proposes a method which does not need the position matching using comparison with intensity image. These approaches are available to AOI (Automatic Optical Inspection) but not available to AVI. Defect classification task has been proposed in papers [4] [5] [6]. Paper [4] classifies defect using neural network but pseudo defect such as dust is not considered. Paper [5] classifies into two classes of true defect and pseudo defect using feature extraction and SVM. Features are taken with much time from images with some noise and generating reference image is required. Paper [6] introduces pre-processing for a specified defect. Then RealAdaboost is introduced to perform the defect classification with SVR as a weak classifier for other defects. Paper [6] is proposed as an approach for the defect classification and this approach uses two kinds of classification consisting of shape based classification and classifier based classifications. Here, shape based classifica-tion has problem such as empirical determination of threshold values. It does not guarantee to be applied to various defect images (as shown in Fig.1).

This paper proposes a new approach without using the corresponding reference image which can get difference image for the defect candidate region. The approach uses Bag of Key points (BoK) and extracted features are used for SVM learning and classification. The performance of the approach is evaluated with actual experiments and better performance is confirmed in comparison with the previous approaches.



(a)Discoloration
(b) Deficit
(c) Foreign body
(d) Dust

Fig.1 Kinds of Defect

2. Previous Approach

2.1 Kinds of Defects of Electronic Board

Fig. 1 shows some defect examples of electronic board in AVI. Fig.1(a) shows examples of discoloration, Fig.1(b) shows examples of deficit, Fig.1(c) shows examples of foreign body, and Fig.1(d) shows examples of dust. Discoloration does not change the shape but there are small changes of color in the lead line part. Feature of deficit is close to that of base part and shape of lead line part changes abnormally. Foreign body makes large changes of intensity in both of base part and lead line part and makes larger change of shape of lead line part. Pseudo defect consists of almost dust in the lead line part. Intensity of dust changes much from that of the lead line part and feature is that the region of dust is small.

2.2 Previous Approach

Here the purpose of AVI is to detect the defect and to judge true defect or pseudo defect. True defects consist of Discoloration, Deficit, Foreign body and so on whose shape becomes different from the mask pattern, while pseudo defects consists of dust or stain. Paper [6] classifies the defect using shape feature of circular degree based on the situation that lead line of electronic board forms circular shape. Then reference image is produced using edge based template matching from the master image. Defect candidate region is detected from banalization of difference image between the test image and corresponding reference image, then features are extracted from the defect candidate region. Support Vector Regression (SVR) is used as a weak classifier and RealAdaboost is constructed for the defect classification.

3. Defect Classification Using Bag of Keypoints

3.1 Outline of Proposed Approach

Although Paper [6] classifies the defect using shape feature of circular degree based on the situation that lead line of electronic board forms circular shape, problem exists in determining empirical threshold value for the circular degree or using master image to produce the reference image (where master image means the large image consisting of master pattern.)

The proposed approach tries to classify the defect without reference image using BoK by extracting features from whole images, where BoK [7] is histogram representation of frequency of Visual Word (VW), as an image classification approach as shown in Fig.2. Here, SIFT features which are robust to scale change, rotation and illumination change are used and extracted from each image data set.

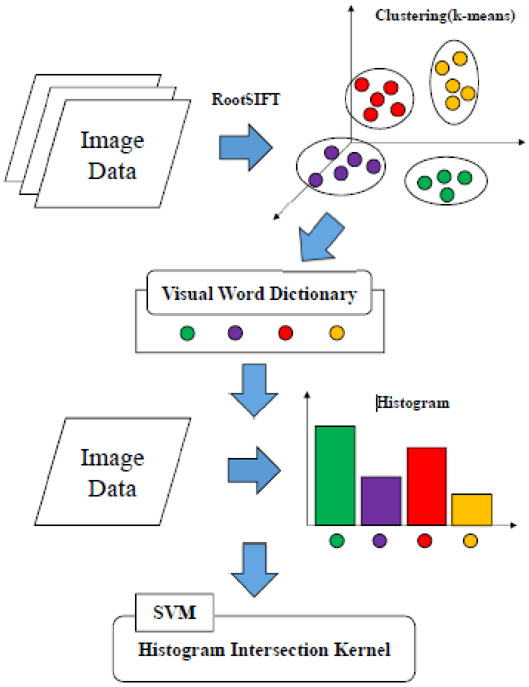


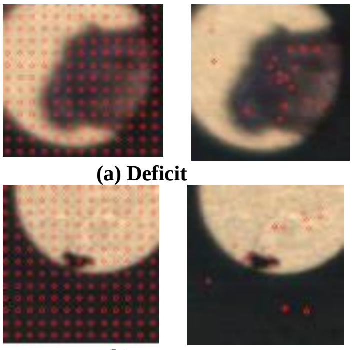
Fig.2 Flow of Proposed Approach

3.2 Extracting of Keypoints

Two samplings are considered where one is Grid Sampling (Grid) and the other is Sparse Sampling (Sparse) as detection approach of keypoints.

Grid takes sampling points periodically without considering intensity change of image, while Sparse represents a detection approach to detect keypoints using Difference of Gaussian (DoG). Points with the large change of gradients for the surrounding points are detected as keypoints. It is recommended that features are extracted from the part of lead line since many defects affect the part of lead line as shown in Fig.1. Grid is recommended for the case of Fig.1(d) where part of lead line is small and base part is large. In this case, keypoints are extracted from the base part. Sparse takes keypoints from part of lead line rather than from base part. Here Sparse is introduced to detect keypoints from the electronic board and SIFT features are extracted. There are some difficult case to detect keypoints for discoloration in Fig.1(a) using Sparse with combination of parameters. Idea to this discoloration problem is to increase the number of keypoints with parameters to detect more keypoints.

Examples of Grid and Sparse sampling are shown in Fig.3 for deficit and dust. Grid is often used in the general object recognition but it is not applicable to the rotation or scale change of image pattern. While Sparse detects local keypoints according to the intensity change and it is robust to the rotation or scale change of image pattern. The disadvantage of sparse is the number of keypoints taken is sometimes insufficient and limited based on the image.



(a) Deficit

(b) Dust

Fig.3 Grid and Sparse Sampling

3.3 RootSIFT

Here, SIFT features are normalized and RootSIFT [8] is introduced by taking the square root. RootSIFT $\boldsymbol{Y}$ is represented as

$$\boldsymbol{Y} = \sqrt{\frac{\boldsymbol{X}}{\sum \boldsymbol{X}}} \quad (1)$$

Distance calculation uses L2 norm in general and let the normalized SIFT vectors be $\boldsymbol{x}$ and $\boldsymbol{y}$ then the L2 norm N is represented as

$$\mathrm{N} = \sum_{i=1}^{n}(x_i - y_i)^2 \quad (2)$$

However it is better to use Bhattacharyya distance which is strong to the outlier rather than L2 norm when histogram is compared. Here Bhattacharyya distance is defined as

$$B = \sum_{i=1}^{n}\sqrt{x_i y_i} = \sqrt{\boldsymbol{X}}^T\sqrt{\boldsymbol{Y}} \quad (3)$$

Eq.(2) is rewritten using RootSIFT as

$$\mathrm{N} = \sum_{i=1}^{n}\left(\sqrt{x_i} - \sqrt{y_i}\right)^2 = 2 - 2\sqrt{\boldsymbol{X}}^T\sqrt{\boldsymbol{Y}} \quad (4)$$

Eq.(4) means L2 norm is approximated with Bhattacharyya distance.

3.4 Histogram Features of VWD

Features are represented by histogram. Histogram features consists of Visual Word Dictionary (VWD) and corresponding generation of histogram from VWD.

K-means clustering is introduced to the whole results of RootSIFT and the center of each cluster is taken as VW. *K* numbers of VW are generated. Visual Word Dictionary (VWD) is constructed from each VW. Then, the nearest VW is searched using VWD for the RootSIFT extracted from each image. Voting the result to VW provides the histogram for features of whole image. This histogram features are used to SVM for the learning and classification.

3.5 Learning and Classification by SVM

SVM is used as a classifier based on the features of BoK Histogram features are used for SVM learning and classification.

Selecting kernel used in SVM gives better performance in generalization based on the target of the problem. Here, since BoK is histogram features and histogram intersection kernel is introduced to improve performance for the accuracy.

Histogram intersection kernel is given by

$$\mathrm{K}(\mathrm{x}_1, \mathrm{x}_2) = \sum_{i=1}^{n}\min(x_1, x_2) \quad (5)$$

where *n* represents the number of dimension.

4. Experiments

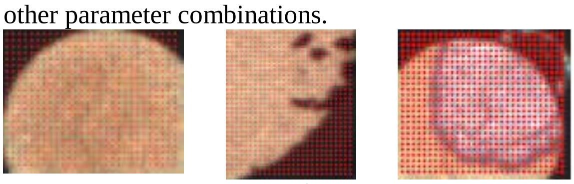
4.1 Extracting Keypoints

Grid sampling and Sparse sampling were applied to the electronic board, where grid sampling was taken with every two pixels apart. Results for Grid are shown in Fig.4.

Sparse changes the number of key points based on the parameter. Optimal parameters are determined using parameter selections among 1.0 to 2.0 for the initial value σ_0 of standard deviation of Gaussian Function convolved to the original intensity image and among 2.0 to 8.0 for parameter s of divided number of scale space where

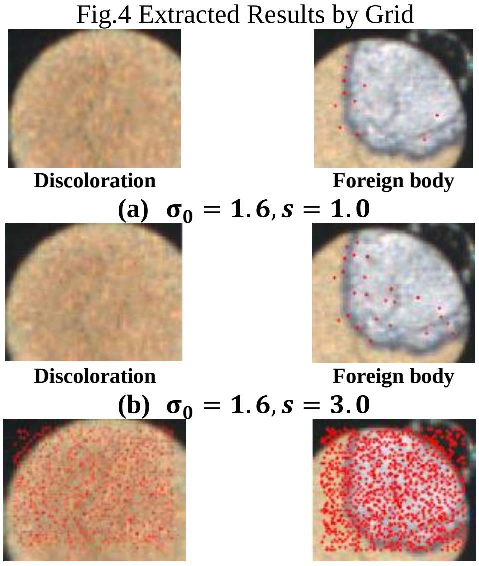
$$p = 2^{\frac{1}{s}}$$

Standard deviation σ of Gaussian function is increased from σ_0 to $2\sigma_0$ with multiplying the factor p. Results for σ_0=1.0 to 2 and s=2.0 to 8.0 are shown in Fig.5. Fig.5 (c) gives better than Fig.5 (b). and σ_0 = 1.0 and s = 7.0 were used in the following experiments since number of keypoints are small in other parameter combinations.



(a)Discoloration (b) Deficit (c) Foreign body

Fig.4 Extracted Results by Grid



Discoloration Foreign body

(a) $\sigma_0 = 1.6, s = 1.0$

Discoloration Foreign body

(b) $\sigma_0 = 1.6, s = 3.0$

Discoloration Foreign body

(c) $\sigma_0 = 1.0, s = 7.0$

Fig.5 Extracted Results by Sparse

4.2 Extracting Keypoints

The performance of the proposed approach was compared with approaches [6] and [7]. Image data set consists of 600 true defect images and 600 pseudo defects images as a total of 1200 images. Performance of SVM is evaluated by Leave One Out (LOO). C-SVM is used and the value of parameter C is determined by the "grid search" between 1 and 100. Number of VW was determined with the cluster number *k* of *k*-means clustering. Number of *k* is determined by changing the value with every 100 between 100 and 1000. The result by Grid and that by Sparse is shown in Fig.6 (where x-axis represents number of k and y-axis represents accuracy). As a result, *k*=1000 by Sparse gave the highest accuracy for the learning data for classification, while it tended that accuracy for over *k*=1000 decreases.

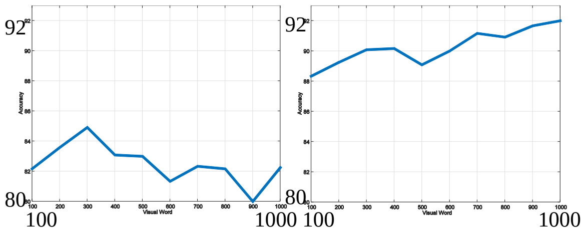


Fig.6 Result by Grid (left) and Sparse (right)

Paper [6] classified with shape features based on circular degree then RealAdaboost was used with 153 kinds of shape features and color features. RealAdaboost used forward sequential feature selection for each weak classifier. RBF kernel is used as kernel function. Parameter σof RBF kernel is determined between 1 and 50, while parameter ϵ of SVR is determined between 0.001 and 0.1 using grid search. In the approach [7], histogram features using BoK using SIFT, while linear kernel was used in SVM and parameter C=90 was used. In the proposed approach, RootSIFT was used and histogram features were constructed using BoK. Histogram intersection kernel was used and parameter C=2 was determined.

Results are shown in Table 1 with the accuracy by classifier for true defects and pseudo defects. Result of Paper [1] shows the integration of results of shape based classification and classifier based classification. Table 1 suggests the proposed approach improves accuracy with 13% in comparison with Paper [6] and reduced incorrect classification between true and pseudo defects. The proposed approach shows the improvement of accuracy with 2.7% in comparison with Paper [7] and reduced incorrect classification between true and pseudo defects too.

Table 1: Classification Accuracy by Classifier

	True Defect		Pseudo Defect		Accuracy[%]
	Correct	Incor.	Correct	Incor.	
Paper [6]	496	104	452	148	79.0
Paper [7]	509	91	562	38	89.3
Proposed	532	68	572	28	92.0

5. Conclusion

This paper proposed a new approach for defect classification using BoK with SVM classifier. The proposed approach was evaluated with the actual images and improved the performance to classify the defect into true or pseudo defect with higher accuracy. How to extract features from the part of lead line is important and further improvement of performance is remained as future subject.

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