Defect Classification of Electronic Board Using Bag of Features and Color Information

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Abstract: This paper proposes a new approach of defect classification using Bag of Features and color information in order to correspond to the various defect images without using any reference images. The purpose of the paper is to classify the true defect and pseudo defect such as dust on the electronic board. First, features are extracted from each image of data set and histogram features are generated and represented by Bag of Features. Next, noise removal is applied and combined features which consist of Bag of Features and color information are used. After extracting features, SVM (Support Vector Machine) is used for the learning and classification. The usefulness of the proposed approach is confirmed by evaluating the accuracy of defect classification in comparison with the previous approaches with the target images of electronic board images which includes the actual defects.

1. Introduction

In the final stage of inspection in manufacturing of electronic board, AVI (Automatic Visual Inspection) is applied in general. AVI is processed to the lamination or coating of board on 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. So AVI is desired to save the cost and reduce the variation of checking level by human.

Defects of electronic board consists of true defect and pseudo defect. True defect includes the scratch, discoloration, bare metal and so on. These defects cannot be shipped to outside. Pseudo defect includes the dust, bright spot, thin stain and so on. These can be removed and can be shipped to outside. However, if true defect is incorrectly classified into pseudo detect, product itself becomes a problem. If pseudo defect is incorrectly classified into true defect, this means the normal electronic board is scrapped and it is essential that both case should be escaped.

Approaches to extract the defect candidate region of electronic board are proposed in papers [1], [2].

Paper[1] sends electronic current to the electronic board and detects the defect using the fact that the heat appears on the leakage current and on corresponding infrared image at the short region where the heat appears based on the leakage current.

Paper[2] proposes the global defect detection using learning based on Mahalanobis distance.

Other defect classification approaches consist of papers [3],[4],[5],[6],[7].

Paper[3] classifies detect based on the shape of defect and Paper[4]classifies defect using NN (Neural Network) but four kinds of feature are used for the learning and 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 from binary images and information is lost and it takes time to generate reference image. Features are extracted from the difference between test image and reference image and SVM is used to classify the true and pseudo defect. However, these methods are applied to AOI but cannot be applied to AVI.

Previous approaches for AVI are proposed in paper [6],[7].

Paper [6] introduces preprocessing for a specified defect, then RealAdaboost is introduced to perform the defect classification with SVR as a weak classifier for the specific defects of AVI. Paper [6] uses shape based features, where circular degree is introduced but threshold value is empirically determined and problem is that the approach cannot guarantee various defect images.

Another paper [7] has been proposed as this improved method. Paper [7] proposes defect classsification which does not use any reference image and classifies with SVM using Bag of Keypoints (BoK) [8] to apply for the various defect images.

However, problem of [7] is that the unique features are not extracted for each defect since feature is extracted from the base region of the electronic board. Intensity information is also used but the difficulty is that this does not depend on the specific feature.

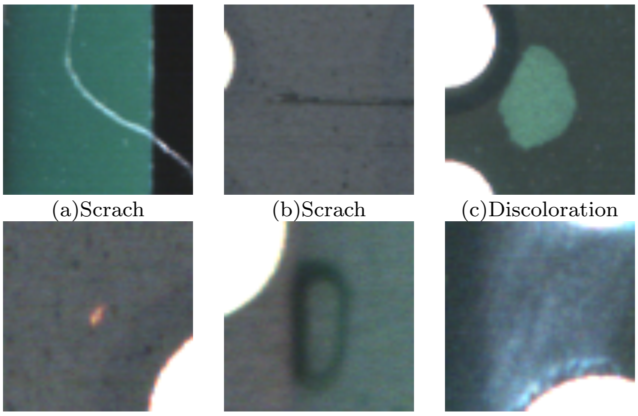
This paper proposes a method which extracts features from defect region by removing features from base region which may cause noise. Color information is used to increase the accuracy for defect classification.

2. Kinds of Defect of Electronic Board

Defect of electronic board consists of two kinds of true defect and pseudo defect. Each defect include further kinds of defects based on color or shape of defect. True defect consists of five kinds of defects such as scratch(Fig.1.(a)(b)), discoloration (Fig.1.(c)), bare metal (Fig.1.(d)), air bubble (Fig.1(e)), and stain (Fig.1.(f)). Scratch has feature of line. Change of color has feature whose color is different from base region with circular shape. Bare metal has feature that metal part has red color and region is small. Air bubble has feature of ring shape. Stain has feature that the range of defect is large.

Pseudo defect has three kinds of defects such as dust (Fig.2.(a)), bright spot (Fig.2.(b)), thin stain (Fig.2.(c)).

Dust has feature which is different from base part and size is not uniform. Bright spot has feature that color is white and the region is small. Thin stain has feature that its color is similar as that of base part.



(a)Scrach (b)Scrach (c)Discoloration

(d)Metal (e)Bubble (f)Stain

Figure 1. True Defect

(a)Dust (b)Bright spot (c)Thin Stain

Figure 2. Pseudo Defect

3. Proposed Approach

This paper proposes an approach using both of BoF and color information in order to correspond to the various defect images without using reference image. As a method for the classification of images, BoF has been proposed to represent number of occurrences of Visual Word (VW) by histogram.

ColorSIFT is used as features of BoF. ColorSIFT calculates features for each H, S and V using SIFT feature which is robust to the scale change, rotation and illumination change. Here, this operation is applied after image is transformed to HSV color representation.

Method to detect keypoint consists of Grid Sampling (Grid) and Sparse Sampling (Sparse). Grid is a method to take key points periodically without considering intensity change. While Sparse is a method to take key points using Difference of Gaussian (DoG) and points with the larger change to the surrounding region are detected as key point. Paper [7] uses Sparse since it is easy to take key points from defect region and difficult to take key points from base part.

This paper also extracts features using Sparse in the similar way as [7]. Next, RootSIFT is used by normalizing SIFT feature and taking those square root. K-means is applied for the clustering of whole RootSIFT features and center of each cluster is used as VW which means representative vector. Visual Word Dictionary (VWD) is generated by gathering these VW. Let VWD generated here be VWD1. Next, closest VW is searched to RootSIFT which is extracted from each image. Voting to VW represents features of whole images by histogram.

Mask image is generated from defect images and features are extracted from the region except defect region. Extracted feature is taken as VWD2 from base part where VWD2 is newly generated. Correlation of VWD1 and VWD2 is calculated. If value of correlation becomes some threshold, bins of histogram are removed and new feature of histogram is used as feature when correlation is over threshold.

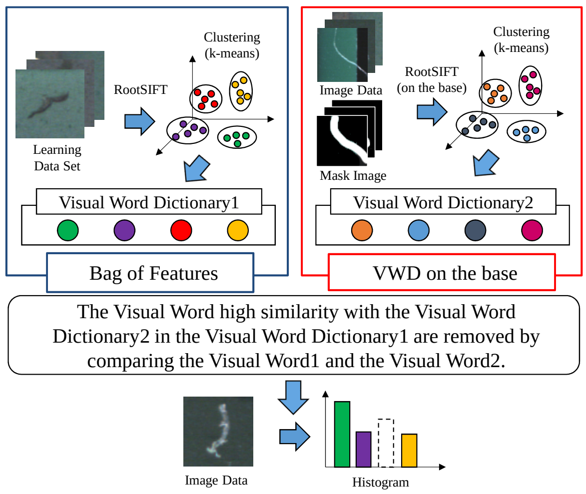


Figure 3. Proposeed Approach

Key points remained by removal are taken from around defect region and color histogram feature is generated from those keypoints. Color histogram reduces color for RBG with 256 levels using some threshold in each of RGB. Features which combine this color histogram and histogram generated by BoF are used to learn and classify SVM.

There are some kernel functions used in SVM and important point is to use appropriate kernel function to output better generalization. Since BoF is histogram feature, the proposed approach histogram intersection kernel is used to get the higher accuracy.

3.1 RootSIFT

Here, SIFT features are normalized and RootSIFT[10] is introduced by taking the square root. Distance calculation uses L2 norm in general and let the normalized SIFT vectors be x and y then the L2 norm N is represented as

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

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

$$B = \sum_{i=1}^{n} \sqrt{x_i y_i} = \sqrt{\boldsymbol{x}}^T \sqrt{\boldsymbol{y}} \tag{2}$$

Eq.(1) is rewritten using RootSIFT as

$$N = \sum_{i=1}^{n} (\sqrt{x_i} - \sqrt{y_i})^2 = 2 - 2\sqrt{\boldsymbol{x}}^T \sqrt{\boldsymbol{y}} \tag{3}$$

Eq.(3) means L2 norm is approximated with Bhattacharyya distance.

3.2 Kernel for SVM

SVM is applied to the nonlinear problem using Kernel. It takes time to separate data which are mapped onto high dimensional space. When dot product used in the mapping into high dimensional space, it is replaced with kernel and the processing becomes fast. Kernel consists of linear, nonliner kernels including RBF kernel. The performance depends on the choice of kernel based the problem to be solved for the generalization.

3.2.1 RBF Kernel

RBF kernel is used in SVM as a general kernel.

$$K(\boldsymbol{x}, \boldsymbol{x}') = \exp\left(-\frac{||\boldsymbol{x} - \boldsymbol{x}'||^2}{\sigma^2}\right) \tag{4}$$

Parameter σ is the parameter which controls the spread of kernel function and parameter value is assigned based on the region of cluster. Larger value is taken for the larger region of cluster.

3.2.2 Histogram Intersection Kernel

Histogram intersection kernel [11] is used as the similarity measure between the histogram x and x'. Histogram intersection kernel is shown in Eq.(5).

$$K(\boldsymbol{x}, \boldsymbol{x}') = \sum_{i=1}^{n} \min(x, x') \tag{5}$$

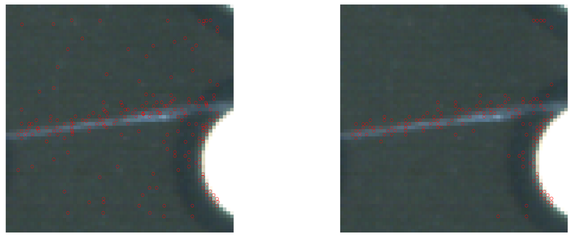
Histogram intersection kernel has the feature that that the processing time is fast without mapping into high dimensional space and it is effective when histogram is used as feature.

4. Experiment

The noise removal for the feature by the proposed approach is evaluated in comparison with paper [7] and [8].

4.1 Noise Removal

Noise removal for the feature is applied using the actual electronic board images. Here, Fig.4(a) shows the extracted result by ColorSIFT, Fig.4(b) shows the noise removal result from that of Fig.4(a) using VWD of the base part.



(a)Before Noise Removal (b)After Noise Removal

Figure 4. Noise Removal

It is shown in Fig.4 that key points are concentrated on the defect region by this noise removal.

4.2 Comparative Experiment

Comparative experiment is done with Paper [7] and [8] to confirm the effectiveness of the proposed method. Paper [7] made histogram feature by BoF using RootSIFT. Histogram intersection kernel is used as kernel function and parameter C in C-SVM was taken to be C=10, while number of VW was taken to be 1000. Paper [8] made histogram feature by BoF using SIFT. Linear kernel is used as kernel function and parameter C in C-SVM was taken to be C=300. Proposed method made histogram feature by BoF using ColorSIFT. parameter C in C-SVM was taken to be C=7 (which was empirically determined). Histogram intersection kernel and number of VW were the same as those of [7]. Correct and incorrect number and accuracy of true and pseudo defects are shown in Table 1.

Table 1. Classification Result

	True		Pseudo		Acc.[%]
	Corr	Incorr	Corr	Incorr	
Paper [7]	95	21	129	14	86.49
Paper [8]	97	19	126	17	86.10
Proposed	102	14	131	12	89.96

It is shown that proposed method improves 3.47% for accuracy in comparison with paper [7] and number of incorrect classification is reduced for true defect and pseudo defect. While the proposed method improves 3.86% for accuracy in comparison with paper [8] and number of incorrect classification is also reduced for true defect and pseudo defect. The result which reduces the number of incorrect classification for true defect is very important and the method and it is shown that the proposed method is effective in the defect classification. This view is from the situation that incorrect classification of true and pseudo defects leads to producing the defective product in the market.

Next, kernel function used in SVM are compared with RBF kernel function which is used in general. Number of correct and incorrect number of true and pseudo defects and accuracy are shown in Table 2.

Table 2. Classification Result

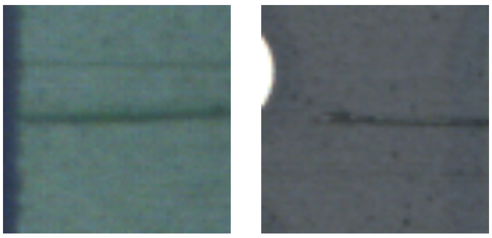
	True		Pseudo		Acc.[%]
	Corr	Incorr	Corr	Incorr	
RBF Kernel	102	14	127	16	88.41
Proposed	102	14	131	12	89.96

It is shown in Table 2 that histogram intersection kernel improves 1.55% for accuracy in comparison with that of RBF kernel and the number of incorrect classification of pseudo defect is also reduced.

The number of kernel parameter of histogram intersection kernel is 1 and that of RBF kernel is 2. This mean the histogram intersection kernel has easier problem to determine optimal parameter using optimization such as lattice point search.

5. Example of Misclassified Image

Examples of misclassified image by the proposed method are shown in Fig.5 and Fig.6



(a)True Defect 1 (b)True Defect 2

Figure 5. Misclassified Defect Images 1

(a)Pseudo Defect 1 (b)Pseudo Defect 2

Figure 6. Misclassified Defect Images 2

The reasons are as follows. Color of defect region of Fig.5 is similar as the base region. White color is included in the color of defect region in the image of Fig.6. The number of this kind of images was small and sufficient learning was not done.

6. Conclusion

This paper proposed a new approach for defect classification using combined feature with color information and BoF which removes noise from the base region of the defect. The previous method used only the gray scale information but this approach used color information and the proposed method gave the higher accuracy from the evaluation in the experiment. Histogram intersection kernel was used for effective performance in the method. More number of dataset should be used and evaluated as further subjects.

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