

# DEFECT DETECTION AND CLASSIFICATION OF ZINC COATED PARTS USING MACHINE VISION

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## Abstract:

A machine vision approach is required for detection and classification of surface defects such as pitting, watermarks, rough surface and color tonality in zinc coated parts. Such an automated visual inspection scheme involves following steps: image acquisition, defect segmentation, feature extraction and classification. Image acquisition of a part with complex geometry and specular surface depends on the effectiveness of illumination. Various illumination techniques such as dark and diffuse with various incident angles were tested for capturing images with maximum contrast and information. Feature extraction of the defects was then carried out to capture the brightness, shape and spectral properties of the defects. Then feature ranking was calculated to obtain the best features for a real-time inspection. Supervised classification was then tested with Support Vector Machine (SVM) for defects other than tonality difference. The color tone is unique to an inspection batch and hence a change in tonality had to be detected in-line. An unsupervised classification method was used as an extra step with in-line learning for this case. Challenges like complex geometry, specular reflection and real-time processing in building the machine vision system for real time inspection is solved by developing various image-processing algorithms. The color tonality inspection is a unique problem faced in this application and that was addressed at two stages by both supervised and unsupervised classification techniques.

**Keywords:** Machine vision, Coating inspection, Defect classification

## 1. INTRODUCTION

Zinc coating of metallic surface improves the mechanical properties of the component and is vital for any machinery. Zinc coating process involves multiple steps with careful choice of process parameters. Such zinc coated parts are prone to defects such as pitting, watermarks, rough surface and change in tonality. Currently, visual inspection of coated parts is carried out manually in industry to detect the defective pieces. Defect detection is followed by classification of defects by which either rework of the part or modification of the coating process parameters is determined. In the current scenario, industries are willing to adapt stringent inspection measures for improved quality. Manual inspection of coating defects is not possible for all the parts and hence the inspection had to be automated for better quality control.

During the initial stages of automatic visual inspection research, defects were segmented from the rolled steel

images using edge operators and defect classification was carried by using statistical trees with binary nodes [1, 2]. The surface defects found in casting process with various geometries was classified using fuzzy logic [3].

Feature selection algorithms was introduced to optimize the classifier performance and also to make the metallic surface inspection process real time [4]. Such algorithms selected a smaller subset of features yielding a better classification rate with Bayesian classifier. Neuro-fuzzy algorithm performed better than Bayesian and fuzzy - knn classifiers to classify the defects of pipes [5]. Defects found on copper strips were classified by considering seven invariant moments using back propagation artificial neural network. [6]. Artificial Neural Network was also used to detect defects that resulted due to metal inert gas welding process [7].

With many features characterizing shape and statistics of gray level along with discrete cosine transform and Gabor filter bank, the classifier Support Vector Machine (SVM) classified 15 defects resulting from grinding and polishing process with 83% accuracy [8]. In pipe defect detection many classifiers were compared and SVM gave the best result with wavelet features [9]. A multi-resolution approach for the inspection is adopted to find local defects embedded in homogeneous copper clad laminate [10]. Rough set theory was used for feature selection and SVM for classification. Decision directed acyclic graph was used to classify defects found in fast tool servo machining and is found to be more accurate than SVM and knn [11]. Process parameters coupled with SVM classified the defects in hot rolled mills [12]. A finite element simulation was performed to obtain such process parameters. Surface defects found in bearing was segmented using adaptive thresholding and classification was carried out by SVM [13]. Otsu method was used for segmentation in some cases to classify the defects in metals with SVM as classifier [14]. There are wide variety of segmentation techniques and features available for visual inspection. SVM classifier produced good defect classification results across many surfaces and products.

This paper presents a machine vision method for detection and evaluation of surface defects found on zinc coated rings. Various illumination methods were tested for good segmentation of defects. Wide varieties of features are tested followed by selection algorithms to arrive at optimal features for classification. SVM classifier was employed for initial defect classification to find defects such as pitting, watermarks and rough surface as they are common across any batch of production. The color tone of the coating may vary with different lots and so clustering of color features was followed in line for tonality inspection.

## 2. MATERIALS AND METHODS

The image is acquired with an industrial CCD camera with ring LED illumination. Illumination plays a crucial role in any machine vision system. Illumination factors such as angle of incidence and intensity will affect the quality of an image. A good contrast image is essential for defect identification and classification. The choice of illumination factors depends on the surface properties of the object such as surface specularity, texture and nature of the defect being inspected. The wider the incident angle, the image acquired has been observed to have more contrast. Consequently there will be a loss of information about defects. Initially defective images were acquired by varying the LED's in the ring light. In Fig. 1a, one LED was used for illumination at a wide angle. The same defective portion is captured in Fig 1b and 1c using 2 and 4 LED's at opposite and corner directions respectively. From the images one can understand the information about the defects is increasing with increase in illumination directions. The same defect is captured with 12 LED's as shown in Fig. 1d. It is observed that there is loss in contrast but many more information is obtained has information such as tonality and texture. This type of illumination was used throughout this study, as both the defects and color tonality can be studied with a single image. If the inspection does not involve tonality, images with high contrast as in Fig. 1c can be used.

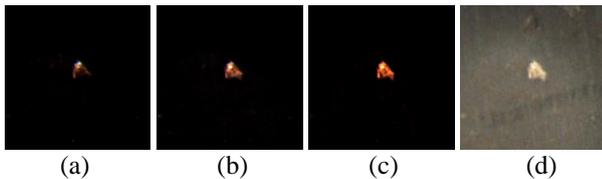


Fig. 1: Effects of illumination angle and intensity (a) 1LED at wide angle (b) 2 LED's at opposite directions (c) 4 LED's at corners (d) 12 LED's surround

Images of coated parts were captured with a resolution of 200 pixels by 200 pixels. The database was prepared with 200 samples out of which 160 were defective, 10 were with tonality difference and 30 were non-defective images of coated parts. Defective samples included all four kinds of defect with 40 samples in each. The labeling of defects was carried out by industrial experts. In this work, all the algorithms were executed using MATLAB R2012a and ran on a personal computer with Intel i7-3770 microprocessor with 8GB RAM.

## 3. ALGORITHM DEVELOPMENT

### 3.1 Defect detection

Segmentation of the objects from the background can be achieved by various methods [15, 16]. In this paper the segmentation of the parts from the background is carried out using moving threshold method as global thresholding methods like Otsu method [17] works well only with uniform illumination. A binary image is obtained by applying the moving threshold method for four kinds of

defects as shown in Fig. 2. The images were converted to gray-level images before thresholding.

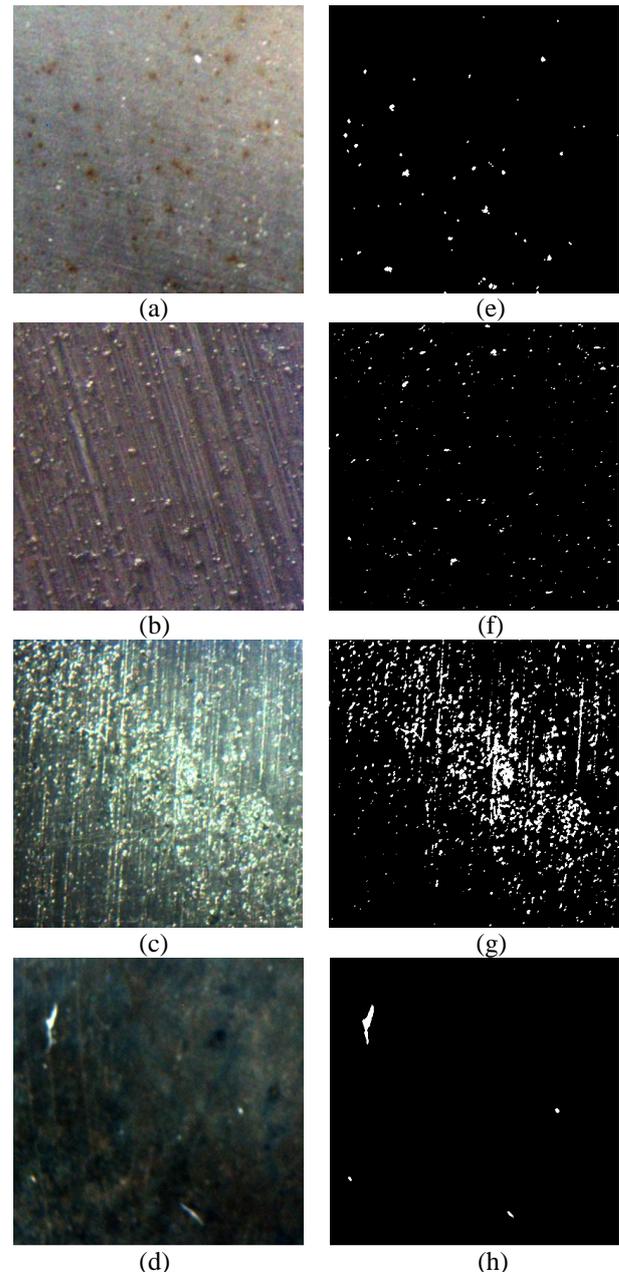


Fig. 2. Segmentation results by moving threshold technique. (a-d) Original images and (e-h) segmented images of pitting, rough surface, watermark and scratches respectively.

### 3.2 Defect classification

Classification of the defects is vital in the visual inspection of zinc coated parts due to following reasons. The parts may be reworked in different ways based on the type of defects. An overwhelming occurrence of particular type of defect may suggest a fault in coating process parameters. A supervised classification is prescribed in this work because of the availability of defective and non-defective images required for learning. The procedure of a supervised classification is to extract features from the images to train and test the classifier. Various features can be extracted

from the segmented defective images describing the defect's attributes. These features should resemble to how humans are able to differentiate between the defects visually. Based on these qualitative variations, features based on spectral, textural, shape and co-occurrence matrices were considered. Then the features were ranked for the optimal performance of the classifiers. Feature ranking was based upon forward selection algorithm and cross validation. Support Vector Machine (SVM) proposed by C. Cortes and V. Vapnik [18] is used in this work for supervised classification.

For tonality inspection mean value of RGB colours of the images is considered. The mean value of the images are clustered in line with unsupervised k-means algorithm [19]. K-means is a clustering algorithm which finds the mean vectors of the expected number of clusters (k) by iterative process. The Euclidean distance is used as a metric. The k was selected as 2 as there are only two classes i.e. the correct and incorrect tonality. The classifier returns a null cluster when there was defective image. K-means initialization was done by Mersenne Twister algorithm [20] for consistent random number generation. The algorithm developed for this work is given in Fig. 3.

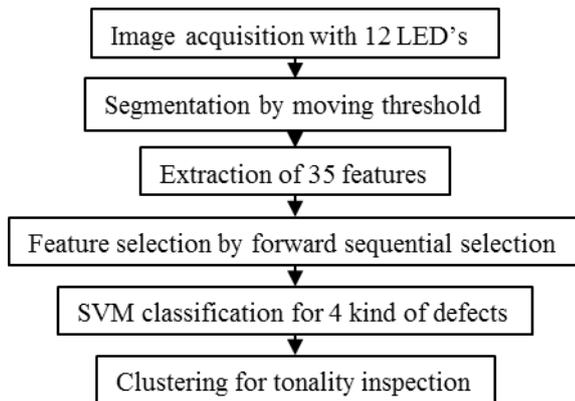


Fig. 3. Inspection algorithm for zinc coated parts.

#### 4. RESULTS AND DISCUSSIONS

The performance evaluation of the proposed methodology is presented in this section. The defects are segmented using adaptive moving threshold. An image was considered defective when the thresholded binary image had any white region. Confusion matrix is good way to check the efficiency of classifier. The accuracy of the defect inspection stage can be calculated from the confusion matrix.

$$\text{Accuracy of classification} = \frac{\text{trace}(CM)}{\text{sum}(CM)}$$

The inspection results are shown in table 1 with an accuracy of 95.5%. A high number of false alarms can be witnessed. This is due to specular coating which gets segmented as defect. To increase the accuracy, the number of training images can be increased. However, if a 2% of white region is given as an allowance for defect detection, the accuracy goes up to 98.2%.

Table 1: Confusion matrix of defect detection results

Actual class	Predicated class		Number of samples
	Non-defective	Defective	
Non-defective	31	9	40
Defective	0	160	160
Total	31	169	200

Accuracy = (31+160)/200 = 95.5%

A total of 35 features were extracted from 160 images of defects in each kind. 10 features were selected from them by forward sequential selection algorithm. Features from 20 images per defect were trained and 20 images per defect were tested by SVM using Radial Basis function. The implementation of SVM by C.C. Chang and C.J. Lin [21] in MATLAB<sup>®</sup> for the kernel is used in this work. The confusion matrix of training set is shown in table 2 and testing images is shown in Table 3. The parameters of the SVM were optimized by grid search. In test stage, scratches were highly misclassified with other defects. If the coating process has uniform colour, the inspection can be stopped with this supervised classification.

Table 2. Confusion matrix of classification using training samples

Actual class	Predicated class				No. of samples
	Pitting	Rough surface	Water mark	Scratch	
Pitting	20	0	0	0	20
Rough surface	1	19	0	0	20
Water mark	1	0	18	1	20
Scratch	1	0	0	19	20
Total	23	19	18	20	80

Accuracy = (20+19+18+19)/80 = 95%

Table 3. Confusion matrix of classification using test samples

Actual class	Predicated class				No. of samples
	Pitting	Rough surface	Water mark	Scratch	
Pitting	19	1	0	0	20
Rough surface	1	19	0	0	20
Water mark	0	0	18	2	20
Scratch	0	1	2	17	20
Total	20	21	20	19	80

Accuracy = (19+19+18+17)/80 = 91.25%

For in line tonality inspection clustering is tested and was accurate (92.5%) as shown in table 4. Yet this step is subjective and based on the assumption that correct tonality pieces will appear in majority. The time taken for deciding the presence of defect is 0.22 seconds, and classification takes 0.43 seconds.

Table 4: Confusion matrix of inline clustering for tonality inspection

Actual class	Predicated class		Number of samples
	Non-defective	Defective	
Non-defective	30	0	30
Defective	3	7	10
Total	33	7	40

Accuracy =  $(30+7)/40 = 92.5\%$

#### 4. CONCLUSION

A machine vision system for defect detection and classification of zinc coated parts is prototyped and algorithms are developed in this study. Various effects of illuminations are studied. Defect detection by few methods shows excellent results. Defect classification by SVM gives high prediction accuracy of 92%. The inline unsupervised classification for tonality inspection is solved by clustering algorithms with good results. The simple hardware implementation which includes a machine vision system and the computationally non-intensive processing of the presented approach is economical with a high potential for automating the inspection of textile rings.

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