Study of Surface Defect Detection in Various Scenarios Using Image Processing

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1. Introduction

Defects are not only about cost or loss, they are more importantly about customer trust and confidence……..

Quality inspection is an important aspect of modern industrial manufacturing. The target to be achieved through this project was primarily aimed at detecting the surface defects belonging to different classes. This was achieved through grabbing the images from the camera, carrying out defect detection on these images and later classifying them. We present a method to automatically detect and localize defects occurring on the surface. Defect regions are segmented from background images using their distinguishing texture characteristics. This relies on the digital image processing toolbox of the mathematical software MATLAB. The method of detecting defects such as black flecks and scratching is proposed here.

2. A brief review of the work already done in the field.

Defect detection methods are mainly categorized in statistical approach, spectral approach and model based approach. These approaches are briefly described as below:

2.1 Statistical Approach

Methods in this approach mainly focus on statistical behavior of different regions of image.

Statistical approach describes spatial distribution of gray level by two representations auto-correlation function and co-occurrence matrix [1].

Auto-correlation Function

Auto-correlation function measures spatial frequency of image and it gives maxima of that frequency at different locations according to the length of repetitive primitive on image. These maxima will be constant for the primitive that has been perfect throughout the image and different for the primitives that are changed and imperfect in replication. As a result those primitives can be considered as defective [1]. This method is mostly used for regular patterned images. It measures regularity and coarseness of pattern. But this method has limitation. It needs reference frame of tonal primitive to carry out analysis of texture.

Co-occurrence Matrix

Co-occurrence matrix is the most widely used method for texture classification. It uses 2D matrices to accumulate various texture features of images such as energy, contrast, entropy, correlation, homogeneity etc [2]. These texture features are characterized as second order statistic which is the measure of spatial dependence of gray values for specific distance [1]. This method has some limitations. The size of co-occurrence matrix is important. So number of gray values must be reduced to meet the memory requirements [2]. If the texture features are constructed using large sized primitive than this methods shows poor performance [1].

Mathematical Morphology

Mathematical morphology takes out useful components from image for the description and representation of regional shape [1]. In this method operations such as erosion, dilation, opening and closing are performed on image using structuring element [1]. The benefit of this method is that it gives response to various defect size and shapes. It is also better for segmentation. It is mostly suitable for unidirectional textures [1].

Edge Detection

Edge detection techniques are also very effective in detection of defects. The distribution of number of edges is the important feature in texture images. In an image point, line and edge defects can be represented using number of gray level transition in an image [3]. These features can be used to detect defects. But this method has also some drawbacks. This approach is only suitable to plain weave fabric images [3]. With these method defects nearby edges are hard to detect.

2.2 Spectral Approach

Methods in these approaches are applicable when texture images are composed of reoccurrence of some basic primitive with acceptance of specific rules of displacement [3]. Therefore, spectral approaches are not suitable for the images with random texture features.

Fourier Transform

Fourier transform can be derived from Fourier series. While spatial domain is sensitive to noise and difficult to detect defect, Fourier transform utilizes frequency domain to detect defects [1]. This transform has the properties of noise immunity, optimal characterization of periodic features and translation invariance. Fourier transform can be categorized in two categories: Discrete Fourier transform and Optical Fourier transform. The DFT based approaches are ineffective for the images in which frequency component of defects appear in image are highly mixed with each other in frequency domain. In OFT, defect detection of fabric image is very easy and fast because it is obtained in optical domain by using lenses and spatial filter [3].

Wavelet Transform

Wavelet transform is another spectral approach for defect detection. Wavelet represents decomposition of multi-resolution signal. Fourier transforms are sinusoidal whereas wavelet transform are small waves of varying frequency and some specific duration called wavelets. Wavelet transform provides more local support from vertical, horizontal and diagonal direction for any inputted image [1]. The multi-scale wavelet representation has the property of shift invariance and it can detect defects by examining image at different scales.

Gabor transform

The general form of Gabor function is in a nonorthogonal basis set. Gabor filter provides optimal joint localization in both spatial and spatial-frequency domain [1]. The texture features that represent frequency content in local region in spatial domain can be extracted by localized spatial filtering. Gabor filters provide this type of filtering [3]. The implementation of Gabor filter is categorized in two ways [1]: 1) Filter bank consisting group of filters with predetermined parameters in frequency and orientation to adequately cover frequency plane.

2) Implementation of optimal filters with the use of few filters but correct choice for that filters is hard and crucial.

Filtering approach

Filtering technique is used in many applications to filter out image for smoothening of image by suppressing high frequency or for enhancing image by suppressing low frequency. Filtering is performed between image neighborhood and filtering mask [1]. In Filtering approach there are three kinds of methods [2]:

1) Spatial domain filtering which is applied directly on pixels
2) Frequency domain filtering which is based on Fourier transforms.
3) Joint spatial-frequency domain filtering.

In spatial domain, images are filtered out by using gradient filters to extract dots, lines and edges. In this approach first Sobel, Canny, Robert, Laplacian, Daubechies and Law filters are used to measure edge density. Many other methods use frequency domain filtering approach in the case when there are no straightforward kernels can be found. In this approach image is first transformed to Fourier domain, multiplied with filter function and then again re-transformed to spatial domain [2]. Example of frequency domain filters are Ring filter and Wedge filters.

2.3 Model based Approach

Texture is usually considered as a complex pictorial pattern. Any random field in mage can be defined by stochastic model which is modeled by simple function of an array of random variables [1]. This modeling based approach has advantage that it can produced texture that can match the observed texture [3]. Model based approaches are mostly suitable to fabric images with stochastic surface variations or for randomly textured fabrics for which the statistical and spectral approaches have not yet shown good results [3]. Model based methods include autoregressive model, fractal model, markov random field model and the Texem model.

Table 1 shows the comparison among the different methods used for the detection of defects in images.

Table -1: Comparison of various defect detection methods

Method	Advantages	Disadvantages
Edge Detection [4]	Identify defects effectively and accurate	It is not working with various defects other than crack and holes.
Morphological Operations [5]	It gives smooth image with less lightning disturbance.	It is sensitive to defect size and shape.
Wavelet Transform [8]	Performs better for line defects such as horizontal, vertical and diagonal line defects	Failed to detect defect in presence of color variance and smooth edges in images.
Thresholding [6]	It selects appropriate threshold value automatically	Work well only with image to be threshold has clear peek and valleys.
Co-occurrence Matrix [7]	Ability to detect defect which has invariant of luminance.	It can only work with invariant environment condition. More demanding in terms of computational and memory requirement.

Effective algorithms for defect detection are developed which consists of following procedure:

i. Background Extraction: Backgrounds are found and separated from the original image captured by cameras

ii. Gray level calculation: Gray levels of backgrounds and original images are calculated for better feature extraction.

iii. Threshold decision and effect of σ : one or more threshold values and σ values are decided and applied to differential gray levels to determine whether pixels are in defect areas or background and pixels in defect areas are marked as suspicious pixels.

iv. Region of Interest (ROI): Searching and merging suspicious pixels and the defect area are called as ROI.

3. Applications

The main problem with this process of defect identification is that several defects may exhibit the same geometry, while the members of the same defect class can be structurally very different and thus they can't be distinguished by merely studying their structural appearance.

a. Rail surface inspection system

Here, we propose an image processing solution to the analysis of image data for the detection of rail surface defects. The images are obtained from many hours of automated video recordings. This huge amount of data makes it impossible to manually inspect the images and detect rail surface defects. Therefore, automated detection of rail defects can help to save time and costs, and to ensure rail transportation safety. However, one major challenge is that the extraction of suitable features for detection of rail surface defects is a non-trivial and difficult task.

b. Glass Surface Defect Detection

Glass is a material which is used in the industry and household. The presence of defects or weaknesses in the glass has serious implications. In a glass substrate, the grey level of defects and background are hardly distinguishable and results in a low contrast image. The primary objective of this proposal is to develop a method for detection of defects in a glass surface image such as subtle defect, bubble defect, dirt defect checks or marks defect etc. Here we propose image processing based methodology to detect the defects in the glass. Gray level Concurrence Matrix (GLCM) has been used for feature extraction. The supervised classifier is responsible for making intelligent classification based on observations done for various types of glass defects

c. Textile Defect Detection

In textile industry production, automated fabric inspection is important for maintain the fabric quality. For a long time the fabric defects inspection process is still carried out with human visual inspection, and thus, insufficient and costly. Therefore, automatic fabric defect inspection is required to reduce the cost and time waste caused by defects. The development of fully automated inspection system requires robust and efficient fabric defect detection algorithms.

d. Steel surface inspection system

Recently, it becomes significant to enhance quality of products as well as to increase quantity of products in the steel manufacturing industry. Surface defect detection plays a significant role in quality enhancement in steel manufacturing. Support Vector Machines and neural networks are the most popular classifiers in this application. Decision trees are also known as other classifiers for steel defect detection yielding a fast but moderate performance. This paper presents an automatic defect identification system for detecting defects of steel products from captured digital radiographic images based on defect classification and segmentation. Image classification will be used for automated visual inspection to classify defect protects from quality one. It will be performed through textures analysis and probabilistic neural network. The textures are extracted using wavelet filters with co-occurrence features. The defect detection process involves the pre-processing, segmentation and morphological filtering to make processing system more flexible with accuracy. Manual inspection used to define the existence of defect becomes an urgent and important task in order to make sure the evaluation is accurate for radiographer to make decision. But, the manual inspection might give in consistent results especially when there are plentiful defects needs to be evaluated due to human factor. Automated defect inspection and evaluation system could assist radiographer to assess the properties of defect accurately.

4. Proposed methodology

Currently defects detection methods based on image processing still have disadvantages such as low speed and resolution. So highly efficient and real-time detection is the key problem needs to be settled down during production.

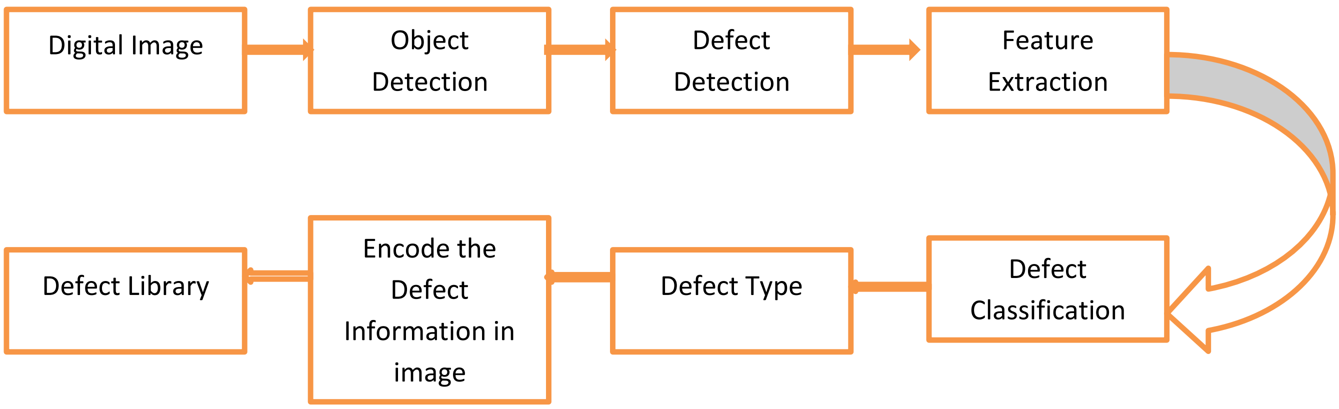

Figure: Block diagram of Defect detection and Classification

Hence, we proposed a defect detection method of the surface of various scenarios in MATLAB. Firstly, Surface image information can be acquired by the image capturing equipment (CCD). Secondly, data will be stored to controlling PCs for early stage processing. Thirdly, edge detecting operators will be applied to acquire the surface information; in the next step we extracted the textural features of the defective image. These textural features are given to support vector machine (SVM) or any supervised classifier for classification of defect type.

5. Expected outcome of the proposed work

This research proposal concerned with the problem of detection of the surface defects included various scenarios including steel surface defect detection, rail track defect detection, textile defect detection and glass surface defect detection using the image processing. By using this technique we can develop the sorting system in various industries from depending on the human which detects the defects manually upon his experience and skills which varies from one to one to the automated system depending on the computer vision. That affect mainly in the classification or sorting operation which also done by human in the industry. People can work effectively for short periods and many different operators are involved in checking the same surface. Continuity over time is not guaranteed and may result in overall poor quality, which may cause customers to complain or even to reject the batch. We will be able to isolate different kinds of defect in various surface images (Rail tracks, Steel, Textile, Glass). Automated defect detection systems would bring numerous benefits to the entire sector with major economic advantages, also guarantee product quality, increase plant efficiency and reduce fixed and periodic investments. The continuous measurement of surface defects gives line production operators to optimize temperature profile, speed and other operating parameters.

References

1. Automated fabric defect detection—A review, Henry Y.T. Ngan, Grantham K.H. Pang , Nelson H.C. Yung, Image and Vision Computing 29 (2011) 442–458.
2. A Review of Recent Advances in Surface Defect Detection using Texture analysis Techniques, Xianghua Xie, Department of Computer Science, University of Wales Swansea, Swansea SA2 8PP, United Kingdom, Electronic Letters on Computer Vision and Image Analysis 7(3):1-22, 2008
3. Computer-Vision-Based Fabric Defect Detection: A Survey Ajay Kumar, Member, IEEE, IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS, VOL. 55, NO. 1, JANUARY 2008.
4. An Algorithm to Detect and Identify Defects of Industrial Pipes Using Image Processing, Md. Ashraful Alam, M MNaushad Ali, Musaddeque Anwar AI-Abedin Syed, Nawaj Sorif, Md. Abdur Rahaman, 978-1-4799- 6399-7114/$31.00 ©20 14 IEEE.
5. Fabric Defect Detection Algorithm Using Morphological Processing and DCT, Mahmoud Abdel Aziz, Ali S. Haggag and Mohammed S. Sayed, Dept. of Electronics and
Communications Engineering, Zagazig University, Zagazig, Egypt, 978-1-4673-2821-0/13/$31.00 ©2013
6. Metal Surface Defect Detection using Iterative thresholding Technique, M.Senthikumar, Dr.V.Palanisamy, Dr.J.Jaya, 2nd International Conference on Current Trends in Engineering and Technology, ICCTET'14, © IEEE 2014.
7. Fabric defect detection based on GLCM and Gabor filter: A comparison, Jagdish Lal Raheja, Sunil Kumar, Ankit Chaudhary, Optik 124 (2013) 6469– 6474.
8. Fabric Defect Detection using Wavelet Filter, Mr. Vaibhav V. Karlekar, Prof. M.S.Biradar & Mr. K.B.Bhangale, 2015 International Conference on Computing Communication Control and Automation, 978-1-4799-6892-3/15 $31.00 © 2015 IEEE.
9. C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, Z. Wojna, "Rethinking the inception architecture for computer vision", 2015.
10. Cui Xuehong, Liu Yun, Wang Chuanxu, Li Hui, "Defect Classification for tire X-ray images using convolutional neural network [M]", Electronic Measurement Technology, vol. 40, no. 5, pp. 168-173, 2017.
11. Pang Na, Zhao Qilin, Rui Ting, Zhu Bin, "Current Situation and Development of Bridge Detection Technology Based on Machine Vision [D]", Modern Transportation Technology, vol. 12, no. 6, pp. 25-31, 2015.
12. X. Gibert, V. M. Patel, D. Labate, R. Chellappa, "Discrete shearlet transform on GPU with applications in anomaly detection and denoising", EURASIP Journal on Advances in Signal Processing, vol. 2014, no. 64, pp. 1-14, May 2014.
13. DENG Xiu-qin, XIONG Yong, PENG Hong, "Effective adaptive weighted median filter algorithm", Computer Engineering and Applications, vol. 45, no. 35, pp. 185-187, 2009.
14. J.J. Cunningham, A.E. Shaw, M. Trosino, Automated track inspection vehicle and method, May 2000.
15. L Fei-Fei, R Fergus, P Perona, "One-Shot learning of object categories", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 4, 2006.
16. FZ Zhuang, P Luo, Q He, ZZ. Shi, Survey on transfer learning research. Ruan Jian Xue Bao/Journal of Software, vol. 26, no. 1, pp. 26-39, 2015.
17. Ze Ping. Yang, Research of unbalanced data based on neural networks, [online] Available: http://www.jos.org.cn/1000–9825/4631.htm.
18. Chu Jinghui, Wu Zehuan, Lu Wei, Li Zhe, "Diagnosis System of Breast Tumors Based on Migration Learning and Deep Convolution Neural Networks [J]", Journal of Laser and Optoelectronics, vol. 55, no. 05, pp. 051004, 2018.
19. Chen-Lin Zhang, Jian-Hao Luo, Xiu-Shen Wei, Jianxin Wu, Defense of Fully Connected Layers in Visual Representation Transfer.
20. N V Chawla, K W Bowyer, L O Hall et al., "SMOTE: synthetic minority over-sampling technique [J]", Journal of Artificial Intelligence Research, vol. 16, no. 1, pp. 321-357, 2002.
21. H Wu, M J Hayes, A Weiss et al., "An evaluation of the Standardized Precipitation Index the China-Z Index and the statistical Z-Score [J]", International Journal of Climatology, vol. 21, no. 6, pp. 745-758, 2001.
22. J J Marais, K C. Mistry, "Rail integrity management by means of ultrasonic testing [J]", Fatigue & Fracture of Engineering Materials & Structures, vol. 26, no. 10, pp. 931-938, 2010.
23. R Yang, Y He, B Gao et al., "Lateral heat conduction based eddy current thermography for detection of parallel cracks and rail tread oblique cracks [J]", Measurement, vol. 66, no. 1/2, pp. 54-61, 2015.

24. R J Greene, J R Yates, E A. Patterson, "Crack detection in rail using infrared methods [J]", Optical Engineering, vol. 46, no. 5, 2007.
25. NakHyeon Kim, Hoon Sohn, SoonWoo Han, "Rail Inspection Using Noncontact Laser Ultrasonics [J]", Detection of Committee, vol. 32, no. 32, pp. 696-702, 2012.
26. Y Zhao, J H Sun, J Ma et al., "Application of the hybrid laser ultrasonic method in rail inspection [J]", Insight-Non-Destructive Testing and Condition Monitoring, vol. 56, no. 7, pp. 360-366, 2014.
27. Ting Sun, Lin Sun, Dit-Yan Yeung, "Fine-Grained Categorization via CNN-Based Automatic Extraction and Integration of Object-Level and Part-Level Features *[J]", Image & Vision Computing, pp. 64, 2017.
28. A. Krizhevsky, I. Sutskever, G. Hinton, F. Pereira, C. Burges, L. Bottou, K. Weinberger, "ImageNet classification with deep convolutional neural networks" in Advances in Neural Information ProcessingSystems25CurranAsso-635 ciates Inc., pp. 1097-1105, 2012.
29. K. Simonyan, A. Vedaldi, A. Zisserman, "Deep inside convolutional networks: visualising image classification models and saliency maps".
30. J. Donahue, Y. Jia, O. Vinyals, J. Hoffman, N. Zhang, E. Tzeng, T. Darrell, "DeCAF:a deep convolutional activation feature for generic visual recognition 565", Proceedings of the International Conference on Machine Learning, pp. 647-655, 2014.
31. M. D. Zeiler, R. Fergus, "Visualizing and understanding convolutional networks", Proceedings of the European Conference on Computer Vision, pp. 818-833, 2014.
32. Z. Liu, P. Luo, X. Wang, X. Tang, "Deep learning face attributes in the wild", Proceedings of the IEEE International Conference on ComputerVision, pp. 3730-3738, 2015.
33. C Szegedy, W Liu, Y Jia et al., "Going deeper with convolutions [C}", IEEE Conference on and Pattern Recognition(CVPR) 2015: Computer Vision, pp. 1-9.
34. Y LeCun, L Bottou, Y Bengio, P Haffner, "Gradient-based learning applied to document recognition [C]", Proc. IEEE, pp. 199R-227R-2324, 1998.
35. Steve Lawrence, C Lee Giles, Tsoi Ah Chung, D Back Andrew, "Face Recognition: A Convolutional Neural Nehvork Approach [J]", IEEE Trans. on Neural Nettvorks (S1045–9227), vol. 8, no. 1, pp. 98-113, 1997.
36. A Krizhevsky, I Sutskever, G E. Hinton, "ImageNet classification with Deep Convolutional Neural Networks [J]", Advances in Neural Information Processing Systems 2012, vol. 25, no. 2, 2012.
37. Y. LeCun, LeNet-5 convolutional neural networks [J], 2015, [online] Available: http://yann.lecun.com/exdb/lenet.
38. H. He, E. A. Garcia, "Learning from unbalanced data", IEEE Transactions on Knowledge and Data Engineering, vol. 21, no. 9, pp. 1263-1284, 2009.
39. N. V Chawla, over-same ling K.W. Bowyer, L.O. Hall et al., "SMOTE: Synthetic minority technique", Journal of Artificial Intelligence Research, vol. 16, pp. 321-357, 2002.
40. H. He, Y Bai, E.A. Garcia, S. Li, "ADASYN: Adaptive synthetic sampling approach for unbalanced learning", IEEE International Joint Conference on Neural Networks (IJCNN), pp. 1322-1328, 2008.
41. M. Kubat, S. Matwin, "Addressing the curse of unbalanced training sets: One-sided selection", The 14th International Conference on Machine Learning, pp. 179-186, 1997.
42. J. Zhang, I. Mani, "KNN approach to unbalanced data distributions: A case study involving information extraction", ICML'2003 Workshop on Learning from Imbalanced Data Sets, 2003
43. X. Y Liu, J. Wu, Z. H. Zhou, "Exploratory under Sampling for class imbalance learning", IEEE Transactions on Systems Man and Cybernetics Part B: Cybernetics, vol. 39, no. 2, pp. 539-550, 2009.
44. D M Kline, V L. Berardi, "Revisiting squared-error and cross-entropy functions for training neural network classifiers [J]", Neural Computing & Applications, vol. 14, no. 4, pp. 310-318, 2005.
45. A. Krizhevsky, I. Sutskever, G. Hinton, "Imagenet classification with deep convolutional neural networks", NIPS, 2012.
46. Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, L. D. Jackel, "Backpropagation applied to handwritten zip code recognition", Neural computation, 1989.
47. Jasper RR Uijlings et al., "Selective search for object recognition", International journal of computer vision, vol. 104, no. 2, pp. 154-171, 2013.
48. R. Girshick, J. Donahue, T. Darrell, J. Malik, "Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation", 2014 IEEE Conference on Computer Vision and Pattern Recognition, pp. 580-587, 2014.