Tire Defect Detection Using Adaptive Dictionary

Yuanyuan Xiang, Shengbao Li and Chuanming Yin*
Shandong Branch of National Computer Network Emergency Response Technical Team/Coordination Center (CNCERT/SD), Shandong, China

*Corresponding author e-mail: ycm@cert.org.cn

Abstract. This paper proposes a new algorithm for detecting tire defects, which is based on principal component analysis and adaptive dictionary learning. Because the defects on the side of the tire are very small and difficult to detect, the dictionary is directly obtained from the test image itself instead of the reference image, thereby improving the soul of adapting to changes in lighting intensity and texture. When using the learned dictionary to represent the test image, patches involving abnormalities in the test image may have larger reconstruction errors than normal errors. Through threshold operation, the defect area can be segmented from the residual image. Compared with the wavelet-based method and the component decomposition method, the experimental results of test images with defects show that the algorithm can adapt to changing light intensity and texture, and also shows more accurate defect detection results.

1. Introduction

Safety performance and service life of tire decided by internal structure, defect detection must be implemented for the internal structure of finished product. Currently, tire inner defect detection based on X-ray image is relied on trained human vision in most tire manufacturers. At present, the manual detection method has low efficiency, labor intensity, high error rate, and can no longer meet the current demand for high-quality mass production. [1].

With the development of computer vision and object detection technology, numerous automatic measurement technology based on computer vision have been proposed [2]. Tsai and Chiang proposed a wavelet-based defect detection method, which improves the detection speed and realizes rapid detection. It is one of the widespread implemented spectral methods that have a low time complexity [3]. The method proposed is based on 3-level wavelet transformation. In the process, it only reserves the data in the first level of 3-level wavelet transformation to reconstruct the original image. The reconstructed image throws the detail information (texture) existed in the second and third wavelet level away. A process of threshold segmentation on the reconstructed image can obtain the detection results. But the accuracy of wavelet-based method is not expected due to the effects of varying illumination intensity and textures (shows in Figure 1). In [4], a tire defect detection method based on component decomposition is proposed, which is better than wavelet-based methods in performance. This method is based on component decomposition, it use a Local Total Variation (LTV) smoothing filter to separate the texture from the background. The defect regions in the background are easy to detect by the next step. Then it subtracts the mean background extracted by a Vertical Mean (VM) filter from the background. The final result is obtained by a threshold segmentation processing on the residual (shows in Figure 2). The detection results of this method are not affected by illumination intensity reflected by
mean background. However, the calculation accuracy of this method is still affected by texture, and the
calculation complexity is too high to achieve. Aimed at the current situation of the present method, this
paper proposes a tire defect detection method based on adaptive dictionary using principal component
analysis (PCA) [5]. The proposed method has a much better results than the previous methods and a low
time complexity.

Figure 1. (a) the original defective image, (b) the reconstruct image without detail texture, (c) the
detection result using threshold segmentation to (b).

Figure 2. (a) the original defect image, (b) the results of (a) by using LTV filter, (c) the background of
(b) obtained by using VM filter, (d) the residual of (b) subtracting (c), (d) the final detection result
using threshold segmentation to (d).

In this paper, principal component analysis and relevant theory are briefly introduced. Subsequently,
laser defect detection method is described in detail. The application of PCA to gray level image detection
and the comparison between PCA and previous methods are presented. The feasibility of proposed
approach is demonstrated through test results. The feasibility and accuracy of the proposed method are
also discussed.

2. Proposed method
In recent years, dictionary learning based on sparse representation has been successfully applied to many
computer vision problems and has received widespread attention. The flexibility of using the learned
complete dictionary and the flexibility of certain signals (such as natural images) determine the success
of the sparse representation. Although sparse representation has advantages [6], for defect detection
problems, a dictionary that can represent the image features of normal tires well but poorly perform
defect images can greatly improve the detection rate. Therefore, the sparse representation using a
complete dictionary is not suitable for tire defect detection. For the defect detection problem, we do not
use an over-complete dictionary to accept sparse representation, but use PCA to learn a small dictionary
that can capture the main components from the patch set [7]. This dictionary can represent defect-free
tire image well and defect image poorly because the defect regions are generally small in size. Then the
defect will be detected by computing the reconstruction error. The detail of this method is described in
follows.
Figure 3. The detection results of the same test image with different parameters via the proposed method.

The mathematical definition of PCA is an orthogonalized linear transformation, which maps data to a coordinate system in which the variance of the projection data on the first principal component (the first coordinate) is the largest, and the projection data on the second principal component is the second largest and the second principal component and the first principal component are perpendicular to each other, and so on. As the fact that defects on tire X-ray image appear to be small in size, the dictionary obtained by selecting few principal components of test image can represent defect-free regions well and defect regions poorly because the dictionary includes those principal components which are the main components of defect-free image region. So the proposed method learns a small-size dictionary using PCA. Then the defect detection results are obtained by computing the reconstruction error and segmenting the reconstruction error using an adaptive threshold.

For a \( m \times n \) test image \( X \), we collect all overlapping \( k_1 \times k_2 \) patches from \( X \), i.e. \( x_1, x_2, \ldots, x_{(m-k_1+1)(n-k_2+1)} \in \mathbb{R}^{k_1 \times k_2} \) where each \( x_i \) denotes the \( i \)th vectorized patch in \( X \). Then subtract patch mean and obtain \( \bar{X} = [\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_{(m-k_1+1)(n-k_2+1)}] \), where \( \bar{x}_i \) is a mean-removed patch. The eigenvectors from the normalized covariance matrix of \( \bar{X} \), \( F_{\bar{X}} = [f_1, f_2, \ldots, f_L] \), corresponding to the \( L \) largest eigenvalues, are computed to form the PCA bases of test image. With the PCA bases \( F_{\bar{X}} \) as a dictionary, we compute the reconstruction coefficient of \( \bar{x}_i \) (\( i \in [1, (m-k_1+1)(n-k_2+1)] \)),

\[
\beta_i = F_{\bar{X}}^T \bar{x}_i. \quad (1)
\]

The reconstruction error of \( i \)th patch is

\[
\varepsilon_i = \| \bar{x}_i - F_{\bar{X}} \beta_i \|_2^2. \quad (2)
\]

The saliency measure is proportional to the normalized reconstruction error (within the range of \([0, 1]\)) [8]. Figure 1 shows some saliency detection results with different size of image patch and different number of eigenvectors. It is clear that the proper parameters are important to the final detection results. Meanwhile, the computational complexity is increase along with the augment of parameters \( (k_1, k_2, L) \).
3. Experiments
In this section, the performance of the proposed method on defects with different types is displayed. When comparing with the previous approaches, the new method needs fewer parameters and is more flexible. Our experimental images are acquired using industrial monitors from Ling Long tire factory, China. These images are in the size of 256 × 256 pixels with 8 bit resolution. Our database includes 300 normal images and 720 defective images. The required parameters of the proposed method are as follows: number of the eigenvector, L=6, the size of patch, k_1=k_2=8. The proposed algorithm is implemented on MATLAB Software platform at a personal computer with a Pentium Core 2 Duo 3.20 GHz processor.

In order to assess the validity of the proposed approach we compare it to the previous methods, experiments show that the proposed method has a better performance than the wavelet-based method and the computation time of proposed method is much less than the component decomposition method. Figure 3 shows the process flow of this method. Figure 4 is a brief process of this method. Figure 4 shows the detection results of image with different defect types and different textures. For image (1), (2) and (3), the experiments demonstrate that our method is anti-interference the test images interfered by the illumination intensity and texture. For image (6), the wavelet-based method and component decomposition method both are invalid while the proposed method can detect the defect when complex texture exists. The operation time of wavelet-based method, component decomposed method and the proposed method are 0.32s (second), 8.56s and 0.93s respectively. Based on considerations of operating time and accuracy, the algorithm is feasible to automatic detection.

Figure 4. The defect detection results of the proposed and wavelet-based method and component decomposition method.

4. Conclusion
The traditional methods based on wavelet transforming are time saving but less accuracy. Though the component decomposition method has a good performance in defect detection, the computing time is too long to implement in industrial inspection. The present paper has presented a method to learn the transformation dictionary with the goals that the dictionary represents the defect-free image well and
defect image poorly. Then the reconstruction errors of test image are used to detect the defect region which has large reconstruction. The dictionary consists of the eigenvectors corresponding to L largest eigenvalues which are come from the PCA of test image. The experiments demonstrate the proposed method has good performance in accuracy and is feasible in real word.

References
[1] Xiang, Y., C. Zhang, and G. Qiang. "A dictionary-based method for tire defect detection." 2014 IEEE International Conference on Information and Automation (ICIA) IEEE, 2014.
[2] Ngan, Hyt, G. Pang, and N. Yung. "Automated fabric defect detection-A review." Image and Vision Computing 29.7(2011):p.442-458.
[3] Tsai, D. M., and C. H. Chiang. "Automatic band selection for wavelet reconstruction in the application of defect detection." Image and Vision Computing 21.5(2003):413-431.
[4] Guo, Q., and Z. Wei. "Tire Defect Detection Using Image Component Decomposition." Research Journal of Applied Sciences Engineering & Technology 4.1(2012): 41-44.
[5] Yang, J., et al. "Linear spatial pyramid matching using sparse coding for image classification." 2009 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR 2009), 20-25 June 2009, Miami, Florida, USA IEEE, 2009.
[6] Zhou, J., and J. Wang. "Fabric defect detection using adaptive dictionaries." Textile Research Journal 83.17(2013):1846-1859.
[7] Jian, Z., et al. "Sparse Dictionary Reconstruction for Textile Defect Detection." Proceedings of the 2012 11th International Conference on Machine Learning and Applications - Volume 01 IEEE, 2012.
[8] Li, X., et al. "Saliency Detection via Dense and Sparse Reconstruction." IEEE International Conference on Computer Vision IEEE, 2013.