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A Dictionary-based Method for Tire Defect Detection

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***Abstract*— In this paper, we propose a new tire defect detection algorithm based on dictionary representation. The dictionary learned from normal images is efficient to represent defect-free images while it has low efficiency to represent defect images due to its capability of capturing key information. Unlike the conventional iterative solution with complicated calculation, the representation coefficients are obtained by multiplying the pseudo-inverse matrix of the learned dictionary and image patch. Moreover, the distribution of representation coefficients is very different between defect-free image and defect image. Therefore, the distribution difference of representation coefficients can be used as a discrimination criterion to detect the defective region. Experimental results demonstrate that the proposed method can accurately detect defects.**

***Index Terms*— Defect detection, *K-SVD*, dictionary representation, Gaussian distribution**

I. Introduction

Automatic visual inspection plays an important role for quality control in modern tire industry. At present, defect inspection suffers from both low efficiency and high labor intensity and cannot meet the needs of high quality mass manufacturing. Application of computer vision techniques to tire defect detection can avoid the limitations of employing human inspectors [1].

In recent decades, numerous algorithms based on computer vision have been proposed to address the problem. Generally, defect detection techniques have been classified into statistical, spectral and model-based categories. Tsai and Chiang [2] proposed a wavelet-based defect detection method which has a fast implementation, and it is one of widespread implemented spectral methods because it has a low time complexity. However, this method will become invalid in the case of illumination intensity affected. Tajeripour *et al.* [3] proposed a method for detecting textural defects in fabrics based on modified local binary patterns.This method is capable to detect all kinds of the defects in fabrics which have regular and periodic textures. But, the method has same drawback with wavelet-based method. In [4], a tire defect detection method based on the component decomposition was presented, which is superior to the wavelet-based method in the performance. Despite the method has accurate detection results, the time complexity of this method is very high. Zhou and Wang [5] proposed a fabric defect detection method using adaptive dictionaries. This method which learns a adaptive dictionary from test image is computationally expensive. The fast defection method proposed by Zhou and Fei [8] learned a dictionary from reference image. This detection algorithm reconstructs test image based on sparse representation coefficients which is computationally expensive.

In this paper, we propose a simple method based on dictionary representation for tire defect detection. Dictionary representation is a powerful image analysis tool which has been successfully applied to many problems including image denoising, face recognition, image compression and so on. Unlike an adaptive dictionary [5], the proposed method learns a dictionary from normal images, which has low computational cost. Different from the conventional iterative solution, the representation coefficients of test image are computed by multiplying the pseudo-inverse matrix of the learned dictionary and image patch, the computational complexity of the proposed method is further reduced correspondingly. Generally, dictionary-based defect detection methods obtain the results by analyzing the restructuring error or distribution of representation coefficients. The proposed method uses the latter way to detect defects. Since the dictionary learned from normal images by K-SVD algorithm [6] is efficient to represent defect-free images due to its capability of capturing key information. But for the defect image, this dictionary has a lower efficiency than defect-free image. Moreover, the representation coefficients of defect-free image patches have a specific distribution, and the representation coefficients of defect image patches have another distinct distribution. Therefore, the distribution difference of representation coefficients can be used as a discrimination criterion to detect the defective region. Experimental results demonstrate that the proposed method can accurately detect defects.

This paper is organized as follows. In Section 2, we first briefly introduce the K-SVD theory. Then the proposed method is introduced in detail. Experimental results and analysis are presented in Section 3. Conclusions are drawn in Section 4.

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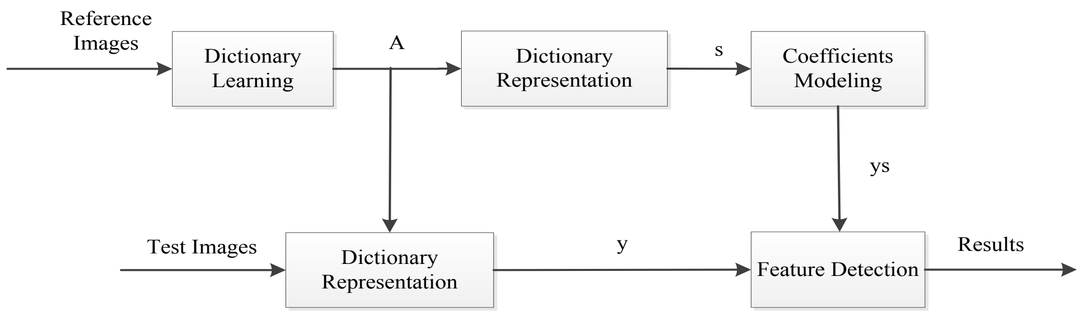

Fig. 1. The flow chart of the proposed method.

II. Proposed Method

We first learn a dictionary A from normal images using K-SVD algorithm. Such a dictionary can efficiently represent defect-free image patches using a linear combination of its elements. Let $A = [a_1, a_2, \ldots, a_n]$, a_i is an element of the dictionary A. If set A to be square, A will be approximately reversible. The proposed method uses the pseudo-inverse matrix of A to compute the representation. Suppose that there is a $n \times m$ data matrix $X = [x_1, x_2, \ldots, x_m]$ ($x_i \in R^n$) that contains m vectors of dimension n in its patch. Let W be the pseudo-inverse matrix of A, the representation coefficients S can be achieved from $S = WX$, this rapid method is developed in [7]. When representing a test image using the learned dictionary, representation coefficients of image patch involving defect are likely to have a distribution which is different from defect-free ones. Then a standard distribution is fitted using representation coefficients of normal image patches. When comparing the distribution of representation coefficients of test image with this standard one, the anomalous regions (defects) can be easily captured in the defect map. The calculation process mentioned above is displayed as a flow chart shown in Fig.1. In the rest of this section, all steps of the flow chart are described in detail.

A. Dictionary Learning

The goal of dictionary representation is to find a linear combination of dictionary elements to approximate a signal with minimum mean squared error. Suppose that there is a $n \times m$ data matrix $X = [x_1, x_2, \ldots, x_m]$. To create an approximation for every vector x_i in X, we need to find a dictionary $A = [a_1, a_2, \ldots, a_n]$, $a_i \in R^n$, that can represent all x_i in X. The problem of finding such a dictionary can be formulated as follows

$$\arg \min_{A, \{s_i\}_{i=1}^m} \sum_{i=1}^{m} \|x_i - As_i\|, 1 \leq i \leq m, \tag{1}$$

where $s_i \in R^n$ is the representation coefficients for x_i in X. Equation (1) is not a jointly convex problem, but convex with respect to A or s_i being fixed. In the learning process, A is iteratively produced by K-SVD algorithm using a given initialized dictionary. For ith iteration of K-SVD algorithm, s_i is computed by Orthogonal Matching Pursuit (OMP) algorithm using the dictionary obtained from $(i-1)$th iteration. The reconstruction error E_i in the iteration is computed using the following equation.

$$E_i = X - \sum_{j \neq i} a_j {x_j}^T. \tag{2}$$

In the update process, a_i is replaced by the first singular vector of singular value decomposition of E_i. When E_i is small enough, the iteration will be stopped. Unlike the over-complete dictionary, dictionary is set to be square so that it is approximately reversible. For example, a dictionary learned by K-SVD algorithm from 300 normal images is shown in Fig.2 A.

B. Dictionary Representation

A simple way obtained representation coefficients by multiplying the pseudo-inverse matrix of the learned dictionary and image patch is used in the proposed method. Given a vectorized image x, the goal of dictionary representation is to find s which satisfies the following equation.

$$x = As. \tag{3}$$

Let W be the pseudo-inverse matrix of the learned dictionary A. The obtained W is shown in Fig.1 W. Then s can be obtained by

$$s = Wx. \tag{4}$$

Since each dictionary element represents a structural primitive in the representation of images, only a small population of elements is activated at one time. In other words, when a defect-free image patch is represented by A, most absolute values of representation coefficients s are small.

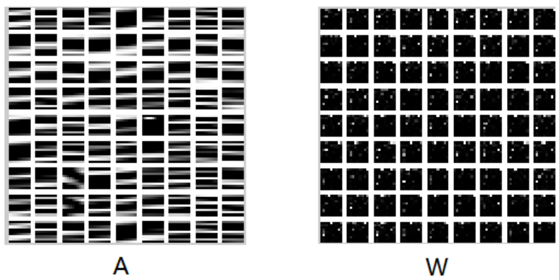

Fig. 2. The learned dictionary A and its pseudo-inverse matrix W

C. Coefficients Modeling

By observing coefficients of 120 defect-free images and 60 defect images, we found that the representation coefficients of defect-free images are obeyed a specific distribution and the defect images have a totally inverse distribution. As shown in the Fig.3 (a), the representation coefficients distribution of defect-free image patches are approximate to a Gaussian distribution. Especially, the distribution of defect images coefficients distribution are distinct from defect-free ones, it is shown in Fig.3 (b). As mentioned above, we can use a Gaussian model to fit a standard curve using representation coefficients of normal image patches. The standard curve is fitted by formulation shown as follows

$$ys = a \cdot e^{-(\frac{y-b}{c})^2}, \tag{5}$$

where y is a statistical data from representation coefficients of normal image patches. The fitting result is shown in the Fig.4 which parameters setting obtained by experiment are as follows: $a = 28.67, b = 9.988, c = 23.36$.

D. Defect Detection

A anomaly map is used to show the detected result. The anomaly value of each pixel reflects the distribution difference of representation coefficients between the $c \times c$ image patch centered this pixel and standard distribution mentioned above. Considering the effects of the boundary, if the size of test image X is $m \times n$, the size of map will be $(m - c) \times (n - c)$. The anomaly value of ith image patch is defined as

$$p_i = \frac{\|ys - y_i\|}{\|ys\|}, \tag{6}$$

where y_i is the distribution of representation coefficients of ith image patch, and ys is a standard distribution fitted in section2.C. The defect regions can be easily enhanced using

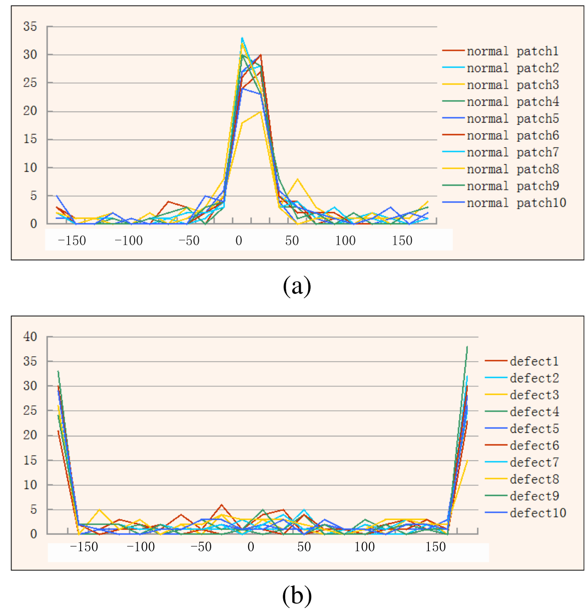

Fig. 3. The distributions of representation coefficients of defect-free image patches shown in (a), the distributions of representation coefficients of defect image patches shown in (b).

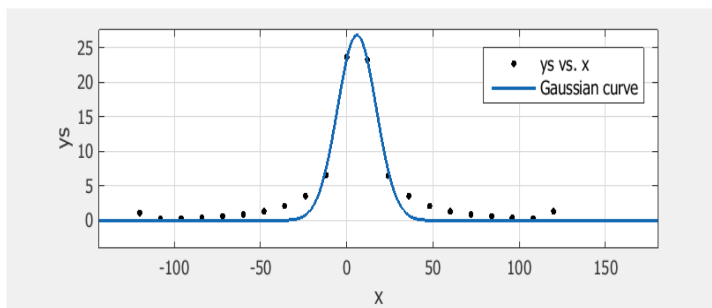

Fig. 4. The Gaussian curve ys fitted by statistical data y computed from representation coefficients of normal images.

a simple threshold operation to segment the defective pixels from the anomaly map.

To summarized, the proposed method is algorithmically described as follows.

1. The preprocessing stage
   a. Learning a dictionary A from normal images and computing the pseudo-inverse matrix of A, i.e. $W = A^{-1}$.
   b. Computing representation coefficients S of the given normal images X, i.e. $S = WX$.
   c. Computing statistical data Y from S and modeling the standard Gaussian curve ys using y.
2. The detection stage
   a. Computing representation coefficients of ith image patch $s_i = Wx_i$.
   b. Computing the statistic data y_i from s_i.

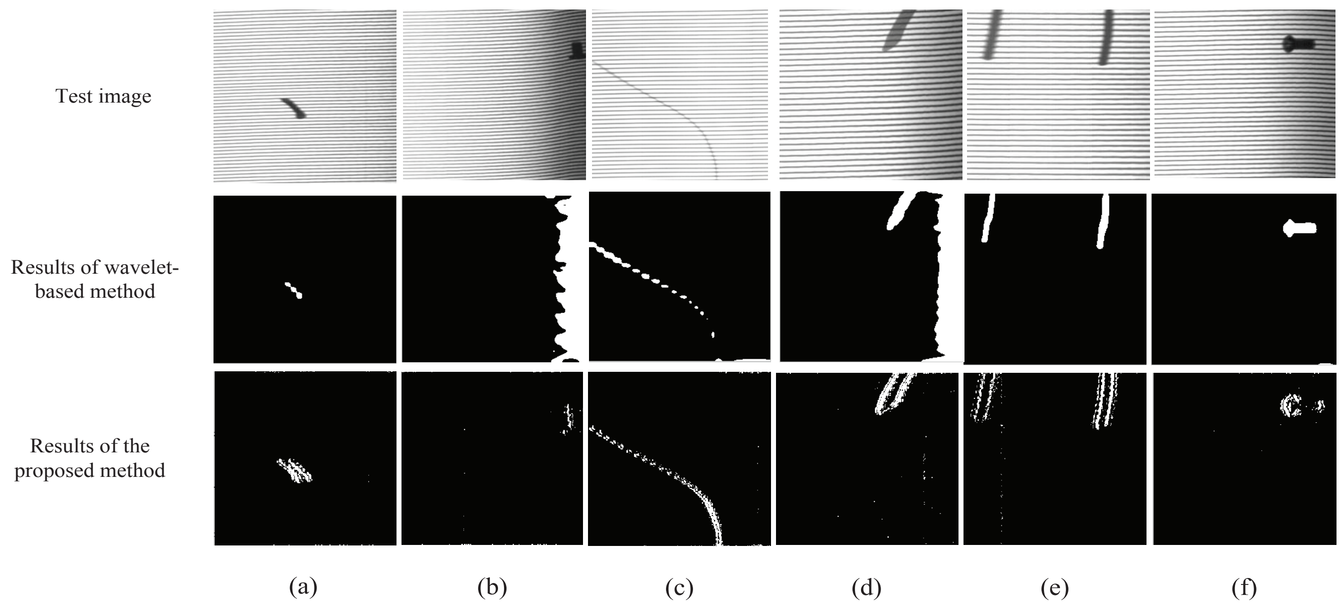

Fig. 5. Exact results of defect detection, significant anomaly values centered on boundary of defect.

c. Computing ith value of anomaly map using equation (6).

III. EXPERIMENTS

In this section, we have shown the experimental results. Since no standard data set exists and source codes of related approaches are not available for comparison, we demonstrate the efficiency of our algorithm by offering two detection efficiency criteria include error ratio (ER) and detection ratio (DR). All images used in this paper are come from a production line where the tire side X-ray images are captured by one machine, and each image has the size 256×256 with 256 gray levels. The proposed algorithms is implemented on a personal computer with a Pentium Core 2 Duo 3.20 GHz processor.

In the experiments, we learn a dictionary A by K-SVD algorithm from 300 normal images. The representation coefficients of 300 normal images are computed by an efficient method mentioned in section2 B by computing the pseudo-inverse matrix of A. The obtained representation coefficients are used to compute statistical data y. Then ys is fitted by y by equation (5) mentioned in section2.C. We select 459 defect-free images and 290 defect image as test data. Generally, an efficient defect detection method should satisfy two conditions, defect-free image should not be mistakenly identified as defect image and defect images should be accurately detected. On the other words, an efficient detection method must has a low ER and a high DR. ER and DR are computed by following equations.

$$ER = \frac{Ne}{Nn}, \tag{7}$$

$$DR = \frac{Nc - Nd}{Nc}, \tag{8}$$

where Ne is the number of defect-free images which are error detected, Nn is the number of defect-free images, Nd is the number of the defect images without being detected and Nc is the number of defect image. In this paper, the obtained ER and DR are 1.9% and 93.4% respectively. The test results show that the proposed method outperforms methods proposed in [4] and [2].

The experimental results show that the proposed method is competent to detect the impurity defects. It has two following advantages. One is time saving as the difficult of learning dictionary is accomplished in one-time preprocess procedure and the computation of representation coefficients just needs a matrix multiplication. Another is accurate to defect the impurity defect. Fig.5 shows the results of our algorithm. From it, we can clearly see the accuracy of the proposed method.

IV. CONCLUSION

In this paper, we propose an algorithm for tire defect detection based on dictionary representation. Since the dictionary is learned from normal images, the proposed method has more lower computational complexity than the conventional detection methods based on an adaptive dictionary. Furthermore, we use a rapid algorithm which obtain the representation coefficients by multiplying a pseudo-inverse matrix of the learned dictionary and image patch to further reduce total computational complexity. Specially, the representation coefficients of defect-free images obey Gaussian distribution and the representation coefficients of defect images have distinct distributions. Defect regions can be detected by comparing the distributions of representation coefficients with defect-free ones. Experimental results clearly show that our method has accurate detection results.

REFERENCES

[1] A. Kumar, "Computer-vision-based fabric defect detection: a survey," *IEEE Trans. Industrial Electronics* , vol. 55, no.1, pp.348–363, 2008.

[2] D. Tsai and C. Chiang, "Automatic band selection for wavelet reconstruction in the application of defect detection," *Image and Vision Computing*, vol. 21, no. 5, pp.413–431, 2003.

[3] F. Tajeripour, E. Kabir, and A. Sheikhi, "Fabric defect detection using modified local binary patterns," *EURASIP Journal on Advances in Signal Processing*, vol. 2008, 783898, 2008.

[4] Q. Guo and Z. Wei, "Tire defect detection using image component decomposition," *Research Journal of Applied Sciences, Engineering and Technology*, vol. 4, no. 1, pp.41–44, 2012.

[5] J. Zhou and J. Wang, "Fabric defect detection using adaptive dictionaries," *Textile Research Journal*, vol. 83, no. 17, pp.1846–1859, 2013.

[6] M. Elad and M. Aharon, "Image denoising via sparse and redundant representations over learned dictionaries," *IEEE Trans. Image Processing*, vol. 15, no. 12, pp.3736–3745, 2006.

[7] X. Hou and L. Zhang, "Dynamic visual attention: searching for coding length increments," *Proceedings of the 2008 Conference on Advances in Neural Information Processing Systems*, pp.681–688, 2009.

[8] W. Zhou, M. Fei, H. Zhou and K. Li, "A sparse representation based fast detection method for surface defect detection of bottle caps," *Neurocomputing*,Vol. 123, Issue 1, 404-414, 2014.