

Tire Defect Detection Using Image Component Decomposition

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Abstract: This study presents a component decomposition based method for fast tire defect detection, which is motivated by the fact that defective tire images mainly consist of three components: texture, background and defect. Thus the proposed method exploits three steps to separate the defect component from the defective image. At the first step, the local total variation filtering is used to extract the texture. Then the background is estimated by the vertical mean filtering. Finally, the defect is detected by thresholding the residual image. Experimental results show that the proposed method is more accurate in locating the defects.

Key words: Defect detection, image decomposition, local total variation, the wavelet transform

INTRODUCTION

Automatic defect detection, as an important step for quality control, is highly demanded by industry to replace the manual inspection (Kumar, 2008 and Xie, 2008). The chief aim of automatic defect detection is to detect the small defects that locally break the homogeneity of texture. Over the past two decades, many attempts have been made to solve this problem. Most of them tackle this problem by extracting the texture features in the spatial domain using co-occurrence matrix (Ramana and Ramamoorthy, 1996), least squares lattice (Meylani, 2006) and structural texture analysis (Zhu, 2009). However, these methods are computational expensive, which is not suitable for real-time detection.

Tsai and Hsiao (2001) and Tsai and Chiang (2003) proposed a wavelet-based defect detection method that has a fast implementation. The basic idea of this wavelet-based method extracts the texture by suppressing low frequency wavelet coefficients. This process, however, can leak a piece of high frequency information (i.e., texture features), which lead to inaccurate detection results.

The local total variation filtering has recently been introduced for image decomposition (Buades *et al.*, 2010). In this paper, we have extended its utilities to the tire defect detection problem. To overcome the drawback of the wavelet-based method, we present an effective and fast method for the tire defect detection, which is based upon image component decomposition. This proposed method is motivated by the fact that defective images mainly consist of three components: texture, background and defect. Therefore, we use two different filtering

methods to successively separate the texture and background components from the defective image. Then the defect is detected by thresholding the residual image. The experiments performed on real defective images clearly indicate that our method is superior to the wavelet-based method in locating defects.

PROPOSED METHOD

For a given defective image f , it can be expressed as sum;

$$f = u + v \quad (1)$$

where u represents the piecewise-smooth component (e.g., background and defect) of f , v represents the oscillatory component (e.g., texture) of f , respectively. The most popular framework for splitting an original image f into two components (i.e., u and v) is given by the Total Variation (TV) model (Rudin *et al.*, 1992), which is to minimize the functional F_λ^v defined by:

$$J(u) + \lambda \|f - u\|_{L^2}^2 \quad (2)$$

where, $J(u) = \int |\Delta u|$ is the TV of u and λ is a regularization parameter. Although the TV model is very suitable to characterize the smooth component, it does not characterize the oscillatory component. To overcome this drawback, Buades *et al.* (2010) proposed a fast image decomposition filter (Buades *et al.*, 2010), which is based upon the fact that TVs of the piecewise-smooth component and the oscillatory component have different reduction characteristics. The Local Total Variation (LTV) is

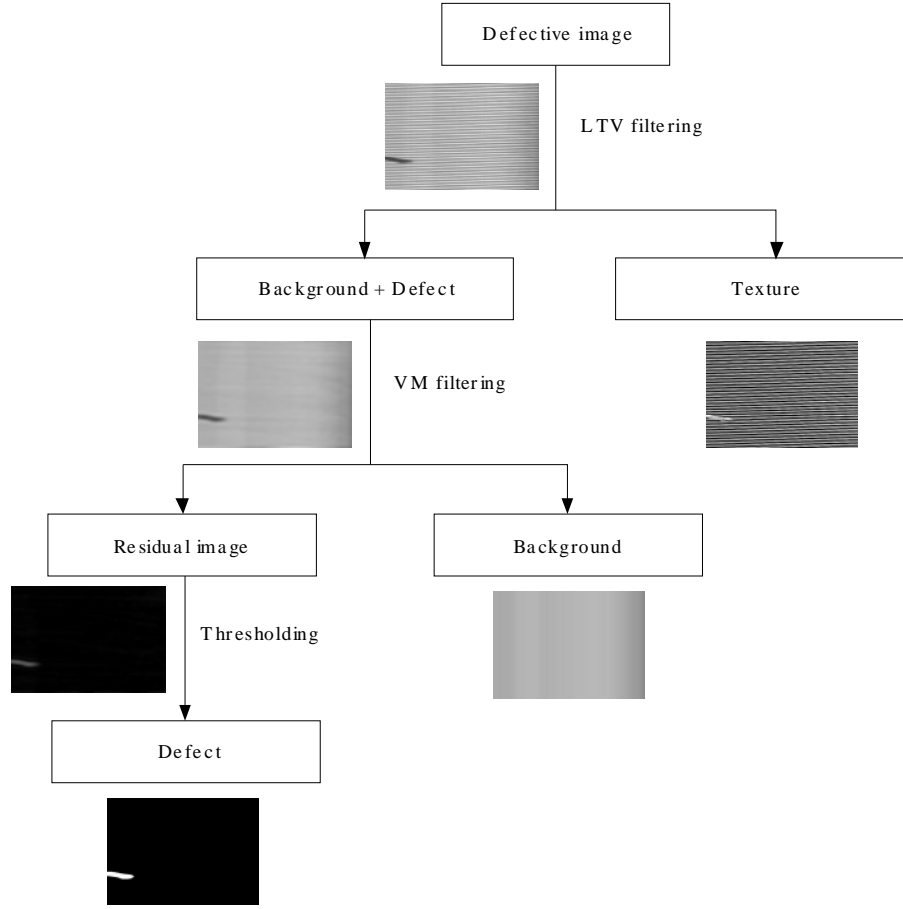


Fig. 1: Block diagram of the proposed method

introduced to describe the reduction characteristics, which is given by:

$$LTV_{\sigma}(f) = L_{\sigma} * |\nabla f| \quad (3)$$

where L_{σ} is defined in the Fourier domain i.e.,

$$\hat{L}_{\sigma}(\xi) = \frac{1}{1 + (2\pi\sigma|\xi|)^4}$$

and σ is the scale parameter of texture. The piecewise-smooth component u is given by:

$$u = g(LTV_{\sigma}(f))(L_{\sigma} * f) + (1 - g(LTV_{\sigma}(f)))f'' \quad (4)$$

where, $g(\cdot)$ is a thresholding function (for more details, see (Buades *et al.*, 2010)). Thus the texture component v can be obtained by $v = f - u$.

In order to extract the defects in defective images, we further decompose u into two components: u_b

(background) and u_d (defect). For u_b , we introduce a Vertical Mean Filter (VMF) to estimate it from u . Let u be a $n \times n$ image, the discrete version of VMF is defined as:

$$u_b[i, j] = \frac{1}{n} \sum_{i=1}^n u[i, j] \quad (5)$$

The u_d , therefore, is given by $u_b = u - u_d$.

Although the main component of u_d is the defect, it still has some residual left. Finally, we exploit the Ng's thresholding to distinguish the defect from the residual (Ng, 2006). Let L be the number of distinct gray-levels, the number of pixels with gray-level i be n_i and N be the total number of pixels in a given image, the Ng's thresholding process can be expressed as:

$$I_d[i, j] = \begin{cases} 1 & \text{if } u_d[i, j] \geq L\lambda \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

where λ is the threshold. The optimal threshold is given as:

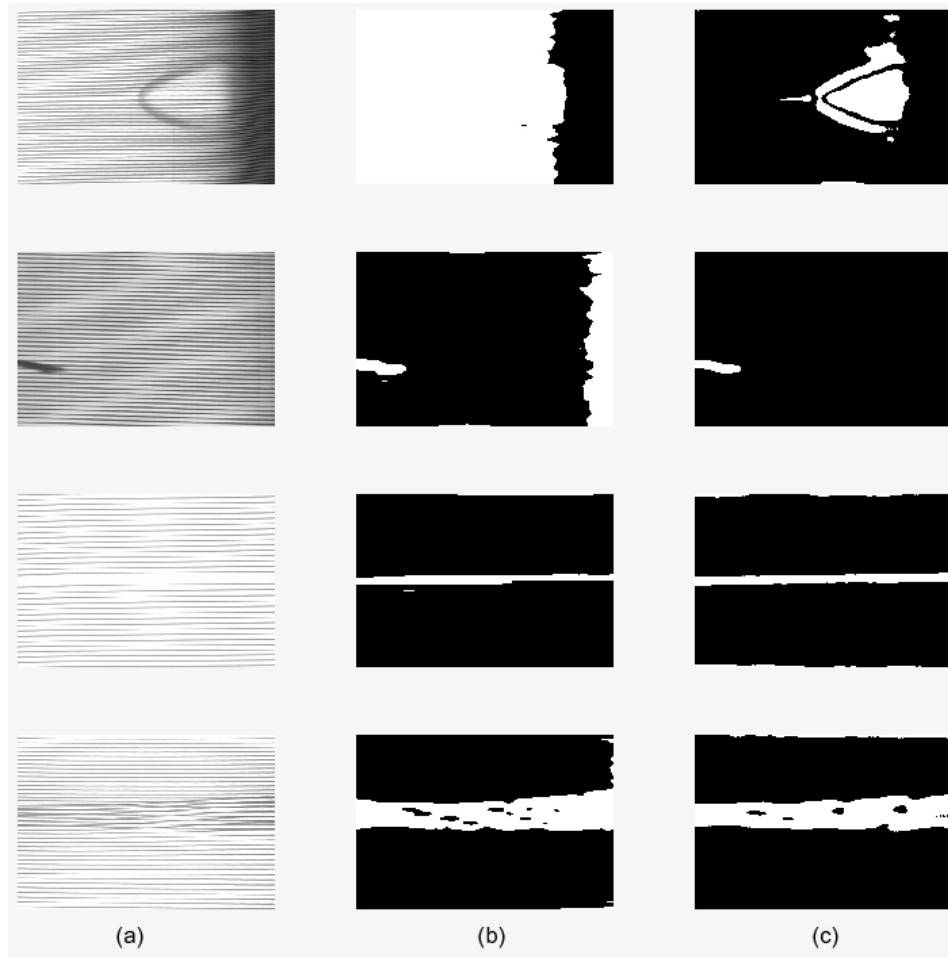


Fig. 2: (a) Test images from top to bottom: bubble, impurity, sparsity and cross; (b) Detection results generated by the wavelet-based method; (c) Detection results generated by the proposed method

$$\lambda = \arg \max_{0 \leq r \leq L} \left\{ (1 - p_t)(\omega_1(t) u_1^2(t) + \omega_2(t) u_2^2(t)) \right\} \quad (7)$$

where,

$$p_i = \frac{n_i}{N}, \omega_1(t) = \sum_{i=0}^t p_i, \omega_2(t) = \sum_{i=t+1}^{L-1} p_i$$

$$\mu_1(t) = \frac{\sum_{i=0}^t i p_i}{\omega_1(t)} \text{ and } \mu_2(t) = \frac{\sum_{i=t+1}^{L-1} i p_i}{\omega_2(t)}$$

Figure 1 illustrates the overall block diagram of our proposed method. The operational procedure can be summarized as follows:

- Extract the piecewise-smooth component u from the input defective image f using the Local Total Variation (LTV) filtering (4).

- Estimate the background u_b using the Vertical Mean (VM) filtering (5).
- Extract the defect component u_d by subtracting the background u_b from u .
- Segment the defect from u_d using the Ng's automatic thresholding (6).

EXPERIMENTS

In the experiments, we use four defective images bubble, cross, impurity and sparsity, which are provided by Linglong Tyre Co. Ltd. The proposed method is evaluated by comparing with the wavelet-based defect detection method. In all comparisons, we use Daubechies wavelet with four vanishing moments over three decomposition levels for the wavelet-based method, and for our method we set the scale parameter of texture equal to 7. The proposed method is implemented in Matlab 7.0. Figure 2 shows the detection results of two methods for

test images. We can observe that our proposed method substantially outperforms the wavelet-based method for detecting defects in texture images, especially for bubble and impurity.

CONCLUSION

Motivated by defective images containing three components: texture, background and defect, we present a tire defect detection method based on the component decomposition. The texture and background components can be extracted by using LTV filtering and vertical mean filtering, respectively. Then the Ng's thresholding is used to separate the defect from the residual image. Experimental results demonstrate that our proposed method is superior to the wavelet-based method.

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