MULTI-SCALE DEFECT DETECTION NETWORK FOR TIRE X-RAY IMAGES

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ABSTRACT

Though automatic detection method has been tremendous improved, with the gradual penetration of deep learning. Defect detection in many industrial processes is one of the remaining challenging tasks due to the diversity of its products. In this work, we focus on detection tasks in tire industry and develop a *Multi-scale Defect Detection Network (MDDN)*, which contains two parallel sub-networks to capture multi-scale defect features. Specifically, high-abstracted semantic features containing defect shapes and locations are mined via a *Semantic-aware sub-network*, simplified by an off-the-shelf fully convolutional network. Furthermore, to complement the details filtered by the deep network, a novel *Texture-aware Sub-network* is used to exploit the small size of the cover edge features and small defects as much as possible. Finally, the pixel-wised detection results are obtained by fusing features with semantic and texture information. Extensive experiments demonstrate that *MDDN* can produce comparable results and achieve significantly performance improvement in small defects detection.

***Index Terms*—** Defect detection, Fully convolutional network, Semantic segmentation, Multi-scale context

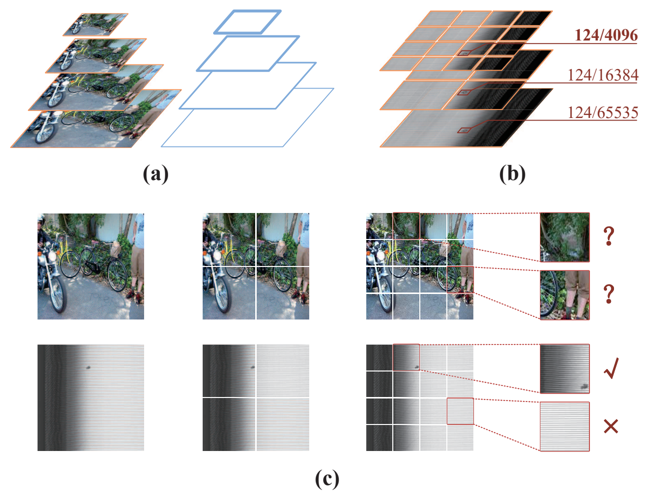

Fig. 1. Detection results of several benchmark architecture. (a) shows input tire images with different defects. From top to bottom, the first four are tire sidewall images, which involve following defect types: impurity, overlap, slack, bubble. The last two are tire tread images, which involve overlaps.

1. INTRODUCTION

Automatic defect detection, used to improve quality and accelerate production, has become an indispensable part in industrial processes, such as fabrics[1, 2, 3], steel[4], semiconductors[5], and solar wafers[6]. Especially in tire manufacturing, numerous detection algorithms have been proposed[7, 8, 9, 10, 11] and aroused extensive attention over the past two decades. In most real-world applications, tire defect detection is first carried out by deriving the defective region from tire X-ray images, which contains various types of defects caused by unclean raw materials and undesired manufacturing facilities[12]. Then, the defective product is hierarchical processed according to the location and size of defects. Due to unique properties of the tire image, for instance complexity and low-quality, illustrated in previous study[13, 14], most inspection processes are performed by human observers, which increases the risk and reduces the efficiency. Therefore, tire defect detection remains one of the most challenging inspection tasks.

At present, existing computer vision based detection methods are mostly devoted to distinguish difference between defective regions and background (defective-free regions). Hence a key issue for such methods is feature extraction. Guo *et al.*[11] exploited a local kernel regression descriptor to derive feature vectors. By comparing the dissimilarity of the corresponding feature between one pixel and its neighbors, anomaly pixels can be located and segmented, even in the tread image. Nevertheless, this method is not suitable for real-time detection tasks because of the high computational complexity. A component decomposition based method was proposed in[12], which separated the background from the image by means of two designed filters.

Then through an adaptive thresholding processing, defects were derived from the residual image. Besides, Independent component analysis(ICA) was also used for defect detection tasks[8, 9]. A major disadvantage of these fundamental methods is the limitation of the information contained in low-level clues and domain features. To address the limitation, Zhang *et al*.[7] and Zhang *et al*.[13] introduced radon transform and mulit-scale transform, for instance curvelet and wavelet transform, in detection tasks respectively. Furthermore, optimized edge detection and total variation algorithm are used to achieve more accurate results[15]. Zhao *et al*.[16] proposed a multiple kernel learning method, which combined various transform kernels to get more differentiated information. However, the representation capability of fixed kernels is not comprehensive enough. In addition, transform process is computationally expensive. Recently, Cui *et al*.[17] attempted to classify tire defects by means of convolutional neural networks(CNN), which has outstanding performance in the recognition and segmentation tasks of natural images. With the excellent feature extraction capability of deep network, Wang *et al*.[14] further implemented the detection and segmentation in tire images by a fully convolutional network(FCN)[18]. However, FCN is not sensitive to small defects and edge details, which is similar to that in dealing with natural image tasks.

2. MULTI-SCALE DEFECT DETECTION NETWORK

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4. CONCLUSION

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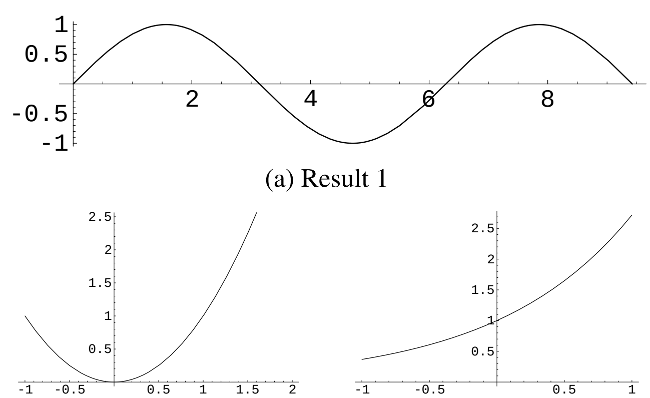

(a) Result 1

(b) Results 3

(c) Result 4

Fig. 2. Example of placing a figure with experimental results.

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