2018 IEEE 7th Data Driven Control and Learning Systems Conference
May 25-27, 2018, Enshi, Hubei Province, China

Yarn-dyed Fabric Defect Detection with YOLOV2 Based on Deep Convolution Neural Networks

Hong-wei Zhang[1], Ling-jie Zhang[1], Peng-fei Li[1],De Gu[2]

1. Xi'an Polytechnic University, JinHua South Road, Xi'an, ShaanXi, 710048, China

2. Key Laboratory of Advanced Process Control for Light Industry (Ministry of Education), Institute of Automation, Jiangnan University,Wuxi 214122, China
E -mail: 379530773@qq.com

Abstract: To reduce labor costs for manual extract image features of yarn-dyed fabric defects, a method based on YOLOV2 is proposed for yarn-dyed fabric defect automatic localization and classification. First, 276 yarn-dyed fabric defect images are collected, preprocessed and labelled. Then, YOLO9000, YOLO-VOC and Tiny YOLO are used to construct fabric defect detection models. Through comparative study, YOLO-VOC is selected to further model improvement by optimize super-parameters of deep convolutional neural network. Finally, the improved deep convolutional neural network is tested for yarn-dyed fabric defect detection on practical fabric images. The experimental results indicate the proposed method is effective and low labor cost for yarn-dyed fabric defect detection.

Key Words: yarn-dyed fabric, deep convolutional neural networks, defect detection, YOLOV2

1 Introduction

Fabric quality control is very important in textile industry [1]. However, due to problems of equipment failure and worker's fatigue, fabric surface defects are inevitable. The efficiency of traditional manual method is low and the miss rate is high due to subjectivity and other shortcoming. Thus an automation fabric defect detection method is necessary for textile industry.

In the literature, fabric defects detection methods are included in six approaches: statistical, spectral, model-based, learning, structural and hybrid approaches [2-3]. Hanbay K et al. proposed a real time fabric defect detection by using Fourier transform, results show that the proposed detection model can successfully detect common circular knitting fabric defects [4]. Some fabric detection methods based on Gabor and Wavelet transform are also proposed [5-6]. Li Wenyu et al [7-8] used the improved Log-Gabor filter and local binary as image features, and used the threshold or matched support vector classifier to implement defect detection and classification of color fabrics, Zhu Dandan et al. [9-10] used autocorrelation function to extract the minimum unit of pattern, and finally used artificially threshold to judge the defect area. In recent years, Neural networks are also gradually being used for detection [11]. Li, Y. D. et al. proposed deformable patterned fabric defect detection with Fisher criterion-based deep learning and used deep learning method for the first time to extract yarn-dyed feature, the experimental results demonstrate the deep learning is fitted for periodic patterned fabric and more complex jacquard warp-knitted fabric [12].

Based on the method above, traditional defect algorithms are only suitable for specific fabric defect detection, and also need to extract features manually. By contrast, convolutional neural networks under deep learning can extract features autonomously [13]. So, this paper presents a yarn-dyed fabric defect detection method with YOLOV2 based on deep convolution neural networks [14-15]. First, a yarn-dyed fabric defect piece samples dataset is created. Second, YOLO 9000, YOLO-VOC, and Tiny-YOLO are used to construct yarn –dyed fabric defect detection models, respectively, for comparison. Then, YOLO-VOC is improved by super-parameter optimization for defect classification and localization. Finally, features extracted from the optimal model are used to classify and locate the defects.

2 Method

There are many network structures in YOLOV2. These network structures have different convolutional layers, pooling layers, hyper parameters, activation function. Many network models can be used in YOLOV2, in this paper, we will use YOLO9000, Tiny-YOLO and YOLO-VOC network model structure for comparative study. Fig.1 shows the overall framework of yarn-dyed fabric defect detection system.

*This work is supported by Natural Science Foundation of Shaanxi Educational Committee (Grant No. 17JK0328) and Key Laboratory of Advanced Process Control for Light Industry（Grant No. APCLI160）

978-1-5386-2618-4/18/$31.00 ©2018 IEEE DDCLS'18

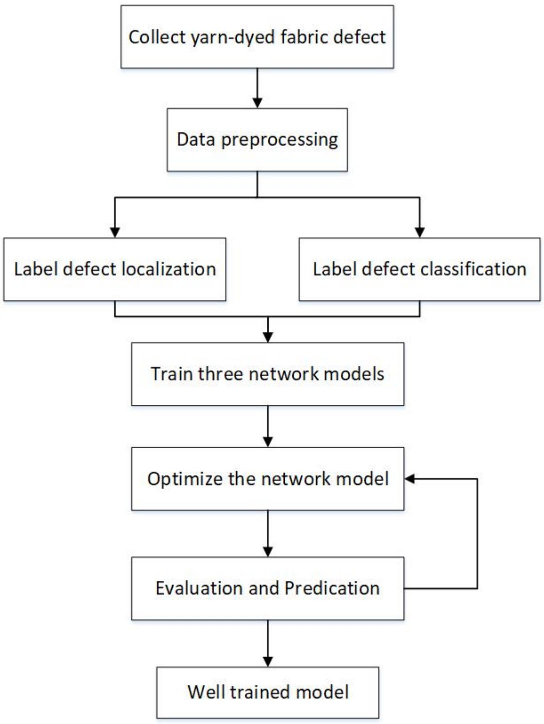

Fig.1 Yarn-dyed fabric defect detection system

2.1 YOLO9000

Table 1 shows the architecture of YOLO9000 network model.544 *544 pixels with three color channels are inputted in the network, and this network model structure is simplified to 24 layers, it has 19 convolutional layers and 5 max-pooling layers, and the last layer of convolution uses average pooling. Leaky ReLU ((Leaky Rectified Linear Unit) function is used as the activation function behind every convolution layer except for the last convolution layer. The softmax function is used as the regression function of the network model. The algorithm uses the Sum-Squared Error (SSE) method to calculate the loss.

Tab.1 YOLO9000 network structure

	layer	Input	output
0	Conv	544*544*3	544*544*32
1	Max	544*544*32	272*272*32
2	Conv	272*272*32	272*272*64
3	Max	272*272*64	136*136*64
4-6	Conv	136*136*64	136*136*128
7	Max	136*136*128	68*68*128
8-10	Conv	68*68*128	68*68*256
11	Max	68*68*256	34*34*256
12-16	Conv	34*34*256	34*34*512
17	Max	34*34*512	17*17*512
18-23	Conv	17*17*512	17*17*28269

2.2 YOLO-VOC

Table 2 shows the architecture of YOLO-VOC network model. In this network model, the input images are size of 256 *256 pixels with three color channels, and this network model structure is more complicated than YOLO-9000, it has 22 convolutional layers and 5 max-pooling layers. Leaky ReLU ((Leaky Rectified Linear Unit) function is used as the activation function behind every convolution layer except for the last convolution layer. The softmax function is used as the regression function of the network model. The algorithm uses the Sum-Squared Error (SSE) method to calculate the loss.

Tab.2 YOLO-VOC network structure

	layer	Input	output
0	Conv	256*256*3	256*256*32
1	Max	256*256*32	128*128*32
2	Conv	128*128*32	128*128*64
3	Max	128*128*64	64*64*64
4-6	Conv	64*64*64	64*64*128
7	Max	64*64*128	32*32*128
8-10	Conv	32*32*128	32*32*256
11	Max	32*32*256	16*16*256
12-16	Conv	16*16*256	16*16*512
17	Max	16*16*512	8*8*512
18-24	Conv	8*8*512	8*8*1024
25	route		
26	reorg	16*16*512	8*8*2048
27	route		
28-29	Conv	8*8*3072	8*8*40

2.3 Tiny-YOLO

Tiny-yolo has less network layer, Table 3 shows the network model of Tiny-YOLO, this network including 9 convolutional layers and 6 max-pooling layers. The softmax function is used as the regression function of the network model. The algorithm uses the Sum-Squared Error (SSE) method to calculate the loss. Leaky ReLU ((Leaky Rectified Linear Unit) function is used as the activation function behind every convolution layer except for the last convolution layer.

Tab.3 Tiny-YOLO network structure

	layer	input	output
0	Conv	416*416*3	416*416*16
1	Max	416*416*16	208*208*16
2	Conv	208*208*16	208*208*32
3	Max	208*208*32	104*104*32
4	Conv	104*104*32	104*104*64
5	Max	104*104*64	52*52*64

6	Conv	52*52*64	52*52*128
7	Max	52*52*128	26*26*128
8	Conv	26*26*128	26*26*256
9	Max	26*26*256	13*13*256
10	Conv	13*13*256	13*13*512
11	Max	13*13*512	13*13*512
12-14	Conv	13*13*512	13*13*35

2.4 Detection and evaluation of criteria

Detection part uses a single CNN to complete the prediction of the entire image's frame and category probabilities, making it possible to achieve end-to-end optimizations while also increasing the speed of the framework. In the detection system, the input image is divided into S*S grid cell, each grid cell predicts B bounding boxes, each containing 5 predicted values: x, y, w, h and confidence. (x, y) is the center coordinate of the detected target window, w and h are the width and height of the target window respectively, and the confidence value represent the confidence level of the predicted target box and the predicted accuracy, where the value is calculated as:

$$confidence = pr(object) * IOU_{pred}^{truth} \tag{1}$$

If there is a goal falling in a grid, the first one should take 1, otherwise take 0. The second is the IOU between the predicted box and the actual situation, the calculation of IOU is:

$$IOU = \frac{Detection\ result \cap Ground\ truth}{Detection\ result \cup Ground\ truth} \tag{2}$$

Each grid also need to forecast a category of information, recorded as C class. S*S grids, each grid to predict B bounding box but also predict C categories. The output is a tensor of S *S (5 * B + C).

At test time, criteria for the test result are based on the values of IOU, Recall, and Precision. Among them, T_P refers to the positive class judged as positive class, F_p refers to the negative class judged as positive class and F_n refers to the positive class judged as negative class. In experiment, we hope three values become larger and better:

$$recall = \frac{T_P}{T_p + F_N} \tag{3}$$

$$precision = \frac{T_p}{T_p + F_P} \tag{4}$$

YOLOV2 has made a series of improvements in the candidate box compared to YOLO, using the idea of anchor in Faster R-CNN to predict each bounding box separately. At the same time achieve multi-target detection, while improving the accuracy of the original speed while maintaining the test, at 67 FPS, YOLOv2 gets 76.8 mAP on VOC 2007. At 40 FPS, YOLOv2 gets 78.6 mAP, based on this, we will use YOLOV2 algorithm to locate and classify the yarn-dyed fabric defects.

3 Experimental

Our experiment is mainly composed of these parts: the preparation of dataset, model training, selection and optimization, and the prediction and evaluation.

3.1 Experimental equipment

The experimental GPU platform Devtop SCW4750 was shown in Figure 2. it uses a CPU Intel i7-i7-5930, this machine has four NVIDIA GeForce TitanX 12G and eight 8G memory. The operating system is Ubuntu 14.04.

Fig.2 Experiment platform

3.2 Dataset

In this paper, the yarn-dyed fabric defect pieces are collected from an enterprise.276 manually labeled defect images contained three classes (Belt yarn, Knot tying, hole) of defects. Part of the yarn-dyed fabric image is shown in Figure 3 below. 72% of the labeled images were randomly selected as the training set, 10% as the test set, and 18% as the validation set.

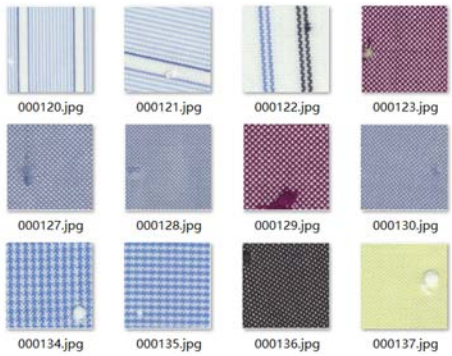

Fig.3 yarn-dyed fabric defect pieces

3.3 Experiment and results

As we described in the previous section, the experiment used an enterprise defect images for training, the trained network models YOLO9000, YOLO-VOC, Tiny-YOLO were iterated 10000 times on the Titan X GPU, respectively. The training experiment of Tiny-YOLO network spent 3 to 4 hours, YOLO9000 spent 4 hours and YOLO-VOC spent 6 hours for training, then a network that was more friendly to the detection was selected for optimization. As can be seen from Table 4, YOLO9000 is not suitable for the detection of the above defect samples, the precision and recall values are 0, the model predicted one image need 0. 066s.Tiny-YOLO has low precision and recall values; the model need 0.0057s to predict one defect image. YOLO-VOC model shows better precision and recall values, two average values were 86.8321% and 88.2484%, respectively, and the value of IOU is stable at about 69% up to 80%, The main reason is that the defects are smaller in the fabric and the frame selection area is smaller too, so the overlap area may be deviated to affect the overall IOU value. In general, when the IOU value is around 50%, defects can be located and classified. And the predicted time of YOLO-VOC trained model is only 0.023s for each image. By comparison, our experiment selected YOLO-VOC network model and continued to improve the learning rate, iteration and network structure of the network model.

Tab.4 Training results evaluation index for three models

Model	YOLO9000	Tiny-YOLO	YOLO-VOC
Average recall	0%	6.038421%	88.2484%
Average precision	0%	36.95737%	86.8321%
Average IOU	0%	9.4%	69.45%
Average predicted time	0.0660s	0.0057s	0.0230s

In experimental process, the accuracy of the experiment is affected by the number of iterations of the network model and the size of the learning rate, the experiment through a comparative study by changing the learning rate to optimize the network model's capability. Two optimization methods was proposed by changing the number of iterations and learning rate. First, the iterations of the network were added to 20000 times, the original learning rate was changed to 0.01. Then, the iterations of the network were added to 30000 times, the original learning rate was changed to 0.01 too. The experimental results were shown in Figure 5, change 1 represented the first optimization, change 2 represented the second optimization, the experimental result show when iterations are 20000, the initial learning rate is setting as 0.01, activation function is setting as leaky ReLU, the precision and recall values of network model is the best one. So the first trained network model was choose as a test model. The test results were shown in Figure 4, this method can locate and classify yarn-dyed fabric defects accurately without manual feature extraction.

Tab.5Model optimization results

Model	Change 1	Change 2	YOLO-VOC
Average recall	93.9633%	92.6179%	88.2484%
Average precision	94.5167%	90.557%	86.8321%
Average IOU	66.7%	66.35625%	69.45%
Average predicted time	0.0230s	0.0230s	0.0230s

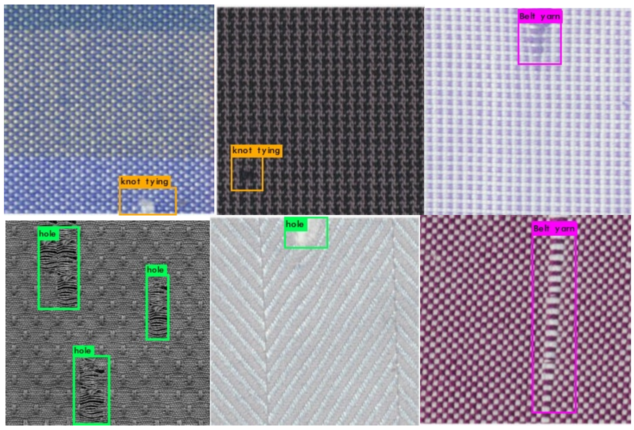

Fig.4 Experimental test results

4. Conclusions

In this paper, a method of YOLOV2 for yarn-dyed fabric defect classification and localization was proposed. Experimental result show that our method only used limited negative samples and can automatically extract defects' features. It's not only meet the accuracy requirement, but also meet the need of real-time industrial inspection of yarn-dyed fabric defects detection. Future work is mainly aimed at optimizing the loss function and improving the evaluation results.

References

[1] Ngan H Y T, Pang G K H, Yung N H C. Automated fabric defect detection—A review[J]. *Image & Vision Computing*, 2011, 29(7):442-458

[2] Schneider D, Merhof D. Blind weave detection for woven fabrics[J]. Pattern Analysis & Applications, 2015, 18(3):725-737.

[3] Hu G H, Wang Q H, Zhang G H. Unsupervised defect detection in textiles based on Fourier analysis and wavelet shrinkage[J]. *Applied Optics*, 2015, 54(10):2963-80.

[4] Hanbay K, Talu MF, Ozguven OF. Real time fabric defect detection by using Fourier transform. *Journal of the Faculty of Engineering and Architecture of Gazi University.* 2017,32(1):151-8.

[5] P. F. Li, H. H. Zhang, J. F. Jing, R. Z. Li, and J. Zhao, "Fabric defect detection based on multi-scale wavelet transform and Gaussian mixture model method," *J. Textile Inst.*, vol. 106, no. 6, pp. 587–592, 2015.

[6] Jing JF, Yang PP, Li PF, Kang XJ. Supervised defect detection on textile fabrics via optimal Gabor filter. *Journal of Industrial Textiles*. 2014,44(1):40-57.

[7] Li, W.Y., W.L. Xue, and L.D. Cheng, Intelligent detection of defects of yarn-dyed fabrics by energy-based local binary patterns[J]. *Textile Research Journal,* 2012. 82(19):1960-1972

[8] Li W Y, Research on automatic detection for yarn-dyed fabric defect based on machine vision and image processing[D]. *Journal of Donghua University*,2014.

[9] Zhu, D.D., et al., Yarn-Dyed Fabric Defect Detection Based On Autocorrelation Function and GLCM[J]. *Autex Research Journal*, 2015. 15(3):226-232.

[10] Zhu D D, Research of defect detection for yarn-dyed fabric based on image analysis[D]. *Journal of Jiangnan University*,2014.

[11] H. I. Celik, L. C. Dulger, and M. Topalbekiroglu, "Fabric defect detection using linear filtering and morphological operations," Indian J. *Fibre Textile Res*., vol. 39, no. 3, pp. 254–259, 2014.

[12] Li Y, Zhao W, Pan J. Deformable Patterned Fabric Defect Detection with Fisher Criterion-Based Deep Learning[J]. *IEEE Transactions on Automation Science & Engineering,* 2017, 14(2):1256-1264.

[13] Hoochang S, Roth H R, Gao M, et al. Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning[J]. *IEEE Transactions on Medical Imaging,* 2016, 35(5):1285-1298.

[14] Redmon J, Divvala S, Girshick R, et al. You Only Look Once: Unified, Real-Time Object Detection. *Computer Science.* 2016:779-788.

[15] Redmon J, Farhadi A. YOLO9000: Better, Faster, Stronger. *arXiv preprint arXiv*:1612.08242, 2016.