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A Practical Machine-Learning-Based Approach for Leather Automatic Defect Inspection

Hao Yuan[1], Xiao Meng[1*], Kai Xu[1], Qing Jia[2]

[1] School of Mechanical Engineering, Jiangsu University, Zhenjiang, Jiangsu, China
285817681@qq.com, mengxiao955@163.com, 1210598500@qq.com
[2] Changzhou Sinajet Science and Technology Co., Ltd, Changzhou, Jiangsu, China
sales@sinajet.cn

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Abstract. Leather manual inspection is common in many industries, these methods are low efficiency and cannot be in line with automated manufacturing. In this paper, we propose a leather automated defect inspection (LADI) method based on machine learning and establish a practical LADI system composed of four modules: image acquisition, image preprocessing, image segmentation, and post-processing. The LADI method which forms the image segmentation module is a combination of multi-layer perceptron (MLP) and principal component analysis (PCA), namely MLP_{PCA}. We propose two new algorithms that image preprocessing and post-processing to enhance the image quality and enrich details of the segmentation result. In the result analysis, compare MLP_{PCA}, MLP, KNN, SVM_{RBF}, GMM, show that MLP_{PCA} has strong competitiveness in performance and execution time. The LADI system has been used in a China leather factory, the feedback shows that it combines the advantages of high inspection accuracy and short execution time.

Keywords: leather, automated defect inspection, practical, MLP, PCA

1 Introduction

Leather is the raw material of superior products that are shoes, bags, sofas, and car accessories. Some reasons lead to the surface of leather has defects, which include scratches, rotten surfaces, and holes, etc. [1]. Before making, a defect inspection needs to be conducted. In many industries, it is common that manual inspection, which has low efficiency and accuracy. It also asks the expert equips with the rich experiences. In the field of medical image and remote sensing image, automatic defect inspection (ADI) technology is widely used, however, the leather automatic defect inspection (LADI) technology in manufacturing industry is slightly later and needs to be further developed.

1.1 Related Works

In recent years, ADI based on deep learning (DL) technology has been continuously developed. Xue *et al.* [2] developed an image acquisition device MTI-100 to collect images, which were divided images into classification datasets (containing 9520 images) and the object inspection datasets (containing 4139 images). They also developed a framework based on R-FCN to detect and locate the defects. The accuracy of defect inspection and location reached 95%. Huang *et al.* [3] improved MTI-100 to collect 188704 tunnel crack images and 110466 tunnel leak images. They trained two fully convolutional network (FCN) models of crack and leakage separately. Their works achieved a false inspection rate of 0.8%. Ren [4] used three public datasets and an industrial dataset to train a DL network as a classifier. They combined the traditional image processing methods with the network, which can achieve zero missed. It can be seen from the above works that the defect detection effect based on DL is state-of-the-art. However, DL needs the support of a huge datasets, which is not available in the leather manufacturing industry.

Except DL technology, traditional image processing methods are also important methods of ADI, including edge detection based methods, texture based methods, methods based on geometric and statistical descriptors, and classifier based methods [5]. Tsai *et al.* [6] proposed the method based on the Gabor filter to detect images. They successfully detected the structural and statistical textures. However, the detection results are affected by the filter window size. Krastev *et al.* [7] applied the fuzzy logic method to judge whether the image have defects. This method is affected by gray values. Aminzadeh *et al.* [8] and Li *et al.* [9] used the image histogram information to inspect defects. They approximately estimated whether there is a defect in the current test leather and the area of the defect by comparing the distribution of the directional gradient histogram. This method can only detect the

* Corresponding Author

defect and cannot locate the defect. Li *et al.* [10] proposed a defect inspection method based on principal component analysis (PCA) to realize glass defect recognition and edge extraction. Tsai *et al.* [11] used PCA to detect the defect in homogeneously textured and non-textured surface images. Their detection scheme used only one single discrimination feature for surface inspection. Pistori *et al.* [12] verified the applicability of texture analysis and machine learning technology to leather defect inspection and classification. They found that support vector machines (SVM) showed the highest accuracy rate in classification problems. One of their important contributions is they applied machine vision to LADI that is an important but not yet widely studied field. Villar *et al.* [13] selected the multi-layer perceptron (MLP) as a classier to classify defects in wet blue leather, which has high reliability detecting defects on leather. Pereira *et al.* [14] used three classifiers, K-nearest neighbor (KNN), MLP and SVM with RBF kernel (SVM_{RBF}) to detect and quality goat leather. According to their works, MLP has good accuracy for the classification and SVM_{RBF} obtained better performance on the qualification.

1.2 Contribution of the Paper

From the above analysis, we can find that DL is not appropriate for the leather defect inspection since the lack of datasets. MLP is a traditional learning technology, it has the advancements of fewer datasets, a simple network, and less training cost. In this paper, we proposed a LADI method based on MLP with PCA and establish a new LADI system based on MLP. LADI system is composed of four modules: image acquisition, image preprocessing, image segmentation, and post-processing. LADI system is different from the other inspection approach in the follows:

(1) The important image processing modules. In this module, an image processing algorithm is proposed to reduce the influence of illumination and leather texture.

(2) The vital segmentation module. Based on MLP theory, an MLP network for leather defect detection is established. It is worth noting that we introduce PCA into this network, namely MLP_{PCA}, to improve its performance.

(3) The detailed post-processing module. It is essential in enriching the details of segmentation and generating the requirements document to facilitate the subsequent production.

(4) Few pieces of research on LADI, our work is a practical work to promote the development of LADI.

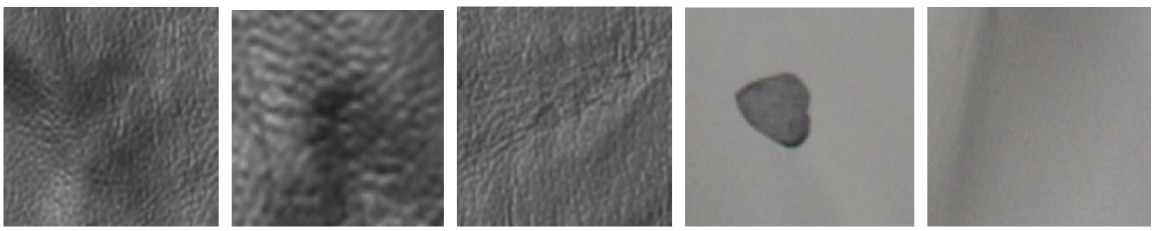
(5) The LADI system has practical value. It has been used in a Machinery Manufactory in China.

1.3 Organization of the Paper

We first introduce the background and motivation of this work. Section 1.1 discussed the related works. Section 1.2 summarizes the contribution of this work. Section 2 explains the leather automatic defect inspection system. Then, Section 3 describes the defect segmentation based on machine learning method. Section 4 presents the experimental results and discussion. Finally, we conclude the work.

2 Leather Automatic Defect Inspection (LADI) System

There are some defects on leather surface, including scars, spots, wrinkles, holes and color difference [15]. The defects are shown in Fig. 1. Before the leather is made into products, defect inspection shall be carried out. To ensure the accuracy of detection, experts conduct pre-inspection and highlight defects with curves close to the boundary. As the holes have obvious boundaries, experts do not mark them. A marking diagram with leather defects is shown in Fig. 2.



(a) scars (b) spots (c) wrinkles (d) holes (e) color difference

Fig. 1. The leather surface defects

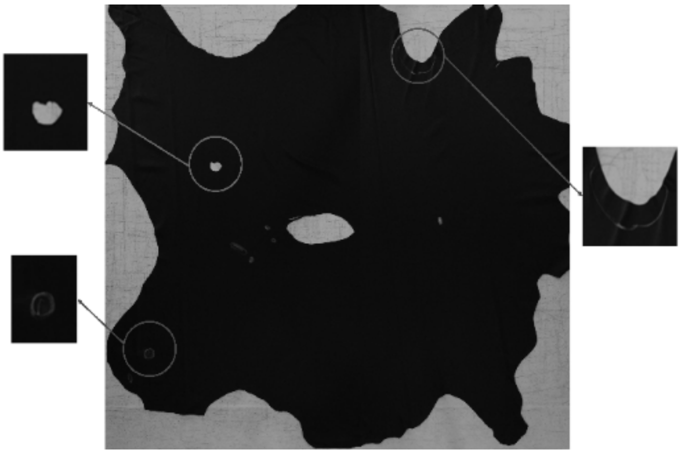


Fig. 2. The marked leather image

In the paper, we establish a LADI system, which integrates four modules: image acquisition, image preprocessing, image segmentation and post-processing. The system structure is shown in Fig. 3.

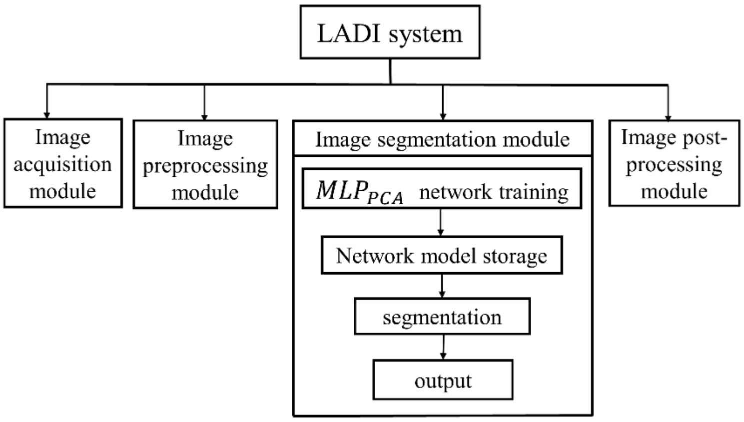


Fig. 3. The structure of LADI system

2.1 Image Acquisition

The image acquisition is composed of light, camera, computer, and digital cutter. The digital cutter has two work-benches to layout and cut respectively. Both cameras and lights are installed above the layout work-bench. 8 uniform LED surface lights to provide the LADI system with stable lighting. The images with 5746×4803 pixels are captured by two CMOS cameras.

2.2 Image Preprocessing

In the actual production environment, illumination and leather texture affect the image quality, resulting in the loss of useful information in the image. In this paper, an image preprocessing algorithm is proposed to reduce noise interference, emphasize interesting features and highlight defects. The algorithm divides the image into three sub-channels, and then, improves the image quality by reducing noise and enhancing the contrast of sub-channels. The color image is separated into three sub-channels: R, G and B. We denoise and enhance the G channel. Then fuse G with the other two sub-channels to obtain the fused image Φ, and then further denoise and enhance Φ. The operation flow is shown in Fig. 4. Where, represents the original image; R, G and B are three sub-channels of Δ respectively; M is the denoising result of G; E is the contrast enhancement result of M; Φ is fused images of M, R and B; Ψ is the denoising image of Φ; Γ is the contrast enhancement result image of Ψ.

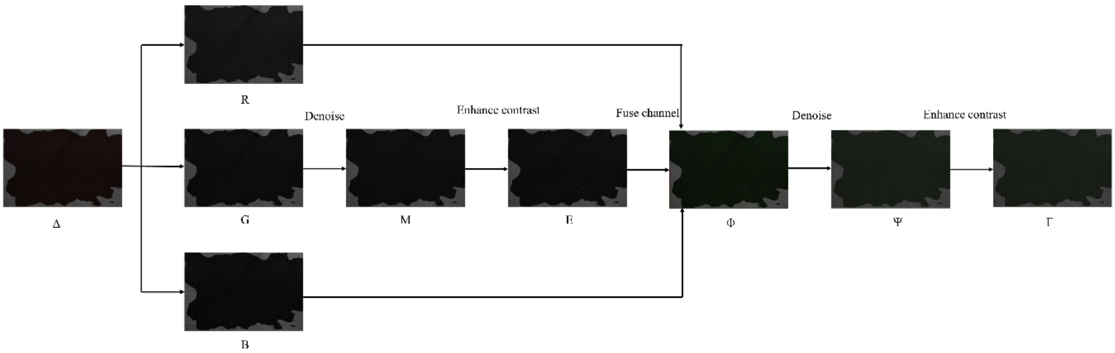


Fig. 4. The leather preprocessing operation flow

2.3 Image Segmentation

The image segmentation module is implemented based on machine learning technology. PCA technology is introduced into MLP neural network (MLP_{PCA}) to realize the preprocessing of input data and improve the efficiency of image segmentation.

2.4 Post-Processing

It should be emphasized that in the expert marking stage, due to the expert's marking habits, there may be an unclosed marking curve. In addition, the segmentation results obtained by MLP_{PCA} have certain details missing. We develop a new algorithm to deal with the problem. The post-processing algorithm is described as follows:

Algorithm 2. Post-processing
Input: The segmentation result Λ.
Output: Vector graph Π.
Step 1. Use the morphology technology to enrich defect details.
Step 2. Edge detection.
Step 3. Connect unclose curves.
Step 4. Convert to vector graph.
Step 5. Output and save.

3 Defect Segmentation Based on Machine Learning Method

3.1 Principal Component Analysis (PCA)

PCA is a data processing method, which can be used to feature selection [16-17] and dimensionally reduction [18]. PCA converts high dimensional data into low dimensional space with minimal loss of the original data quality, it is an effective tool in defects inspection [19]. Specifically, set input feature vector as $X = \{x_1, x_2, x_3, ..., x_n\}$; the objective of PCA is to mapping the n-dimensional image space into m-dimensional feature space by linear transform, and $m < n$ [10]. The linear transform principle as following:

$$Y = PX. \tag{1}$$

Where, P is an orthogonal matrix, composed by the eigenvector corresponding to the m largest eigenvalues of the covariance matrix (C). The covariance matrix defines as follows:

$$C = \frac{1}{n-1}\sum_{k=1}^{n}(x_k - \mu)(x_k - \mu)^T, k = (1,2,3,\dots,n). \tag{2}$$

μ represents the mean value of eigenvectors, $\mu = \frac{1}{n}\sum_{k=1}^{n} x_k$. According to the knowledge of Matrix theory, we calculate the eigenvalues and eigenvectors of covariance by Equation (3).

$$P = \max_{Q} |Q^T C Q| = [p_1, p_2, p_3, \dots, p_n]. \quad \textbf{(3)}$$

The eigenvalue and its corresponding eigenvectors are the basis vectors of the feature defect decomposition and represent the largest difference. Use those eigenvectors as the input of the LADI system can accelerate the computing and more effectively complete inspection.

3.2 Multi-Layer Perceptron Based on Principal Component Analysis MLP_{PCA}

MLP is also called artificial neural networks, which is a simple machine learning model. We combine PCA technology with MLP. We use PCA to process the original multi-dimensional data to generate new data. The new data as the input of MLP. Therefore, we propose a new network, the multi-layer perceptron based on principal component analysis (MLP_{PCA}), the structure is shown in Fig. 5.

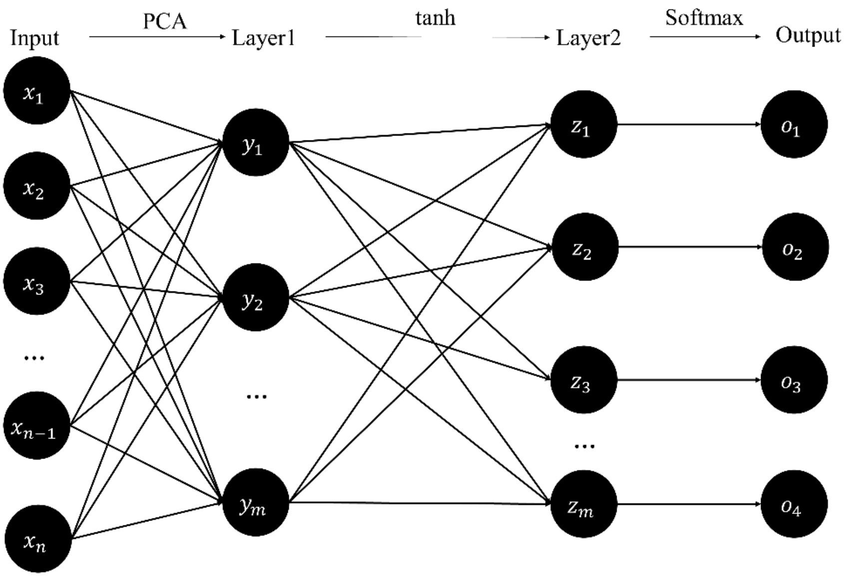


Fig. 5. The MLP_{PCA} network

The MLP_{PCA} composed of the input layer, hidden layer1, hidden layer2, and output layer. Every neural node of the hidden layer is a neuron, its value $a_s^{(1)}$ calculated by Equation (4).

$$a_s^{(1)} = \sum_{t=1}^{n_o} \omega_{st}^{(1)} \alpha_t + b_s^{(1)}, s = 1,2,3, \dots, n_o. \quad \textbf{(4)}$$

Among them, α_t is the input variable, w_{st} is the weights of α_t in neuron s, b_s represents the bias of neuron s, n_0 is the total number of neurons in the hidden layer.

We use the hyperbolic tangent function as an activation function to add to the neurons in the hidden layer. The activation function value z_s is calculated by Equation (5).

$$z_s = \tanh(a_s^{(1)}), s = 1, 2, 3, \dots, n_0. \quad \textbf{(5)}$$

In the paper, we add the softmax function to the output layer to activate the color classification, therefore the output value y_s can be calculated by Equation (6).

$$y_s = \frac{\exp\left(a_s^{(2)}\right)}{\sum_{s=1}^{n_o} \exp\left(a_s^{(2)}\right)}, s = 1,2,3, \dots, n_o. \tag{6}$$

4 Results and Discussion

The experiments are conducted on a computer with Windows 10 system, Intel(R) Core(TM) i7-8700 CPU，NVIDA GTX1060 GPU (6GB graphics memory). The LADI system environment is set with Halcon12.0.

4.1 Datasets and Evaluation Criteria

150 leather images are collected by the image acquisition module and preprocessed using the image preprocessing algorithm. The processed images increased to 656 images by data enhancement operations: the deformation, random angle rotation, and miscut transformation. 656 images are divided into training dataset and testing dataset by 1:9. Four object categories including background, marked, and workbench were defined. All these images are labeled manually, each image can generate three ground truth labels at least.

The performance indicators of the segmentation algorithm based on machine learning include PA (Pixel accuracy), mPA (mean Pixel accuracy), mIoU (mean intersection over union), and frequency weighted IoU (FWIoU). The calculation rules are as shown in Equation (7-10).

- PA (Pixel accuracy)

$$PA = \frac{\sum_{i=0}^{k} P_{ii}}{\sum_{i=0}^{k} \sum_{j=0}^{k} P_{ij}}. \tag{7}$$

- mPA (mean Pixel accuracy)

$$mPA = \frac{1}{k+1} \sum_{i=0}^{k} \frac{P_{ii}}{\sum_{j=0}^{k} P_{ij}}. \tag{8}$$

- mIoU (mean intersection over union)

$$mIoU = \frac{1}{k+1} \sum_{i=0}^{k} \frac{P_{ii}}{\sum_{j=0}^{k} P_{ij} + \sum_{j=0}^{k} P_{ji} - P_{ii}}. \tag{9}$$

- frequency weighted IoU (FWIoU)

$$FWIoU = \frac{1}{\sum_{i=0}^{k} \sum_{j=0}^{k} P_{ij}} \sum_{i=0}^{k} \frac{P_{ii}}{\sum_{j=0}^{k} P_{ij} + \sum_{j=0}^{k} P_{ji} - P_{ji}}. \tag{10}$$

Among them, i represents true value, j represents predicted value, for example, P_{ij} represents the number of true values i whereas predicted values j, and $k + 1$ is the number of categories.

4.2 The Image Preprocessing Results

The objective of image preprocessing module is to enhance contrast of the background and defects. As shown in Fig. 6, the histograms of the original image Δ are smooth that means the contrast is not high to distinguish the background and defects. After enhancing the contrast of the G channel, the histogram peak heightens. After adding the reduced noise operation, the inflection points of histogram become more prominent, which can be seen from the green circle on the bottom histogram.

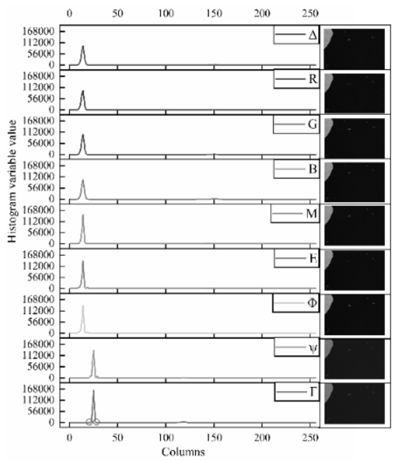


Fig. 6. The preprocessing result and histogram of each operation

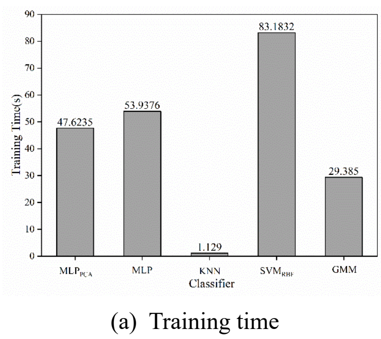
4.3 The Comparison of Classifiers

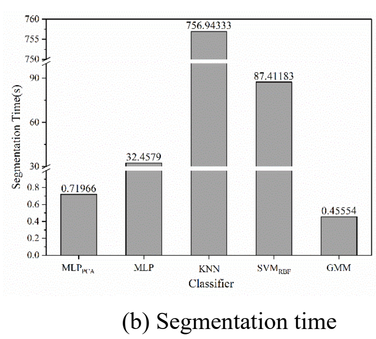
In the paper, we compare the performance indicators and execution time of four classifiers with the proposed classifier MLP_{PCA}. The first classifier is KNN by searching approximately the nearest neighbors and returning their classes as result. The dimension of the feature vector K is the only parameter. For the experimental datasets, K = 3. The second classifier is GMM creates a gaussian mixture model for classification. The third classifier is the SVM with RBF kernel (SVM_{RBF}). The vital penalty parameter C of SVM_{RBF} is set to 0.1. The fourth classifier is MLP. In this case, the learning rate η = 0.1. Except KNN does not require training, the other classifiers all have 200 iterations. The performances (PA, mPA, mIoU, FWIoU of five classifiers are shown in Table 1. It is worth noting that all performance of MLP_{PCA} exceeds 99%. Compared with SVM_{RBF}, the performances mPA and MIoU are increased by 5.77 and 6.93.

Table 1. The performance comparison of classifiers

Classifier	PA	mPA	mIoU	FWIoU
MLP_{PCA}	99.63	99.53	99.32	99.58
MLP	95.04	92.95	91.43	94.97
KNN	90.42	88.91	87.35	91.05
SVM_{RBF}	95.78	93.76	92.39	95.98
GMM	85.70	80.19	79.61	82.67

The execution times (training time and segmentation time) of five classifiers are shown in Fig. 7. As can be seen from Fig. 7 that KNN has minimal training time and maximal segmentation time. The training time of GMM, MLP_{PCA}, MLP, SVM_{RBF} increases sequentially. SVM_{RBF} needs maximal training time, which is twice as long as MLP_{PCA}. The segmentation time of MLP_{PCA} and GMM are both less than 1s.



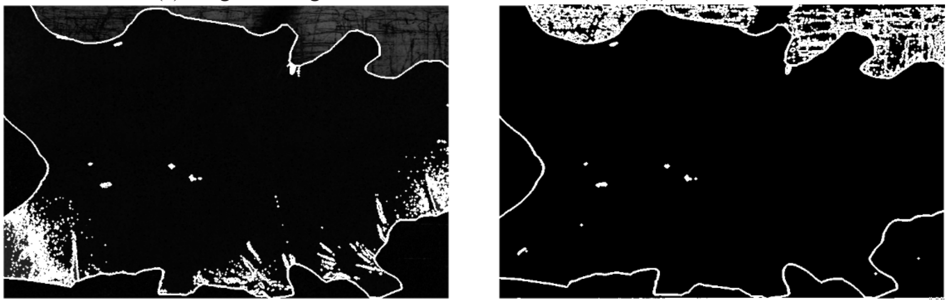


(a) Training time (b) Segmentation time

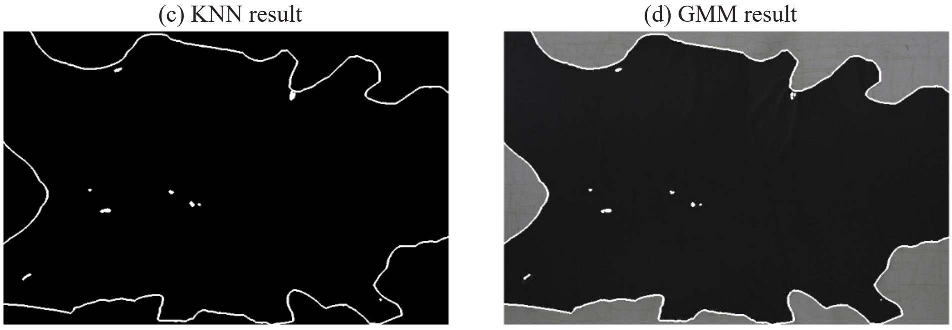
Fig. 7. The execution time of 5 classifiers

Fig. 8 shows the segmentation results of five classifiers. The segmentation results of KNN, GMM, and MLP have a lot of noise. SVM and MLP_{PCA} obtain approximal segmentation results of accurate defects contours. From the above analysis, it can be seen that compared with other classifiers, MLP_{PCA} has strong competitiveness in performance indicators, execution time and segmentation results.

(a) Original image (b) MLP result



(c) KNN result (d) GMM result

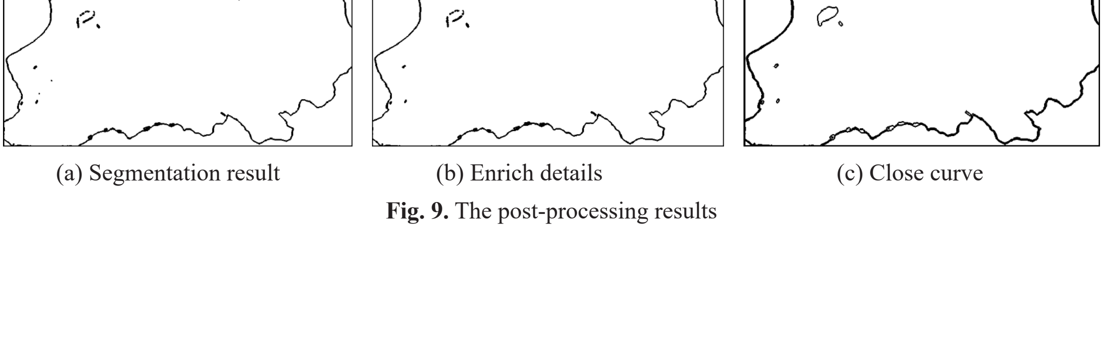


(e) SVM_{RBF} result (f) MLP_{PCA} result

Fig. 8. The segmentation results of five classifiers

4.4 The Post-Processing Results

As we all know, the image segmentation implemented by the classifier is segmentation at the pixel level, which results in low segmentation accuracy. We add the post-processing algorithm to achieve the purpose of enriching the segmentation results and improving the segmentation accuracy. Fig. 9(a) is the segmentation result obtained by the MLP_{PCA} classifier. We perform morphological and smoothing operations on the segmentation results to obtain Fig. 9(b). Fig. 9(b) reduces noise in Fig. 9(a), and the contour is smoother. However, there is an unclosed curve in Fig. 9(b), and the closed curve operation makes up for this defect, as shown in Fig. 9(c).



(a) Segmentation result (b) Enrich details (c) Close curve

Fig. 9. The post-processing results

5 Conclusion

This paper proposes a leather defect inspection method based on the MLP with PCA. And establish a practical LADI system includes four modules: image acquisition, image preprocessing, image segmentation, and post-processing. The image acquisition solves the lack of data and is committed to enriching the leather database. The image preprocessing module is based on a new image processing algorithm to guarantee the consistency of image quality. The image segmentation, MLP_{PCA}, introduce PCA into the MLP neural network. MLP_{PCA} processes the input data to accelerate the speed of the network to increase the segmentation accuracy. The post-processing module is also based on a new algorithm to enrich the details of the defect and strengthen the practicability of the LADI system.

We present the results of image preprocessing and post-processing. We also compare the performance, execution time, and segmentation results of five classifiers: KNN, GMM, MLP_{PCA}, MLP, and SVM_{RBF}. All of the results show that MLP_{PCA} has great segmentation ability and the LADI system is very practical. This LADI system has been put into use in a Chinese leather manufacturing company. It has high inspection accuracy and a short execution time. It can be well adapted to the inspection stage of leather manufacturing.

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