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Fabric defect detection algorithm based on PHOG and SVM

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In order to effectively improve the detection probability for different types of fabrics and defects, a fabric defect detection method based on pyramid histogram of edge orientation gradients (PHOG) and support vector machine (SVM) has been proposed. The algorithm combines fabric texture statistical method and machine learning method. It has two main parts, namely the feature extraction and classification. The detection process mainly includes image segmentation, PHOG feature extraction, SVM model training and detection classification. The simulation results show that, based on the detection rate and the false alarm rate, the algorithm has a good detection and classification effect, has a certain robustness, and can be applied to the actual production department.

Keywords: Defect detection, Fabric image, Pyramid histogram of edge orientation gradients, Support vector machine

With the development of automation technology, the automatic level of fabric production line is becoming higher and higher, along with the demands on product quality. Fabric defect detection, as a popular research topic in automation, is a necessary and essential quality control process aimed at identifying and locating defects. At present, instead of heavy manual tasks for detecting fabric defects, the automatic system based on machine vision has become a hot topic, and fabric defect detection algorithm is one of the key technologies.

Learning method[1] is a popular research topic in recent years. Neural networks have also been utilized for fabric defect detection and classification. In general, such methods select some features to characterize texture, employ organization principles to train models and detect the defections. Their weaknesses include their difficulty in coping with abundance of features and concomitant variations in scale, position, orientation and their inability to analyze a texture without a reference and to work with large textural primitives.

Conventional methods[2] for fabric defect detection proceed in a two-phase fashion, namely feature extraction and feature identification. The key issue lies in the process of designing and distinguishing features. Features could be in the spatial domain, such as LBP[3], HOG[4] and covariance matrix, or in the transform domain, such as Fourier transform, Wavelet transform and Gabor transform.

In general, a perfect detection success rate is almost impossible to achieve, this is because, fabric style includes all varieties, fabric defect has many types, and the number of samples collected is limited. Because PHOG[5,6] feature has spatial structure description ability with insensitivity in scale, position and orientation and SVM[4] possesses outstanding advantages in solving small sample learning and prediction. This study will use SVM to classify the extracted PHOG features of fabric images into different categories (defect or defect-free) to improve the fabric defect detection success rate.

Experimental

The TILDA database[7] was used for experiment. This database consists of four class directories (C1, C2, C3, C4), and each class directory contains two subdirectories. Therefore, each subdirectory contains one fabric type image, each of which is partitioned into 8 subdirectories containing each 50 texture images. The first subdirectory named “E0” contains defect-free images, while the other subdirectories (“E1”–“E7”) contain defective images.

Here four different pattern fabric images stored in C1 and C3 are selected, which are fabric with stripes, gingham fabric, twill fabric and plain fabric (Fig.1). And there are four defect types for each pattern, i.e. streak, stain, thick bar and clip mark. Each original image of size 768-by-512 pixel stored in the database is departed to six images of size 256 -by-256 pixel without overlapping. Totally, evaluation is conducted by using 7540 images of size 256 -by-256 pixel, of which 5999 were used as

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training samples and 1541 as testing samples. Table 1 shows the number of training and testing samples of different fabric types.

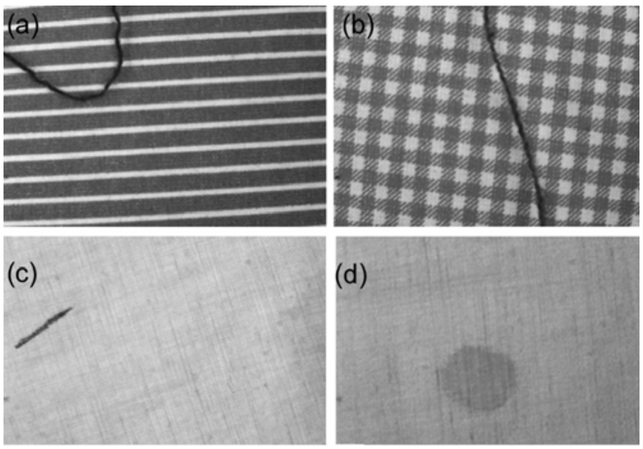

Fig.1 — Fabric images from TILDA database (a) fabric with stripes, (b) gingham fabric, (c) twill fabric and (d) plain fabric

Methodology

The proposed method conceptually contains two parts, namely training and testing; both parts share the same block that is PHOG feature exaction. Figure 2 illustrates the procedure.

Training Process:

The training process involves the following procedural steps:

(i) Divide the training fabric image into a series of nonoverlapped regions of size N-by-N pixel.

Table 1 — Number of training and test samples for different types of fabric

Fabric type	Train sample	Test sample
Fabric with stripes	1258	423
Gingham fabric	1836	354
Twill fabric	1522	399
Plain fabric	1383	365

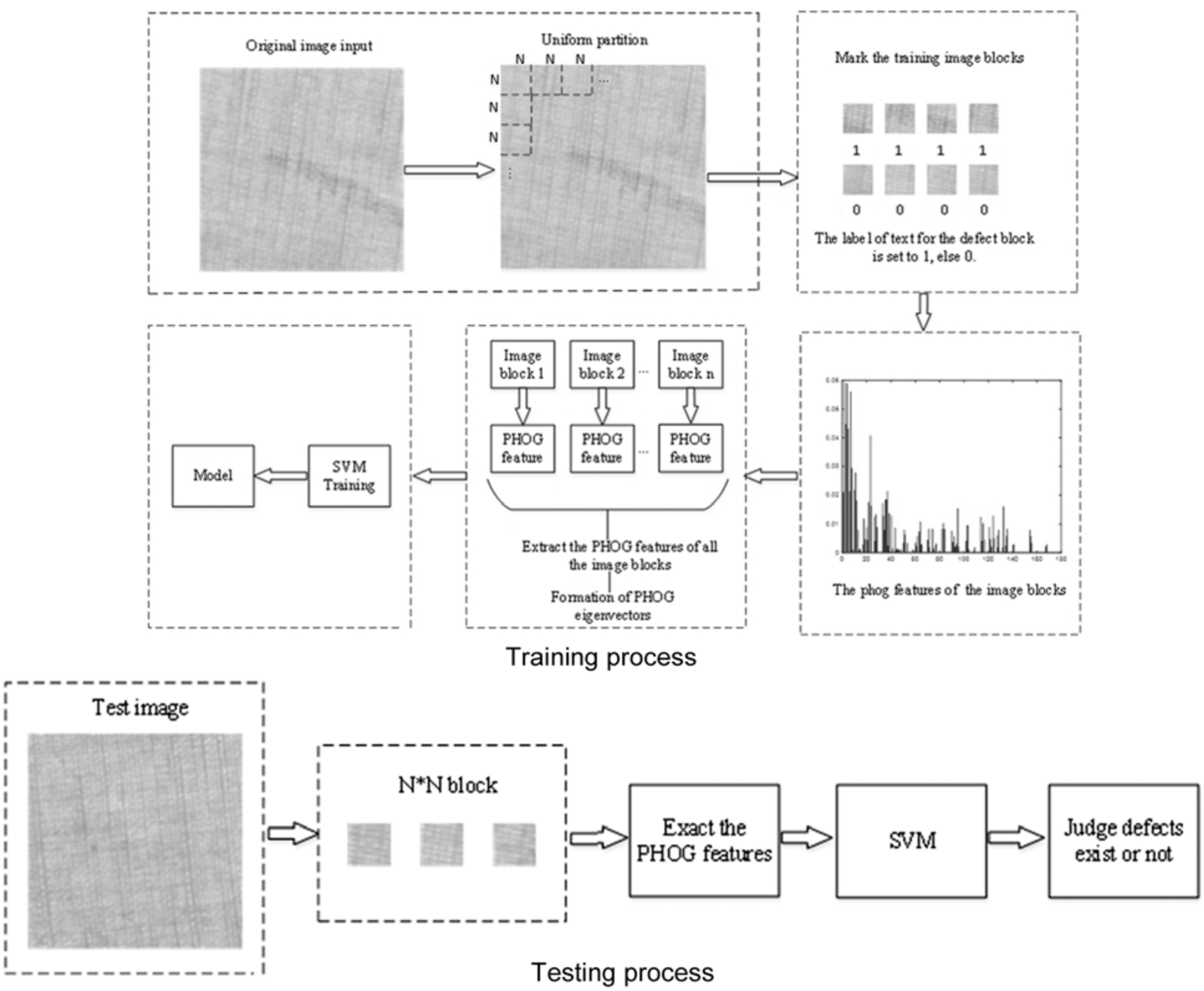

Fig.2 — Flowchart of training and testing processes

To ensure to capture spatial structure of the fabric, the region size N can be set to a value larger than the texture cycle T(N>T).

(ii) Mark the training image blocks with 0 and 1. The label of text for the defect block is set to 1, else 0.

(iii) Extract the PHOG features of all the image blocks. The depth of PHOG is set to 3

(iv) Train and determine the SVM classification model by using the PHOG features as input and the defect labels as output.

Testing Process:

The testing process involves the following procedural steps:

(i) Divide the testing fabric image into a series of nonoverlapped regions of size N-by-N pixel.

(ii) Exact the PHOG features of all the regions. The depth of PHOG is set to 3.

(iii) Input the PHOG features to the SVM classification model and mark the defect regions according to the output.

Results and Discussion

Figure 3 shows the detection results of some fabric images based on the proposed method. Here, the fabric image size is 256×256 pixel, and they are divided into image patches with size of 32×32 pixel for localizing the defect region. The odd columns are the original images and the even columns are the detection results. From Fig.3, it is observed that the algorithm has good adaptability for different texture patterns and different defect types, and the location of the defects can be accurately marked.

Table 2 shows the detection rate and the false alarm rate of different texture pattern fabrics based on SIFT, HOG, PHOG feature and SVM detection algorithms. SIFT and HOG features exploit block-based histogram representation and thus are robust to noise, affine, geometric, and photometric changes. Pyramid of histograms of oriented gradients (PHOG)

Table 2 — Test results based on SIFT & SVM, HOG & SVM, PHOG & SVM

Defect type	Size 16-by-16		Size 32-by-32	
	Detection rate, %	False alarm rate, %	Detection rate, %	False alarm rate, %
SIFT & SVM				
Streak	72.35	8.75	74.83	10.69
Stain	70.50	9.50	73.68	7.65
Thick bar	75.83	10.98	73.11	5.22
Clip mark	71.67	8.76	70.58	9.39
HOG & SVM				
Streak	91.59	6.57	95.79	9.86
Stain	89.88	9.89	92.26	5.23
Thick bar	93.53	10.78	91.18	5.39
Clip mark	87.44	6.91	83.72	7.83
PHOG & SVM				
Streak	93.93	5.63	98.13	1.88
Stain	90.75	2.62	91.91	3.49
Thick bar	94.12	7.78	94.12	3.59
Clip mark	91.63	1.54	87.91	3.69

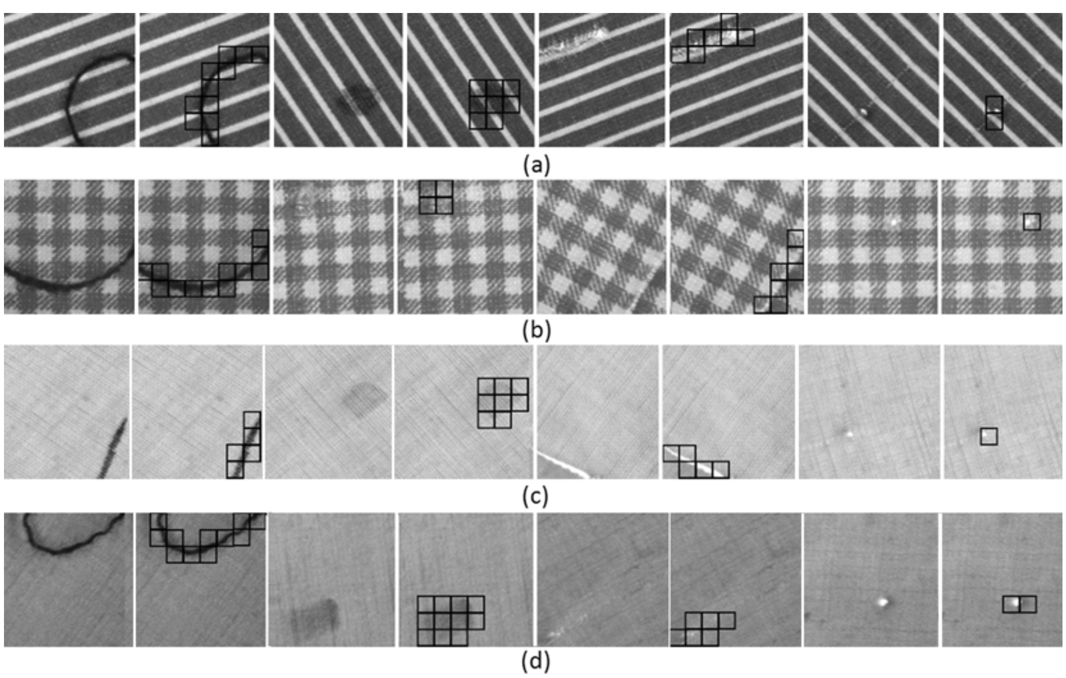

Fig.3 — Each row depicts the defect inspection exemplars of different texture pattern

Table 3 — PHOG algorithm detection results based on different image block sizes

Fabric type	Size 16-by-16		Size 32-by-32		Size 64-by-64	
	Detection rate, %	False alarm rate, %	Detection rate, %	False alarm rate, %	Detection rate, %	False alarm rate, %
Fabric with stripes	91.23	4.63	93.42	3.68	95.43	3.42
Gingham fabric	90.25	7.79	91.26	6.59	92.85	3.26
Twill fabric	94.68	3.48	96.12	2.35	93.52	3.26
Plain fabric	96.63	2.54	97.53	1.63	94.82	2.05

description is more resilient to scale, shift, and other geometric transformations, since it includes extraction of HOG at different levels. It is obvious that different features affect detection rate and false alarm rate. The detection rate based on PHOG and SVM detection algorithms is the highest and the false alarm rate is the lowest.

Table 3 shows the PHOG algorithm detection results based on different image block sizes. It is obvious that the size of the image block also has a greater impact on the detection results. The different size of the image block will produce different detection effects. For fabric with stripes and gingham fabric, the detection rate is highest and the false alarm rate is the lowest when the image block size is 64×64 pixel. And for twill and plain fabrics, the detection rate is highest and the false alarm rate is the lowest when the image block size is 32×32 pixel. Here, the texture cycles of fabric with stripes is 30, gingham fabric is 48, twill fabric is 15, and plain fabric is 16.

In the actual detection, when the size of the image block is too small, it cannot contain the complete texture information of the fabric. But when the scale of the image block is too large, it is beneficial to depict the texture information of the fabric. It will reduce the proportion of the defect area in the image block and affect the detection precision. Therefore, it is necessary to select the appropriate image patches for different fabrics. The experiment shows that this method has more actual values than traditional method. This algorithm still faces challenges in detecting defect in pattern fabric and motif based because of large texture variation.

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