AUTOMATED PATTERNED FABRIC FAULT DETECTION USING IMAGE PROCESSING TECHNIQUE IN MATLAB

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ABSTRACT--This paper provides a review of automated patterned fabric fault detection methods developed in recent years. Fabric fault detection, as a popular topic in automation, is a indispensable and vital step of quality control in the textile manufacturing industry. This method analyzes the cartoon and texture structures to examine and envision defective objects in a patterned fabric image. The performance of the proposed scheme is evaluated by using a wide variety of patterned fabric images with different types of common fabric defects. The test results obtained show signs of accurate defect detection with low false alarms, thus showing the efficacy and sturdiness of the proposed detection method. In addition, the proposed detection method is further evaluated in real time by using a prototyped automated inspection system. This paper shall benefit researchers and practitioners alike in image processing and computer vision fields in understanding the characteristics of the different defect detection methods.

Keywords – Patterned fabric inspection, Quality control, Image processing, Matlab R2009a, Gray image, Histogram, Thresholding.

I. INTRODUCTION

Automated patterned fabric inspection [15] has been an admired research topic in manufacturing and quality control for over twenty years. It aims to spot and sketch defects on the surface of patterned fabrics at some stage in manufacturing. Previously, it was mainly achieved by visual inspection of skilled workers, yet it has disadvantages such as high error rates due to human exhaustion, high labor costs, and sluggish inspection speed. Automated visual inspection [3] improves such inspection efficacy and offers gratifying detection accuracies for the quality control in textile industry. Patterned fabric like wallpaper and ceramic is generated by a repetitive unit–motif, through a set of predefined symmetry rules [13] and it can be classified as one of 17 wallpaper groups. In the literature, patterned fabric inspection methods are based on statistical, spectral, model-based, learning, structural, and motif-based approaches (see the recent survey in [15]).

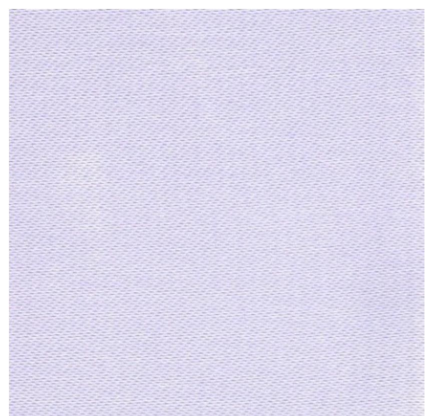

Fig. 1. Defect Free Patterned fabric images.

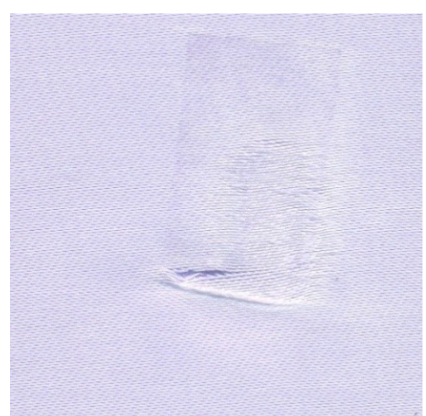

Fig. 2. Defective Patterned Fabric Image

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It is normal to study the correlation between the underlying patterned fabric structure and the geometrical defective objects in fabric images. Previously, Fourier transform [18] and Wavelet transform [17] were in use to identify defective objects in simple plain and twill fabric images [Fig. 1(a)][1] via transformation and reconstruction processes. However, it is very complex to apply those concepts to figure out the correlation between defective objects and patterned fabric for more complex patterns in the dot-, box-, and star-patterned fabrics [Fig. 1(b)–(d)][1]. In this paper, the basis of ID is subjugated to develop a new patterned fabric inspection method. We consider that a defective fabric image is the superposition of defective objects and patterned fabric. We make use of the total deviation in negative Sobolev space to normalize cartoon and semi norm in negative Sobolev space to normalize texture structures. A minimization process (Section III-A2) can separate the faulty objects in terms of geometrical cartoon structure and the patterned fabric in terms of recurring patterns. Derived by mathematics, we can fester patterned fabric images, recognize, and envisage defective objects accordingly. To exhibit our idea, Fig. 2(a)[1] shows a dot-patterned fabric faulty image, containing several flawed objects. After ID, the resultant flawed objects (i.e., cartoon) and the remaining patterned fabric (i.e., texture) are shown in Fig. 2(b) and (c)[1]. This research has four main contributions. Firstly, we propose a new ID method to deal with patterned fabric inspection and apparition. This model can be solved competently by our recent operator splitting method in convex optimization. Secondly, the projected method requires only one defect-free fabric image to optimize the ID method with respect to the largest correlation between a given fault-free fabric image and the texture structure of input fabric images. This approach is different from the other conventional inspection methods [15]. Also, the output cartoon structure from the ID method is identified for examination and apparition. Thirdly, defective manual-labeled image databases of dot-, star-, and box-patterned fabrics are newly constructed for the performance estimation, while most of earlier literature did not have these and only simply counted the quantity of white pixels in the resultant images to determine accuracies. Fourth, a rigorous performance assessment is conducted on the databases. Based on defective manual-labeled images, the proposed method achieves 94.9% 99.6% of fault detection accuracies. We also apply a FPR-CPR graph (FPR stands for false positive rate and CPR stands for correct positive rate) analysis, which is new in literature, to show the robustness of the proposed method compared to the other methods.

This paper is organized as follows. Section II presents related work for patterned fabric inspection. Section III delivers mathematical representations of defective objects and patterned fabrics in the proposed method. Section IV offers intensive performance evaluation of the proposed method to demonstrate its robustness and effectiveness. Finally, a conclusion is drawn in Section V.

II. RELATED WORK

Patterned fabric inspection [2], [6], [21] has been intensively focused on the plain and twill fabric [Fig. 1(a)][1], i.e., the p1 group in [13], which can be categorized as statistical, spectral, model-based, learning and structural approaches. The statistical approach has a promising fractal method [2] (97.5% accuracy). The spectral approach has a state-of-the-art adaptive wavelet-based method [21] (97.5%/93.3% accuracies of known/unknown defects). The learning approach has a three-layer back-propagation neural network method [6] (94.3% accuracy). Besides, both model-based and structural approaches do not have promising results. All methods above were not evaluated on complicated patterned fabrics in other 16 groups [13]. An early attempt by a golden template method [4] to inspect complicated patterned fabrics was not efficient. On the other hand, gray relational analysis [7], direct thresholding (DT) [10], wavelet-preprocessing golden image subtraction (WGIS) [10], local binary pattern (LBP) [16], Bollinger Bands (BB) [11], and Regular Bands (RB) [12] methods have been developed for inspecting complicated patterned fabrics. The DT, LBP methods were a spectral approach, while the WGIS, BB, and RB methods were a mixture of statistical and filtering approach. Both BB and RB methods employed the regularity property in the patterned texture, which is further developed to detect defects on simple patterned texture (p1 group) using a multiband-pass filter [19]. The DT, WGIS, LBP, BB, and RB methods achieved 88.3%, 96.7%, 98.58%, 98.59%, and 99.4% accuracies, respectively, for complicated patterned fabrics. In short, all the approaches above can be classified as a non-motif-based approach which treats the whole input fabric image for inspection. Contrarily, a motif-based approach [13], [14] means to break down a testing patterned fabric image into a fundamental unit–motif, for the texture analysis and fabric inspection.

There are two approaches in patterned fabric fault detection methods: a non-motif based approach, and a motif-based approach using motif as a basic manipulation unit. At present, there is no other motif-based method than the one being proposed in the reference paper[22], while the non-motif-based

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method can be further divided into two categories: those that explicitly tackle the p1 wallpaper group and those that can be used for other wallpaper groups. Many existing defect detection methods deal with the p1 group, which includes plain, twill and leather fabrics (also known as the homogenous fabrics [23]). Broadly, they fall into three main groups: statistical, spectral and training approaches. Statistical approach involves first order statistical measures and second order statistical measures [24]. Statistical approach defines various features, such as directionality, roughness, linearity and density, and finds the appropriate decision boundaries within the feature space. A major weakness of first order statistical method is its inability to identify defects with poor contrast. Then again, the second order statistical methods are computationally intensive and need reference primitives for analysis, though they can provide spatial relationships between pixels. The highest fault recognition success rate for first order and second order statistical methods are 91% [25] on plain fabric (with no specified testing condition) and 91.25% [24] on leather fabric (with 80 defective samples in the testing), respectively.

Spectral approach for plain and twill fabric defect detection mainly includes Fourier transform (FT) [20], wavelet transform (WT) [6] and Gabor transform (GT). FT set aparts the frequency contents and is strong in describing the directionality of line patterns. As in Reference [20], defects appear as irregularities in the spatial-frequency spectra, which can be identified reasonably well. On the contrary, wavelet and Gabor filters make use of spatial frequency analysis when the Fourier bases do not provide local spatial domain support for indicating the local defects. Although WT and GT reduce data size and restrict defects, they are computationally rigorous. In addition, GT can also fester the images in multi-scales and multi-orientations. Hence, the Ref. [17] has proposed Gabor wavelet features in twill fabric defect detection, but not all defects can be detected. Also, the standardWT may not capture the most eminent features for all kinds of defects since the wavelet basis, in general, is to be heuristically selected. Therefore, Ref. [21] designed adaptive wavelets to characterize defects on twill fabric images. If the defect type is known, it achieves a detection success rate of 97% (460 defect-free and 460 faulty samples), otherwise its best detection rate drops to 93.3% (780 defect-free and 180 defective samples). The main limitation of these methods is that a large database of fault free and faulty samples is needed for training in order to achieve good adaptability and defect recognition result.

III. IDENTIFICATION OF DEFECTIVE OBJECTS

The ID method for patterned fabric inspection has three main steps (Fig. 3): 1) preprocessing; 2) image decomposition; and 3) detection enhancement.

1) Preprocessing: Typically, patterned fabric images acquired from a digital (or charge-coupled device, CCD) camera are embedded with errors like noise, fickle shadows, and illumination changes, which would appear like defective objects caused in manufacturing and affect the image quality. To dampen the bad effects from those errors, a preprocessing step is first conducted for the sampled images. As the histogram equalization is one of the most well-known methods for contrast enhancement, we exploit it to enhance the pixel values of patterned fabric images. Concretely, we use the MATLAB syntax histeq(f,2) to preprocess any fabric image and produce a binary image. Fig. 4 indicates that the preprocessing step is vital to pinpoint the sizes, sharpen the edges of the defective objects and offer much accurate detected results than those without.

2) Image Decomposition: Here comes to the stage of attaining the cartoon (i.e., to dig the defective objects out) by executing ID on the preprocessed patterned fabric images. ID is a fundamental research in image processing (see, e.g., [1], [8], [20]). For this step, we tag along the ID method in [9]: for splitting a fabric image f.

$$\min_{u,g} \tau \ \| \nabla u \|_1 + \frac{1}{2} \| u + div\, g \ - f \|_2^2 + \ \mu \| g \|_p , \qquad p \geq 1$$

Here, ∇ is the first-order derivative operator and $div\ g = -\nabla^{\mathrm{T}}$ is the divergence operator; τ and μ are positive parameters to balance three terms in the objective function; u and $v = div\ g$ represent the cartoon and texture components of f, respectively; In the objective function of model (1), $\| \nabla u \|_1$ is the well-known total variation norm for recovering piecewise smooth functions and preserving its sharp discontinuities; the second term represents the restoration discrepancy; $\| g \|_p$ approximates (by taking $p \rightarrow \infty$) the norm of the space of oscillating functions introduced by Meyer [8] for penalizing the texture structure. Computationally, we exploited the alternating direction method with Gaussian back substitution (ADM-G) recently developed in [5] for solving the model (1).

As an interception, we address our rationale of selecting the tradeoffs (τ, μ) in model (1). Recall the outputs of the model (1), a cartoon (i.e., $u(\tau, \mu)$) possessing defective objects in patterned fabric image f and a texture (i.e., $v(\tau, \mu) = \ div\ g$) containing the

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image pattern can be theoretically acquired (see Fig. 2). The texture structure should be in a high correlation with the reference image (i.e., defect-free image) $f*$ in patterned fabric databases, i.e., the magnitude of

$$Corr(v(\tau,\mu), f^*) = \frac{cov(v(\tau,\mu), f^*)}{\sqrt{var(v(\tau,\mu)).var(f^*)}} \quad (2)$$

is close to 1, where and are the variance and covariance of given variables, respectively.
We suggest selecting (τ,μ) for the model (1) which can offer higher $Corr(v(\tau,\mu), f^*$ values. Specifically, the tradeoffs (τ,μ) are derived by a learning process, for which is described as follows. Given a certain patterned fabric database, say the dot-patterned fabric, we choose one reference image $f*$ and a defective image f from the database. By conducting ID on defective image f with different doublet (τ,μ) 's in model (1), we record the $Corr(v(\tau,\mu), f*)$ value corresponding to individual (τ,μ) of ADM-G recursions. The empirically "optimal" tradeoff (τ,μ) is thus attained by plotting the three dimensional surface of parameters correlation figure. Fig. 5 plots the parameters-correlation figures for dot- and star patterned fabrics. The "optimal" tradeoffs (τ,μ)'s are typically achieved at the peaks of those surfaces. Eventually, from the contours of those surfaces, we have that the "optimal" tradeoffs (τ,μ) are ≈ (0.3, 1), ≈ (0.4, 1), and ≈ (0.6, 1.5) for the dot-, star-, and box patterned fabrics, respectively. Fig. 6 illustrates some detected results, i.e., the cartoons derived from model (1), at different doublets$\boldsymbol{A}$i's in Fig. 5.

3) Detection Enhancement: The cartoon structure yielded by the model (1) includes any defective objects on patterned fabric image. Basically, the defect locations can be visualized for most fabric images (see Figs. 4 and 6)[1]. However, the colormap and edges of those defective objects are visually inharmonious and indistinguishable. We hence exploit a simple detection enhancement step. By rescaling the pixel values of decomposed cartoon as 0 or 1, we convert the cartoon image into a binary image whose 1-valued pixels represent defective objects, while 0-valued pixels are defect-free regions. A simple threshold is selected (e.g., all samples of dot-patterned fabric with "Hole" defects use an identical threshold) so that it yields the doublets (FPR, CPR) in a FPR-CPR graph (see Section IV-A) close to the perfect classification point (0,100).

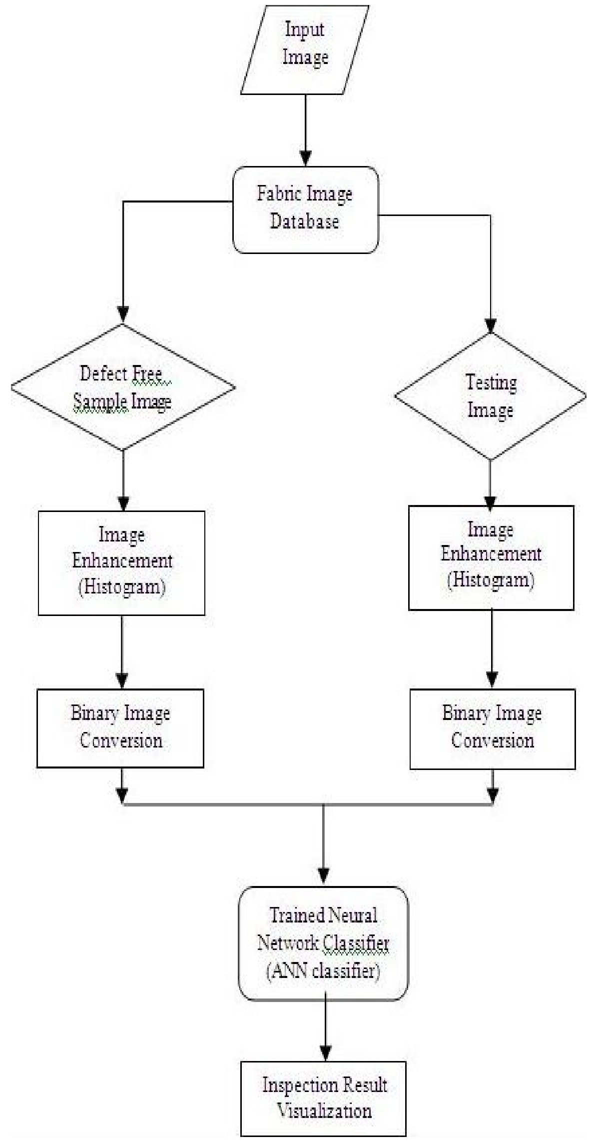

Fig. 3. The flowchart of the Image Decomposition method for pattern fabric inspection.

IV. EXPERIMENT RESULTS

A. Measurement Metrics
We would utilize some measurement metrics to enumerate the efficiencies of different methods. Firstly, the numerical comparisons between detected images (binary images after detection enhancement step) and defective manual-labeled images are conducted in a pixel-by-pixel approach. Concretely, both pixels in the detected and defective manual-labeled images are 1 as *true positive (TP)*, while 0 as *true negative (TN)*. The pixel in the detected image is 1 and that of the defect manual-labeled image is 0 as *false positive (FP)*, while the reversed situation is

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false negative (FN). The following measurement metrics are used to compare various methods:

Precision $PN = (TP + TN)/(TP + TN + FP + FN)$

Correct Positive Rate $CPR = TP/\ (TP + FN)$

False Positive Rate $FPR = FP/(FP + TN)$

Positive Prediction Value $PP = TP/(TP + FP)$

Negative Prediction Value $NP = TN/(TN + FN)$

We utilize the FPR-CPR graph, which is produced by scattering the doublets (FPR, CPR), i.e., FPR and CPR as and axes, respectively.

In theory, the best classification method tends to capitulate the coordinates (FPR,CPR) at the top-left corner of the FPR-CPR graph, i.e., near to the point (0,100) which is called the *perfect classification point* and far from the line $y = x$ and is denoted as the *random guess line*.

B. Numerical Comparisons

We have the databases of 256-by-256 fabric images belonging to three patterns: dot- (110 defect-free and 120 defective samples), star- (25 defect-free and 25 defective samples) and box-patterned fabrics (30 defect-free and 26 defective samples). We have noted that most of the earlier methods (i.e., DT, WGIS, LBP, BB, and RB) in literature only simply counted the number of white pixels as threshold of a resultant image to determine whether it is faulty or not, and corresponding the detection accuracies. Majority of the methods nearly achieved very similar detection accuracies for all faulty and fault-free images in various patterned fabric samples. Consequently, this criterion, using the number of the white pixels, is not effective to differentiate how precise detection of a method is. In order to perform an intensive evaluation and unmistakably understand how precise the detection of a method, we now compare the ID method with the tradeoffs attained in Section III-A2 to the BB [11] and RB [12] methods (which have uncertain best accuracies and visual results in literature), with the measurement metrics above, on the newly constructed defective manual-labeled databases for patterned fabric inspection.

Tables I & II[1] list the results of the BB, RB, and ID methods. The quantity of each defect type is recorded in the brackets of the tables. In Table I[1], the ID method achieved all ACCs greater than 94.9% and all CPRs larger than 50.9% for dot patterned fabric images. In Table II[1], the ID method also obtained promising CPRs for all star-patterned fabric images and only performs a little inferior in “Thin Bar.” Figs. 7–9[1] show samples of detected results by three testing methods. Some remarks can be drawn from Tables I & II[1] and Figs. 7–9[1] as follows: (i) the CPRs induced by the ID method are much higher than those by the BB and RB methods; (ii) most ACCs of detected results by three testing methods are higher than 95%; (iii) the FPRs induced by the ID method are typically the highest among all testing methods. The reason is that the ID method inspects the defects as dilated regions but the defects in the defect manual-labeled images are in discrete forms (see Figs. 7–9)[1]. The defect manual-labeled images thus favor the BB and RB methods numerically; (iv) the ID method could outline the defective regions better than the BB and RB methods (see Figs. 7–9)[1], especially for “Broken End” defect in the dot patterned fabrics, “Netting Multiple,” and “Thin Bar” in the star-patterned fabrics. In short, the ID method achieves compelling performances among all compared methods, both in numerical results and visualization for three patterned fabrics.

The binary image thus obtained by the ID method is fed to the ANN (Artificial Neural Network) classifier. The ANN classifier is trained with various samples. Thus the ANN classifier can be trained to detect a variety of defects such as oil stain, stab cut, etc based on our necessity. Hence the method of superimposing ID over an artificial neural network needs only a few samples for fault analysis of patterned fabric images. A variety of sample images has been processed using the ID method and the results are used to train the ANN classifier.

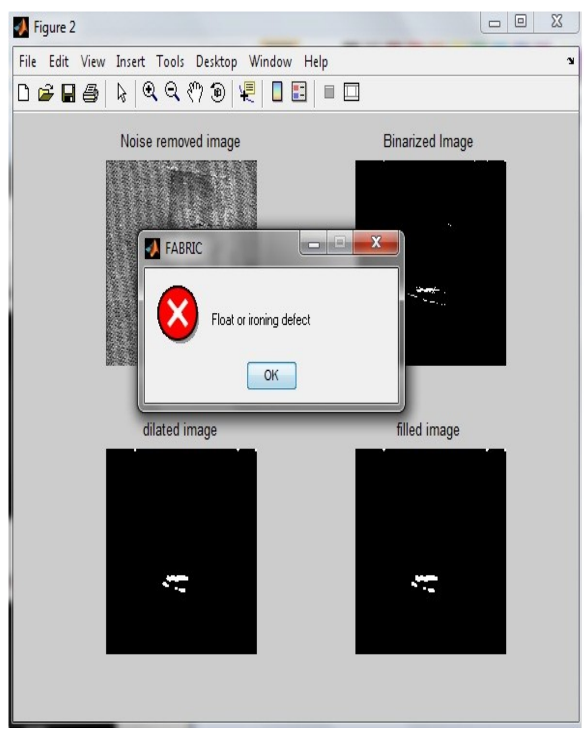

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Fig. 4. Images of fabrics at different process of defect detection, the corresponding binary detection results and classification of defect by ANN classifier.

Parameter	ID Method without ANN	ID followed by ANN Classifier
Percentage Accuracy	95%	95%
Classification of Fabric Faults	Not Possible	Done by Trained ANN
No.of samples needed for classification	Not applicable	One sample for each type of defect(For Training ANN)

Table 1: Comparison of ID followed by ANN with ID method alone.

Based on our obtained results of over 20 samples, the ANN shows a promising 95% accuracy with only a single error sample. The Table 1 illustrates that the ID method along with ANN classifier provides best defect detection results among all testing methods and enables us to classify the defective and defect free fabric images rather than using the ID method alone just to detect the faults in fabric images.

V. CONCLUSION

In this paper, we propose a novel Image Decomposition method for patterned fabric inspection which can proficiently pinpoint the locations of faulty objects in patterned fabric images with sharp edges and applies the ANN classifier to separate the faulty fabric from the fault free ones. As this can separate the faulty and fault free fabrics, an automated visual inspection machine can be implemented as future work based on this concept.

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