Patterned fabric inspection and visualization by the method of image decomposition

Michael K. Ng  
*Hong Kong Baptist University*, mng@hkbu.edu.hk

Henry Y.T. Ngan  
*Hong Kong Baptist University*, ngan.henry@gmail.com

Xiaoming Yuan  
*Hong Kong Baptist University*, xmyuan@hkbu.edu.hk

Wenxing Zhang  
*University of Electronic Science and Technology of China*

Follow this and additional works at: [https://repository.hkbu.edu.hk/hkbu_staff_publication](https://repository.hkbu.edu.hk/hkbu_staff_publication)

Part of the [Mathematics Commons](https://repository.hkbu.edu.hk/hkbu_staff_publication)

This document is the authors' final version of the published article.

Link to published article: [http://dx.doi.org/10.1109/TASE.2014.2314240](http://dx.doi.org/10.1109/TASE.2014.2314240)

**APA Citation**

This Journal Article is brought to you for free and open access by HKBU Institutional Repository. It has been accepted for inclusion in HKBU Staff Publication by an authorized administrator of HKBU Institutional Repository. For more information, please contact repository@hkbu.edu.hk.
Patterned Fabric Inspection and Visualization by the Method of Image Decomposition

Michael K. Ng, Henry Y. T. Ngan, Senior Member, IEEE, Xiaoming Yuan, and Wenxing Zhang

Abstract—This paper analyzes the cartoon and texture structures to inspect and visualize defective objects in a patterned fabric image. It presents a method of an image decomposition (ID) and solves it by a convex optimization algorithm. Our experimental results on benchmark fabric images are superior to those by other methods.

Note to Practitioners—This paper is motivated by an ID method to examine how to newly represent defective objects and repeated patterns in fabric images. We decompose a fabric image into two components: cartoon structure as defective objects and texture structure as repeated patterns. The ID is optimized by the largest correlation between a given defect-free fabric image and the texture structure of a testing image. Its merit is requiring only one defect-free image to optimize the inspection. The resulting cartoon structure is identified for inspection and visualization. An intensive performance evaluation is conducted on dot-, star- and box-patterned fabric images and the detection accuracies range from 94.9% ∼ 99.6%. This research is beneficial to the practitioners for quality control in textile, ceramics, tile, wallpaper, printed circuit board, and aircraft window industries.

Index Terms—Patterned fabric inspection, image decomposition, operator splitting method, convex optimization, classification

I. INTRODUCTION

AUTOMATED patterned fabric inspection [15] has been a popular research topic in manufacturing quality control of automation over twenty years. It aims to detect, identify and locate defects on the surface of patterned fabrics during manufacturing. Previously, it was mainly achieved by visual inspection of skilled workers, yet it has disadvantages such as high error rates due to human fatigue, high labor costs and slow inspection speed. Automated visual inspection [3] improves such inspection and offers satisfying 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 pre-defined 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 [15]). It is natural 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 employed to detect defective objects in simple plain and twill fabric images (Fig. 1(a)) via transformation and reconstruction processes. However, it is not clear how to extend these methods to figure out the correlation between defective objects and patterned fabric for more complicated patterns in the dot-, box- and star-patterned fabrics (Fig. 1(b)-(d)).

M.K. Ng and Henry Y. T. Ngan are with the Centre for Mathematical Imaging and Vision, and Department of Mathematics, Hong Kong Baptist University, Hong Kong (e-mail: mng@math.hkbu.edu.hk; ngan.henry@gmail.com). The first author is supported by RGC Grants and HKBU FRG Grants. The second author is supported by HKBU FRG Grant: FRG1/12-13/075.

X.M. Yuan is with the Department of Mathematics, Hong Kong Baptist University, Hong Kong (e-mail: xnyuan@math.hkbu.edu.hk). This author is supported by the General Research Fund of Hong Kong: 203712.

W.X. Zhang is with the School of Mathematical Sciences, University of Electronic Science and Technology of China, Chengdu, China (e-mail: wxzh1984@126.com). This author is supported by NNSFC: 11301055

In this paper, the rationale of ID is exploited to develop a novel patterned fabric inspection method. We consider that a defective fabric image is the superposition of defective objects (cartoon structure) and patterned fabric (texture structure). We employ the total variation and semi-norm in negative Sobolev space to regularize cartoon and texture structures, respectively. A minimization process (Section III-2) can separate the defective objects in term of geometrical cartoon structure and the patterned fabric in term of repetitive patterns. Derived by mathematics, we can decompose patterned fabric images, identify and visualize defective objects accordingly. To illustrate our idea, Fig. 2(a) shows a dot-patterned fabric defective image, containing several defective objects. After ID, the resulting defective objects (i.e., cartoon) and the remaining patterned fabric (i.e., texture) are shown in Fig. 2(b)-(c).

This research has four main contributions. First, we propose a novel ID method to deal with patterned fabric inspection and visualization. This model can be solved efficiently by our recent operator splitting method in convex optimization. Second, the proposed method requires only one defect-free fabric image to optimize the ID method with respect to the largest correlation between a given defect-free fabric image and the texture structure of input testing images. This approach is different from the other traditional inspection methods [15]. Also, the output cartoon structure from the ID method is identified for inspection and visualization. Third, defect manual-labeled image databases of dot-, star- and box-patterned fabrics are newly constructed for the performance evaluation while most of previous literature did not have these and only simply counted the quantity of white pixels in the resultant images to determine accuracies. Fourth, an intensive performance evaluation is conducted on the databases. Based on defect manual-labeled images, the proposed method achieves 94.9% ∼ 99.6% of detection accuracies. We also apply a FPR-TPR graph (FPR for false positive rate, TPR for true positive rate) analysis, which is new in literature, to show the robustness of the proposed method compared to the other methods.

The rest of the paper is organized as follows. Section II presents related work for patterned fabric inspection. Section III delivers math-
emathematical 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)), 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-processing 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 multi-band-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.

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 damen 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(ε, 2) to preprocess any fabric image f 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 follow the ID method in [9]

\[
\min_{u,\varepsilon} \|\nabla u\|_1 + \frac{1}{2} \|u + \text{div} g - f\|_2^2 + \mu \|g\|_p, \quad p \geq 1
\]

for splitting a target image f. Here, \(\nabla\) is the 1\textsuperscript{st}-order derivative operator and \(\text{div} = -\nabla^T\) is the divergence operator; \(\tau\) and \(\mu\) are positive parameters to balance three terms in the objective function; \(u\) and \(v = \text{div} g\) 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 \(u\) and preserving its sharp discontinuities; the second term represents the restoration discrepancy; \(\|g\|_p\) approximates (by taking \(p \to \infty\)) 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 trade-offs \((\tau, \mu)\) 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., \(v(\tau, \mu) = \text{div} g\)) containing the 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

\[
\text{Corr}(v(\tau, \mu), f^*) = \frac{\text{cov}(v(\tau, \mu), f^*)}{\sqrt{\text{var}(v(\tau, \mu)) \cdot \text{var}(f^*)}} \tag{2}
\]

is close to 1, where \(\text{var}(\cdot)\) and \(\text{cov}(\cdot, \cdot)\) are the variance and covariance of given variables, respectively.

We suggest to select \((\tau, \mu)\) for the model (1) which can offer higher \(\text{Corr}(v(\tau, \mu), f^*)\) values. Specifically, the trade-offs \((\tau, \mu)\) are

![Image]: Fig. 3. The flowchart of the ID method for patterned fabric inspection.

![Image]: Preprocessing-free case

![Image]: Preprocessing case

Fig. 4. Samples of detected “Thick Bar” defects with/without preprocessing.
we choose one reference image Given a certain patterned fabric database, say the dot-patterned fabric, (b) Star-patterned fabric.

Fig. 5. Parameters-correlation surface of testing patterned fabrics. (a) Dot-patterned fabric, (b) Star-patterned fabric.

<table>
<thead>
<tr>
<th>$f$</th>
<th>The trade-offs $(\tau, \mu)$ at doublets $A_2$ in Fig. 5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$A_1$</td>
</tr>
<tr>
<td>(0.05, 1)</td>
<td>(0.15, 1)</td>
</tr>
<tr>
<td>(0.12, 1)</td>
<td>(0.26, 1)</td>
</tr>
</tbody>
</table>

Fig. 6. Detected “Broken End” defects by solving model (1) with different trade-offs $(\tau, \mu)$’s.

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 $(\tau, \mu)$’s in model (1), we record the $\text{Corr}(v(\tau, \mu), f^*)$ value corresponding to individual $(\tau, \mu)$ of ADM-G recursions. The empirically “optimal” trade-off $(\tau, \mu)$ 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” trade-offs $(\tau, \mu)$’s are typically achieved at the peaks of those surfaces. Eventually, from the contours of those surfaces, we have that the “optimal” trade-offs $(\tau, \mu)$ are $\approx (0.3, 1)$, $\approx (0.4, 1)$ and $\approx (0.6, 1.5)$ for the dot-, star-, and box-patterned fabrics, respectively. Fig. 6 illustrates some detected results, i.e., the cartoons $u$ derived from model (1), at different doublets $A_i$’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, 6). However, the colormap and edges of those defective objects are visually inharmonious and indistinguishable. We hence exploit a simple detection enhancement step. By re-scaling 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, TPR) in a FPR-TPR graph (see Section IV-A) close to the perfect classification point (0,100).

IV. EXPERIMENTAL RESULTS

A. Measurement Metrics

We would employ some measurement metrics to quantify the efficiencies of different methods. First, the numerical comparisons between detected images (binary images after detection enhancement step) and defect manual-labeled images are conducted in a pixel-by-pixel manner. Concretely, both pixels in the detected and defect 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 false negative (FN). The following measurement metrics are used to compare various methods: accuracy $\text{ACC} = \frac{TP+TN}{TP+FP+FN+TN}$, true positive rate $\text{TPR} = \frac{TP}{TP+FN}$, false positive rate $\text{FPR} = \frac{FP}{TP+FP}$, positive predictive value $\text{PPV} = \frac{TP}{TP+FP}$ and negative predictive value $\text{NPV} = \frac{TN}{TN+FN}$.

We utilize the FPR-TPR graph, which is produced by scattering the doublets (FPR, TPR), i.e., FPR and TPR as $x$ and $y$ axes, respectively. Theoretically, the best classification method tends to yield the coordinates (FPR, TPR) at the upper-left corner of the FPR-TPR graph, i.e., near to the point (0,100) which is called a perfect classification point and far from the line $y = x$ which 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 previous methods (i.e., DT, WGIS, LBP, BB, RB) in literature only simply counted the number of white pixels as threshold of a resultant image to determine whether it is defective or not, and corresponding the detection accuracies. Most methods nearly achieved very similar detection accuracies for all defective and defect-free images in various patterned fabrics. Therefore, this criteria, using the number of the white pixels, is not effective to distinguish how accurate detection of a method is. In order to perform an intensive evaluation and clearly understand how accurate detection of a method, we now compare the ID method with the trade-offs attained in Section III-2 to the BB [11] and RB [12] methods (which have tentative best accuracies and visual results in literature), with the measurement metrics above, on the newly constructed defect manual-labeled databases for patterned fabric inspection.

Tables I-II 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, the ID method achieved all ACCs greater than 94.9% and all TPRs larger than 50.9% for dot-patterned fabric images. In Table II, the ID method also obtained promising TPRs for all star-patterned fabric images and only perform a little inferior in “Thin Bar”. Figs. 7–9 show samples of detected results by three testing methods. Some remarks can be drawn from Tables I-II and Figs. 7-9 as follows: (i) the TPRs 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). 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), especially for “Broken End” defect in the dot-patterned fabrics, “Netting Multiple”, “Thick Bar”, “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.

To visually distinguish the effectiveness of the BB, RB and ID methods among various defects, we plot the FPR-TPR graphs in Fig. 10 for patterned fabric images by all test methods. It illustrates that the ID method can provide the best detected results in the sense of the FPR-TPR graphs among all testing methods.

V. CONCLUSION

In this paper, we propose a novel ID method for patterned fabric inspection which can efficiently pinpoint the locations of defective objects in patterned fabric images with sharp edges. As the ID method in [9] can also be applicable for images with corruptions, e.g., blurry and/or missing pixels, we will investigate how to detect patterned fabric images with corruptions in our future research.

REFERENCES


