International Organization of Research & Development (IORD)
ISSN: 2348-0831
Vol 12 Issue 01 | 2024

Video Template Matching Algorithm for Construction Projects-a Hadamard Domain Approach

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ABSTRACT

In order to accurately detect defects in patterned fabric images, a novel detection algorithm based on Gabor-HOG (GHOG) and low-rank decomposition is proposed in this paper. Defect-free pattern fabric images have the specified direction, while defects damage their regularity of direction. Therefore, a direction-aware descriptor is designed, denoted as GHOG, a combination of Gabor and HOG, which is extremely valuable for localizing the defect region. Upon devising a powerful directional descriptor, an efficient low-rank decomposition model is con- structed to divide the matrix generated by the directional feature extracted from image blocks into a low-rank matrix (background information) and a sparse matrix (defect information). A noncon- vex log det(·) as a smooth surrogate function for the rank instead of the nuclear norm is also exploited to improve the efficiency of the low-rank model. Moreover, the computational efficiency is further improved by utilizing the alternative direction method of multipliers (ADMM). Thereafter, the saliency map generated by the sparse matrix is segmented via the optimal threshold algorithm to locate the defect regions. Experimental results show that the proposed method can effectively detect patterned fabric defects and outperform the state-of-the-art methods.

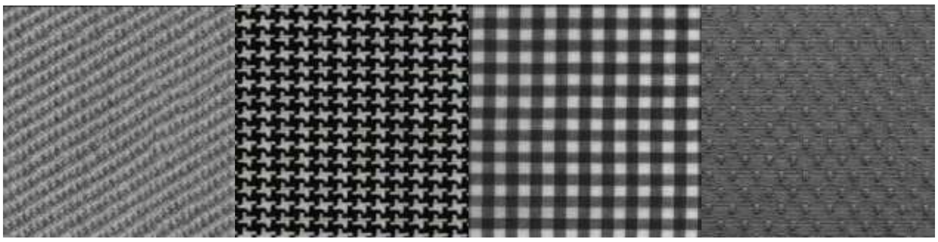
Index Terms—patterned fabric, defect detection, GHOG, low- rank decomposition, ADMM.

1. INTRODUCTION

Fabric defect detection always plays a key role in the quality control of textile industry. Currently, it is mainly performed visually by skilled workers. However, its reliability is restricted by eye fatigue and human errors. An automated detection system based on machine vision can provide a promising solution that not only minimizes labor costs, but will also improve accuracy and efficiency. Moreover, an automated system is better equipped to deal with different kinds of fabric patterns, from the non-motif pattern (plain and twill fabrics, as shown in Fig.1 (a)) to the motif pattern (star-, box-, and dot-patterned fabrics, as shown in Fig.1 (b-d)).

Most existing defect detection methods focus on simple plain and twill fabrics, which can be classified into four categories: statistical method [1], frequency analysis method [2], model method [3], and dictionary learning method [4].

The aforementioned defect detection methods achieve high detection accuracy. However, because of the complexity and sophisticated design on patterned fabric, these proposed meth- ods cannot be extended to detect patterned fabric defects. Moreover, few studies have been conducted on patterned fabric so far. In this paper, our research is focused on defect detection in patterned fabric.



(a) (b) (c) (d)
Fig. 1. (a) Plain and twill. (b) Star-patterned fabric.(c) Box-patterned fabric (d) Dot-patterned fabric.

The patterned fabrics are defined as fabrics with repetitive patterned units in their designs. Even within the same class of 'patterned' fabrics, there are still many categories, and the pattern sizes are different. Therefore, patterned fabric defect detection is a challenging task. Traditional methods cannot efficiently recognize the normal pattern; furthermore, they fail to localize the defect region. Some methods devised for pattern fabric defect detection, such as the ELO rating (ER) method [31], and wavelet-preprocessing golden image subtraction (WGIS) [21], et al.,which are performed in a supervised approach, require non-defective samples; moreover, the detection accuracy of these methods depends on precise alignment and choosing a suitable template.

Visual attention mechanism can enable machine and bio- logical vision systems to quickly find the most salient regions or objects from a scene [5]. Generally, pattern fabric images always exhibit a high periodic texture among sub-patterns. However, the defect will disrupt their periodicity (regularity), resulting in the defects outstanding from homogeneous back- ground. Therefore, visual saliency models provide a promising method for pattern fabric defect detection.

Many saliency models have been proposed to detect salient objects [5]. A representative series of papers are based on the low-rank matrix decomposition (LR) theory [6,7]. The background usually lies in a low-dimensional subspace, while the objects that are different from the background can be considered as noises or errors. Therefore, these methods divide an image into a low-rank matrix plus a sparse matrix in a learned feature space, where the low-rank matrix represents the background regions, and the sparse matrix indicates the salient object regions.

For different kinds of patterned fabrics, the background of the fabric has a visually homogeneous texture, and any defects stand out from the background. Compared with object detection in a natural scene, patterned fabric defect detection better fits the low-rank decomposition model.

However, using low-rank decomposition directly in a color space or in some other feature space of images does not deal with the task of pattern fabric defect detection with any sort of efficiency. This is because sub-parts have different colors or other features locally, but globally they belong to the normal texture. Therefore, a new powerful descriptor should be proposed to efficiently characterize the fabric texture, and should be required to possess the following attributes: (1) defect regions should have a totally different feature descriptor compared with the background; (2) the background should have a similar feature descriptor (that can be easily regarded as the low-rank part).

Defect-free pattern fabric images have a specified direction, while defects damage their regularity of direction. Therefore, a direction-aware descriptor can better represent the fabric feature, which is extremely valuable for separating a salient defect from a non-salient background.

Therefore, in this paper, a direction-aware descriptor, de- noted as GHOG, is designed to be a combination of Gabor and HOG. Upon devising a powerful directional descriptor, an efficient low-rank decomposition model is constructed to divide the matrix generated by the directional feature extracted from image blocks into a low-rank matrix (background information) and a sparse matrix (defect information). Moreover, we also propose the use of a non-convex log det() as a smooth surrogate function for the rank as opposed to the nuclear norm in order to improve the model's efficiency. Finally, the saliency map generated by the sparse matrix is segmented to locate the defect regions.

The reminder of this paper is organized as follows. Section 2 introduces the related works of fabric defect detection. In Section 3, we focus on the proposed algorithm and its specific procedures. Section 4 evaluates the performance of the proposed algorithm and compares it with other state-of- the-art methods. Finally, we conclude the paper in Section 5.

2. RELATED WORKS

Defect detection plays an important role in the fabric quality control process. Many different fabric defect detection methods have been proposed to solve this problem, and are generally used to detect defects in plain and twill fabrics. These methods are divided into the following categories: spatial statistical analysis, spectral analysis, model-based methods, and dictionary learning. Spatial statistical methods detect defects by calculating gray values contrasted with their surroundings, including histogram character analysis [8], morphology [9], local contrast enhancement [10], and the fractal method [11]. The detection results of these methods depend largely on the size of a selected window and its discrimination threshold; it is difficult to detect smaller sizes defects for them. Additionally, these methods cannot effectively exploit the image's global information, and are always influenced by noise.

Spectral analysis methods transform the image to the spec- tral domain by choosing a suitable orthogonal basis, which can make better use of the image's global information detect defects. These methods include the Fourier transform (FT)[12], the Gabor transform [13] and the orthogonal wavelet transform [14]. However, these methods always have high computational complexity and poor detection performance for the complex texture fabric images.

Model-based methods first extract image texture features through modeling and parameter estimation techniques. Defect detection is realized by discriminating whether the test image conforms with the normal texture model. Existing methods include the Gaussian-Markov random field (GMRF) [15], and the Gaussian mixture model (GMM) [16, 17]. These methods have obtained satisfactory detection performance; however, they usually share a high computational complexity, and these methods cannot efficiently detect smaller size defects.

Dictionary learning-based methods learn a dictionary of training images or test images, and then reconstruct the defect- free fabric image; thereafter, defect detection can be realized by subtracting the recovered image from the test image [18, 19]. In a different way, dictionary learning based methods also reduce the dimension of an image block by projecting the im- age block into a dictionary learning from reference image, then the SVDD is adopted to discriminate whether an image block is a defect block [20]. However, these methods are unable to achieve ideal detection performance because the reconstructed image by the dictionary learning from themselves may exist some defects, or the self-adaptability of these methods are reduced if the dictionary learns from the reference images.

Regarding complicated patterned fabrics, several meth- ods have been recently published, such as the wavelet- preprocessing golden image subtraction method (WGIS) [21], the Bollinger band method (BB) [22], the regular band method (RB) [23], template matching for discrepancy mea- sures (TMPM) [24], the pattern matching and subtraction approach [25-28], the Hash function method [29], and the regularity and local orientation (RLO) method [30].

The WGIS method utilized a golden image to perform a moving subtraction of each pixel along each row of every wavelet-pre-processed tested image. The BB and RB meth- ods, designed by different combination of moving averages and standard deviations, utilized the regularity property of a patterned texture to carry out on dot-, box-and star-patterned fabrics. The TMPM method used a golden image-like ap- proach to exploit a discrepancy measure as a fitness function to detect defectson patterned textures. The patterned matching and subtraction method performs a point-to-point comparison, which is inherently sensitive to image noise, misalignment and distortion. The hash function method utilizes the offset properties between defect-free and regular patterns to detect the defects; it is fast but is also sensitive to noise and unable to show the shape of any defects after segmentation. The ELO rating (ER) method [31], is a method in which the detection of fabric defects is similar to carrying out fair matches in the spirit of good sportsmanship. However, this method depends on partition size, the number of randomly located partitions, *w*-variable and constant *K*.

The above pattern fabric defect detection methods adopt traditional approaches to characterize the fabric texture, such as wavelet transform, Gabor transform, average value, standard deviation and regular bands. They devised the feature descriptors, but did not consider the characteristics of the pattern fabric image. On the other hand, most of the complicated pattern fabric defect detection methods adopted template-

1) Gabor directional filtered map generation. The com- plex function expression of a 2-D Gabor filter is described as follows [34]:matching technology to localize the defect; they are performed in a supervised approach. The detection accuracy depends on precise alignment and choosing a suitable template. There- fore, in this paper, a powerful direction-aware descriptor was designed, denoted as GHOG.

3. THE PROPOSED ALGORITHM

Defect-free pattern fabric images have a specified direction, while defects damage their regularity of direction. More- over, compared with the object detection in a natural scene, patterned fabric defect detection can better fit a low-rank decomposition model. Therefore, our paper proposes a novel method of patterned fabric defect detection, based on GHOG and low-rank decomposition, and it includes the following four steps: 1) GHOG feature extraction; 2) low-rank decomposition model construction; 3) optimal solution of the model; 4) the generation and segmentation of the saliency map.

3.1 GHOG feature extraction

Highly effective fabric defect detection algorithms should resort to meaningful and powerful feature descriptors to facilitate uniqueness measurements and warrant sufficiently discriminative capabilities. Defect-free patterned fabric images have a specified direction, while defects damage their regular- ity of direction. Therefore, a direction-aware descriptor can better represent the fabric feature.

Due to the outstanding mathematical properties of the Gabor filter and its analogy to human visual mechanisms, the two- dimensional (2D) Gabor filter has been widely applied in the texture analysis. In this paper, a bank of Gabor directional filters have been adopted to extract directional information, and generate the directional Gabor filtered maps.

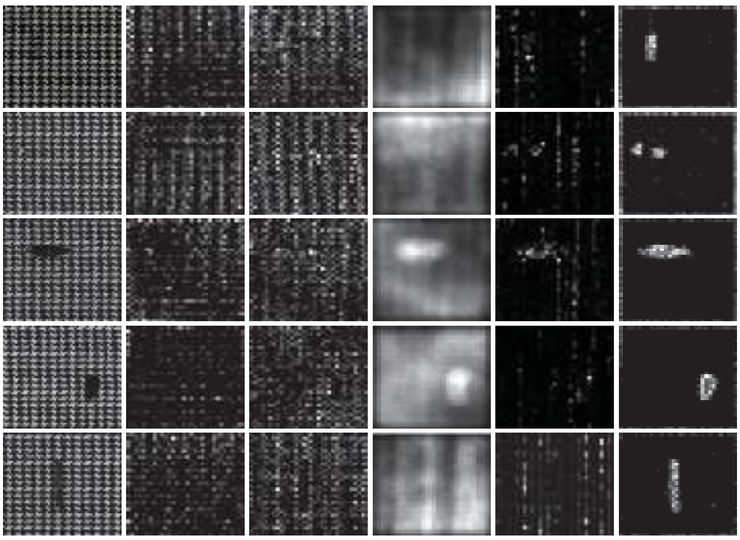
In addition, the gradient space of an image provides a measure of change in intensity over the pixels, as opposed to the absolute values of the pixels' intensity values. Al-where $x' = x \cos\theta + y \sin\theta$, $y' = -x \sin\theta + y \cos\theta$, λ is wave length, which is always greater than or equal to 2, but not more than 1/5 of the size of the input image; θ represents directions, their values ranging from 0 to 2π; ψ indicates phase shift, whose range is from $-\pi$ to π, 0 and π correspond to center-on and center-off functions, respectively, while $-\pi/2$ and $\pi/2$ correspond to anti-symmetric function; γ is the length-width ratio, also known as the ratio of the vertical and the horizontal, which determines the ellipticity of the Gabor function; if $\gamma = 1$, the shape is round, if $\gamma < 1$, shape stretches along the direction of parallel stripes, in this paper, γ is set to 0.5; σ is the Gaussian factor standard deviation of the Gabor function.The value of σ cannot be preset directly, its change just depends on the variation of the bandwidth b. b must be a positive constant, which is related to the ratio of σ/λ, we usually set it as 1. Then the relationship of σ and λ is $\sigma = 0.56\lambda$. In this paper, empirically, we choose eight orientations with one scale to filter the patterned fabric image, and accordingly generate eight directional filtered maps I_{Go} (o=1,2,...,N, N=8 here) that capture the directional features.

2) Uniformly sampling for the Gabor filtered maps. Once these directional filtered maps of all quantized directions are obtained, they are exploited as the inputs for the next computing histogram of orientated gradients features over the same image region. For each generated Gabor filtered map , the size of which is the same as the given original image, is equally decomposed into segments $I_{Go}{}^{i}_{\,i=1,2...K}$ with sizes of $N_b \times N_b$; where o indicts the orientations, and o=1,2,...8,

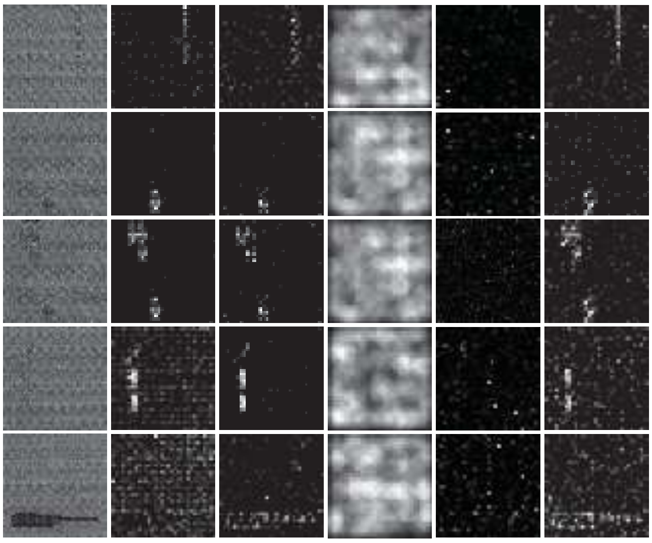
4. EXPERIMENTAL RESULTS AND ANALYSIS

In order to verify the effectiveness of the proposed algo- rithm, we chose images from the dot-, box-, and star-patterned fabric databases for performance evaluation. The size of the fabric image is 512 pixels × 512 pixels. The dot-patterned fabric database contains 30 defect-free and 30 defective im- ages, the star-patterned fabric database contains 25 defect- free and 25 defective images, and the box-patterned fabric database contains 30 defect-free and 26 defective images. All the defective images have a corresponding ground-truth that shows the defect-free regions as black and defective regions as white. All experiments in this paper were implemented in an Inter(R) Core(TM) i3-2120 3.3GHZCPU environment, using software MATLAB 2011. the art visual saliency models, including the wavelet transform (WT) method [40], the prior guided least squares regression method (PGLSR) [41], the textural differential visual saliency model (TDVSM) [38] and the local statistic features and global saliency analysis model (LSF-GSA) [39].

As is shown in Figure 5, WT [40] first transformed the image into a frequency domain, and then generated the saliency map by analyzing the wavelet coefficient. However, even in a normal background with a complicated pattern, its wavelet coefficients are larger, which will lead to incorrect detection results. The PGLSR method [41] could effectively detect defects in the patterned fabric, but similarities in texture between the background and the defect lead to inaccurate shape descriptions of the defects. In Li et al. [38], saliency was calculated by comparing their textural features with the average texture features, it obtains a successful performance for fabric images with a stochastic texture, while the method fails to detect defects in a patterned fabric image, especially



(a) Saliency map for box-patterned fabric imagec



(b) Saliency map for dot-patterned fabric image

5. REFERENCES

[1] Selver, M. A., Avsar, V., & Özdemir, H. (2014). Textural fabric defect detection using statistical texture transformations and gradient search. Journal of the Textile Institute, 105(9), 998-1007.

[2] Jing, J. (2015). Automatic defect detection of patterned fabric via com- bining the optimal gabor filter and golden image subtraction. Journal of Fiber Bioengineering & Informatics, 8, 229-239.

[3] Allili, M. S., Baaziz, N., & Mejri, M. (2014). Texture modeling using contourlets and finite mixtures of generalized gaussian distributions and applications. Multimedia IEEE Transactions on, 16(3), 772-784.

[4] Zhou, J., Semenovich, D., Sowmya, A., & Wang, J. (2014). Dictionary learning framework for fabric defect detection. Journal of the Textile

[5] Borji, A., & Itti, L. State-of-the-art in visual attention modeling. Pattern Analysis and Machine Intelligence, IEEE Transactions on,2013, 35(1), 185-207.

[6] Lang C, Liu G, Yu J, et al. Saliency detection by multitask sparsity pursuit [J]. Image Processing, IEEE Transactions on, 2012, 21(3): 1327-1338.

[7] Chen C, Li S, Qin H, et al. Structure-Sensitive Saliency Detection via Multilevel Rank Analysis in Intrinsic Feature Space[J]. Image Processing, IEEE Transactions on, 2015, 24(8): 2303-2316.

[8] Selver, M. A., Avsar, V., & Özdemir, H. Textural fabric defect detection using statistical texture transformations and gradient search [J]. Journal of Thoracic Oncology Official Publication of the International Association for the Study of Lung Cancer, 2014, 6(105):2017-2023.

[9] Hu J, He Z, Weng G, et al. Detection of chemical fabric defects on the basis of morphological processing [J]. Journal of the Textile Institute, 2015:1-9.

[10] Guan S, Shi H, Zhao T. Image segmentation of fabric defect based on object rarity feature [J].Textile Research Journal, 2015,36(11): 45-50.

[11] Hanmandlu M, Choudhury D, Dash S. Detection of defects in fabrics using topothesy fractal dimension features [J]. Signal, Image and Video Processing, 2015, 9(7): 1521-1530.

[12] Sakhare K, Kulkarni A, Kumbhakarn M, et al. Spectral and spatial do- main approach for fabric defect detection and classification [C]//Industrial Instrumentation and Control (ICIC), 2015 International Conference on. IEEE, 2015: 640-644.

[13] Jing J, Chen S, Li P. Automatic Defect Detection of Patterned Fabric via Combining the Optimal Gabor Filter and Golden Image Subtraction [J]. Journal of Fiber Bioengineering and Informatics, 2015, 8(2): 229-239.

[14] Wen Z, Cao J, Liu X, et al. Fabric defects detection using adaptive wavelets [J]. International Journal of Clothing Science and Technology, 2014, 26(3): 202-211.

[15] Xiaobo Y. Fabric defect detection of statistical aberration feature based on GMRF model [J]. Journal of Textile Research, 2013, 4: 026.