FABRIC DEFECT DETECTION BASED ON IMPROVED LOW-RANK AND SPARSE MATRIX DECOMPOSITION

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ABSTRACT

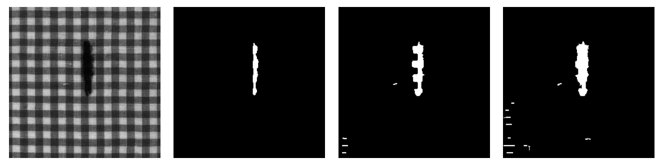
In this paper, we propose an effective approach to detect defects in fabrics. Based on the observation that fabric textures usually form a low-rank structure and the structure can be violated by the presence of defects, we formulate the task as a low-rank and sparse matrix decomposition problem. Moreover, the prior that defects tend to be continuous regions is considered in our model and the estimation of defect levels is properly solved by introducing an integration mechanism. Experimental results demonstrate that our proposed method can not only detect defects accurately but also have greater ability to preserve defect details than traditional approaches.

Index Terms— Fabric Defect Detection, Low-rank and Sparse Matrix Decomposition, Integration Mechanism

1. INTRODUCTION

Defect detection plays an important role in the production of fabrics. As can be seen in [1] , the price of textile fabrics can be dramatically reduced by 45% to 65% due to the presence of defects, so detecting flaws in fabrics accurately and efficiently has practical significance for textile enterprise.

Traditionally, the detection task is manually performed by skilled workers, whose inspection suffers from both low accuracy and low efficiency. In the past decades, researchers have proposed numerous approaches for automatic fabric defect detection and these methods can be roughly divided into three categories: spectral, statistical and model-based approaches. Regular patterns and periodic textures for most fabrics make spectral approaches [2, 3, 4] become the mainstream. However, their performance usually hinges heavily on the chosen filters. Statistical approaches employ co-occurrence matrix [5], modified local binary patterns [6] and other statistical features to identify defective regions. Unfortunately, both spectral and statistical methods can hardly detect stochastic surface variations appeared in randomly textured fabrics [7], but model-based methods can work it out. In [8], wavelet packet frame is combined with Gaussian mixture model to accomplish texture classification and segmentation. Feed-forward neural network [9] is employed to detect local textile defects. In general, model-based methods are more complicated than the aforementioned two types of approaches.



(a) (b) (c) (d)

Fig. 1. Detection results of (a) the original fabric image obtained by naive GoDec with different values of the cardinality parameter: (b) $k = 1000$, (c) $k = 3000$, and (d) $k = 5000$.

Recently, low-rank and sparse matrix decomposition has been a research hotspot and found abundant applications in computer vision [10, 11, 12]. A given fabric image can be regarded as combinations of repeated patterns, whose texture features are highly correlated and thus form a low-rank structure. However, this structure can be destroyed by defects, which usually account for a small portion of the whole image. Consequently, we propose to detect fabric defects based on a randomized low-rank and sparse matrix decomposition model named GoDec [13], which decompose a matrix into a low-rank matrix, a sparse matrix and a noise matrix corresponding to defect-free background, defective regions and interference noise, respectively. As shown in Fig.1, the selection of the cardinality parameter in naive GoDec has a direct impact on detection results. To produce more satisfying outcomes, our main contributions are summarized below:

- The prior that defects tend to be continuous regions is considered to update the sparse matrix so as to make the detected defects more complete.
- An integration mechanism is proposed to handle the problem of incomplete defects and residual noise caused by selecting a fixed cardinality parameter in naive GoDec.

The reminder of this paper is organized as follows. Section 2 highlights our proposed method, which includes a revised low-rank and sparse model with reasonable parameter selection strategy and the design of binarization and postprocessing. In section 3, we present and analyze experimental results, followed by conclusions in section 4.

2. PROPOSED METHOD

2.1. Low-Rank and Sparse Matrix Decomposition

GoDec differs from the well-known low-rank and sparse model named RPCA [14] in that it decomposes a matrix into three components, that is:

$$X = L + S + N, \tag{1}$$

where X is an input matrix, L denotes a low-rank matrix, S represents a sparse matrix while N stands for a Gauss noise matrix. The objective function of GoDec is:

$$\min_{L,S} \|X - L - S\|_F^2 \; s.t. \, rank\,(L) \leq r, card\,(S) \leq k, \tag{2}$$

where r and k denote the upper bound of the rank of L and the cardinality of S, respectively. GoDec supposes that these two parameters can be determined beforehand, making it much more flexible than RPCA, which is a blind seperation. The solution of (2) can be obtained by alternatively solving the following two subproblems until convergence:

$$\begin{cases} L_t = \arg \min\limits_{rank(L) \leq r} \|X - L - S_{t-1}\|_F^2; \\ S_t = \arg \min\limits_{card(S) \leq k} \|X - L_t - S\|_F^2 . \end{cases} \tag{3}$$

More specifically, [13] further indicated that L_t and S_t can be updated via implementing singular value hard thresholding to $X - S_{t-1}$ and entry-wise hard thresholding to $X - L_t$, i.e.,

$$\begin{cases} L_t = \sum\limits_{i=1}^{r} \lambda_i U_i V_i^T, svd\,(X - S_{t-1}) = U \Lambda V^T; & (4) \\ S_t = P_\Omega\,(X - L_t)\,, \Omega : \left|(X - L_t)_{i,j \in \Omega}\right| \neq 0 & \\ \quad and \geq \left|(X - L_t)_{i,j \in \overline{\Omega}}\right|, |\Omega| \leq k, & (5) \end{cases}$$

Since our task is to detect defects, we are more concerned about the updating process of sparse matrix S_t in (5). It can be observed that only the largest k non-zero elements in $X - L_t$ are used for updating S_t in each iteration. In other words, only the magnitude of the elements in $X - L_t$ is considered but their neighbor information is ignored. However, compared with discrete pixels having large gray values, those compact pixels are more likely to form real defects. Considering there is a noticeable gap between gray values of a discrete noise pixel and its adjacent pixels, a function $Nei(x)$ that reflects pixels' spatial information is defined to modify the updating strategy of S_t. Mathematically, $Nei(x)$ is given by

$$Nei\,(x) = \exp\left(- |x_{mean} - x_c|\right), \tag{6}$$

where x_c and x_{mean} denote the gray value of a central pixel and the average of its neighbor pixels, respectively. In our experiment, x_{mean} takes the average of pixels' gray values in an eight neighborhood.

Up to this point, a revised version of (5) can be described by

$$\begin{aligned} {S_t}' = P_{\Omega'}\,(T)\,, \Omega' : \left|(Nei\,(T) \otimes T)_{i,j \in \Omega'}\right| \neq 0 \\ and \geq \left|(Nei\,(T) \otimes T)_{i,j \in \overline{\Omega'}}\right|, \; |\Omega'| \leq k, \end{aligned} \tag{7}$$

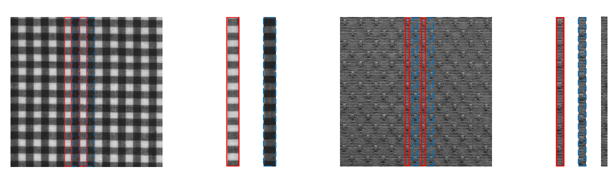
where $T = X - L_t$ and $\otimes$ signifies element-wise multiplication. By taking pixels' neighbor information into consideration, the newly-proposed (7) is capable of choosing compact elements with relative large values to update the sparse matrix, thus the detected defects will be more complete.

2.2. Parameter Selection

Notice that there are two parameters in GoDec need to be determined before it can be used for fabric defect detection, but the choice of various parameter values remains an open problem. In this part, the way to select a rank parameter r is firstly introduced. As for cardinality paramter k, we come up with an integration mechanism rather than select it directly.

2.2.1. Rank Parameter

In linear algebra, the rank r of a matrix L refers to the dimension of vector space spanned by its columns. As discussed previously, a fabric image can be regarded as combinations of repeated patterns, and we can sensibly set the rank parameter to the number of patterns existed in the current fabric image. Examples can be found in Fig.2. A box-patterned fabric image is shown in Fig.2a with two basic patterns exhibited in Fig.2b, so its rank parameter can be set to 2. Similarly, the dot-patterned fabric image in Fig.2c can be decomposed into three kinds of primitives presented in Fig.2d, in which the right one denotes the plain portion between the two different dot patterns. Accordingly, we can set its rank parameter to 3. As for unpatterned fabrics, the rank parameter can be set to 1.



(a) (b) (c) (d)

Fig. 2. Decompose fabric images into patterns.

2.2.2. Cardinality Parameter

As shown in Fig.1, cardinality parameter k in naive GoDec is tightly correlated to detection results. Therefore, how to choose this parameter becomes a key issue. In [15, 16], GoDec was used for hyperspectral image denoising and

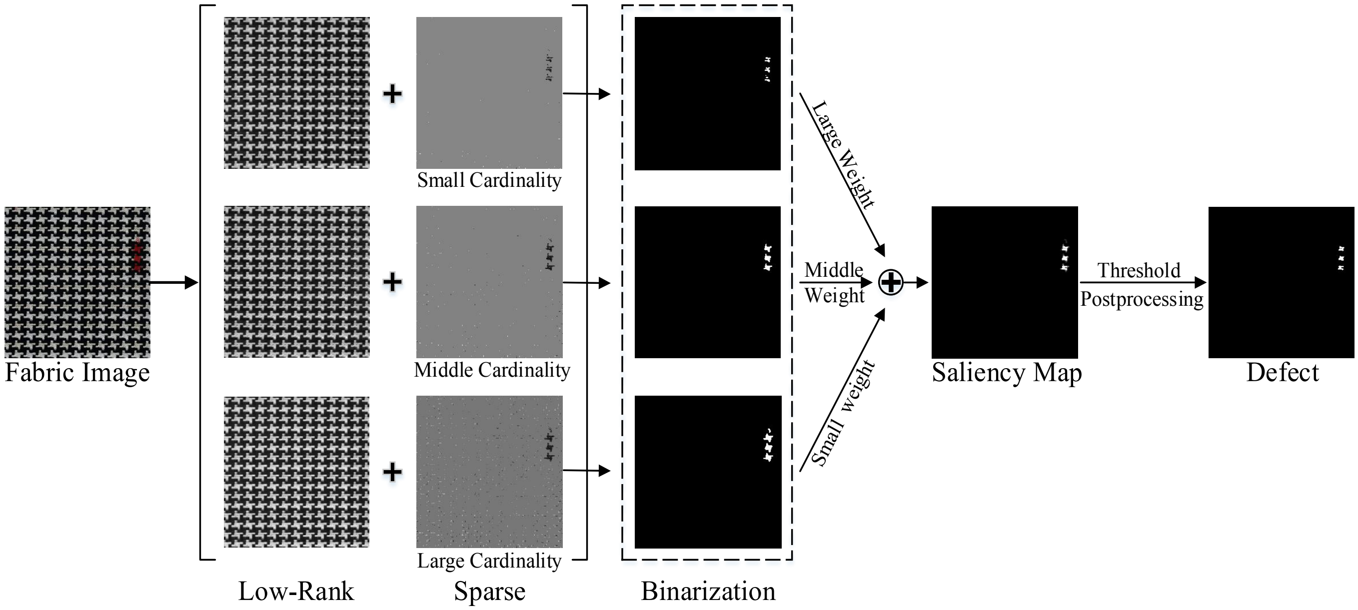


Fig. 3. Three-level weighted integration mechanism.

restoration, and a fixed cardinality value was adopted according to researchers' experience. Nevertheless, the selection of k in detection task should depend on defect levels, and the adaptability of the proposed method may be largely constrained by empirically selecting a fixed value. Inspired by spatial pyramid matching model [17], we propose a weighted integration mechanism to handle the above problems.

As can be seen from Fig.1, a smaller k means that fewer pixels will be selected, resulting in the incompleteness of the detected defects. Instead, a larger one implies that more pixels are collected, in which there may exist much noise. In other words, the binarized sparse matrix generated with a small cardinality value has a higher probability to indicate real defect pixels than those with a large one, and this inspires us to assign it a large weight for its highly matching with the real defects. In contrast, more and more noise will appear in the binarization results with the increase of the cardinality values, so small weights are needed to weaken their impacts. Based on the above analysis, we propose a weighted integration mechanism and an example of three-level weighted integration is shown in Fig.3. The weights assigned to the binarized sparse matrices are in reverse proportion to their cardinality values. More specifically, we manully divide cardinality values into Q levels, and the weight assigned to the i-th level is simply given by

$$w\left(i\right)=\frac{1}{2^{i}},\ \ i=1,\cdots,Q. \tag{8}$$

With the increase of cardinality values, noise starts to gradually appear while elements representing real defect pixels always exist in sparse matrices. Therefore, compared with noise assigned with small weights, defect pixels will have larger values in saliency map, which is generated by summing weighted binarization results together. Then, an auto-threshold algorithm [18] combined with the customized postprocessing is performed on saliency map to obtain ultimate detection results.

2.3. Binarization and Postprocessing

In our scheme, we need to integrate several binarization results generated with different cardinality values, making binarization to sparse matrices an important operation. Considering the peculiarity of detection task, we customize a binarization process as follows. To remove residual noise, a median filtering is firstly implemented to sparse matrices. Then, all non-zero elements are set to 1 indicating defect pixels and thus form some defect regions. Finally, several binarization results are weighted differently in terms of their cardinality values and summed together to generate a saliency map. After automatically thresholding the saliency map, the resulting image may still contain some small connected regions that are usually not regarded as defects, so a postprocessing is necessary. In our experiment, we only preserve defect regions with area larger than ten pixels.

3. EXPERIMENTS AND RESULTS

To verify the effectiveness, we test our proposed method on a widely used fabric image dataset collected by Dr. Henry Y.T. Ngan [19]. Box-patterned, dot-patterned and star-patterned fabric images are included in this dataset, and examples can be found in Fig.4. In our experiments, the cardinality parameter k is set to the range from 1000 to 3000, and a three-level weighted integration is employed with two intermediate points set to 1600 and 2400, respectively. That is, the binarization results generated with cardinality values range from 1000 to 1600, 1600 to 2400, and 2400 to 3000 are assigned with weights 0.5, 0.25 and 0.125, respectively.

Our proposed method was compared with two low-rank-based approaches: PG-LSR [20] and naive GoDec model. In order to integrate prior knowledge, the former computes reference feature vectors by utilizing fabric image blocks, which are chosen at random and have a high probability to be defect-free regions. The latter is used to confirm the superiority of our modified updating strategy for sparse matrix and proposed integration mechanism for cardinality parameter selection.

Detection results of several fabric images are compared visually in Fig.4. It can be found that PG-LSR is basically able to detect defects for most cases but easy to produce over-complete detection results and lose some details, such as edge information, shape description. The cardinality parameter in naive GoDec is fixed to 2200, which is the optimal value chosen by experiment. Note that its performance is somewhat similar to ours, while carefully selecting the cardinality parameter is not required in our method. Besides, detection results obtained by our method are usually detail-preserving and less contaminated by noise.

Note that several of previous work [4, 9, 21] did not quantitatively evaluate their methods. To facilitate this situation, we chose 15 representative fabric images with typical defects and labeled the groundtruth manually for evaluation. A patch-wise manner with patch size of 4×4 was adopted to evaluate different methods, allowing the existance of a certain error caused by our labeled groundtruth. The Precision, Recall and F-measure are computed for each image and the average values of these three indexes for all 15 images are given in Table 1. The over-complete detection results of PG-LSR lead to low precision and existance of noise in detection results of naive Godec causes low recall. The result shows that our method achieves fairly balanced performance.

Table 1. The performance of the three methods

	PG-LSR	naive GoDec	Our method
Precision	0.3954	0.8666	0.7954
Recall	0.8124	0.7465	0.8288
F-measure	0.4871	0.7949	0.8055

4. CONCLUSION

In this paper, a novel approach to detect flaws in fabrics is proposed. As undamaged fabrics generally show homogeneous textures, which can be disrupted by defects that usually occupy small regions, we naturally formalize the task as a low-rank and sparse matrix decomposition problem. Considering that defect pixels are inclined to be compact, a function is defined to integrate this prior so as to make the detected defects more complete. Since different fabric images have different defect levels, a weighted integration mechanism is utilized to yield better detection results. Experimental results demonstrate the effectiveness of our proposed method. As for defects that have a large area and fail to fit the sparse condition, our method may get stuck and thus exploring the representation ability of low-rank and sparse model will be our future work.

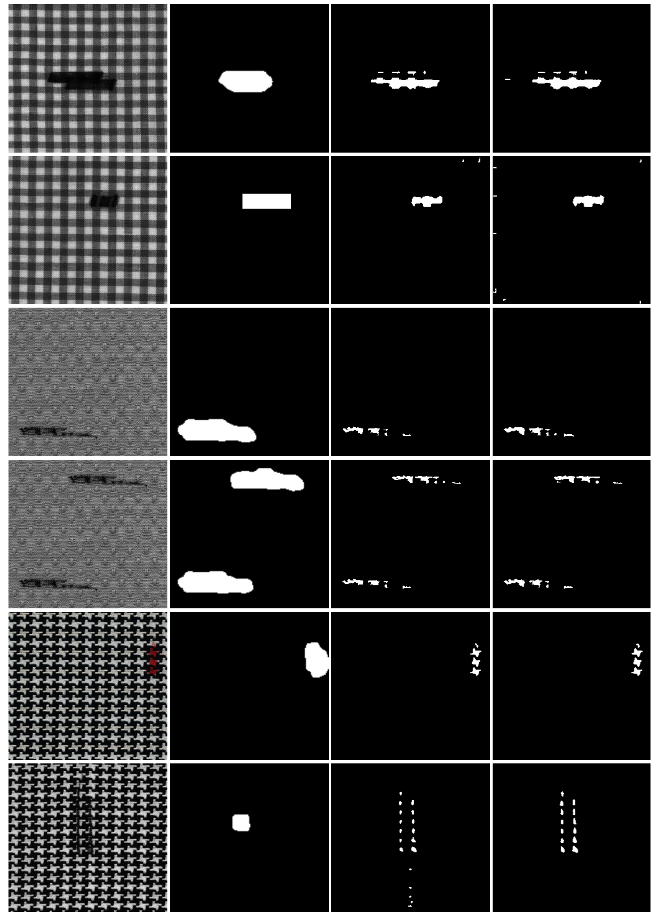


Fig. 4. Comparison of detection results. The original fabric images, the detection results obtained by PG-LSR, naive GoDec and our method are listed from left to right.

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5. REFERENCES

[1] K. Srinivasan, P.H. Dastoor, P. Radhakrishnaiah, and Sundaresan Jayaraman, "FDAS: a knowledge-based framework for analysis of defects in woven textile structures," *Journal of the Textile Institute*, vol. 83, no. 3, pp. 431–448, 1992.

[2] Chi-ho Chan and Grantham K.H. Pang, "Fabric defect detection by Fourier analysis," *IEEE Transactions on Industry Applications*, vol. 3, no. 5, pp. 1267–1276, 1999.

[3] Zhijie Wen, Junjie Cao, Xiuping Liu, and Shihui Ying, "Fabric defects detection using adaptive wavelets," *International Journal of Clothing Science and Technology*, vol. 26, no. 3, pp. 202–211, 2014.

[4] Ajay Kumar and Grantham Pang, "Defect detection in textured materials using Gabor filters," *IEEE Transactions on Industry Applications*, vol. 38, no. 2, pp. 425–440, 2002.

[5] Chung-Feng Jeffrey Kuo and Te-Li Su, "Gray relational analysis for recognizing fabric defects," *Textile Research Journal*, vol. 73, no. 5, pp. 461–465, 2003.

[6] F. Tajeripour, E. Kabir, and A. Sheikhi, "Fabric defect detection using modified local binary patterns," *EURASIP Journal on Advances in Signal Processing*, vol. 2008, no. 1, pp. 1–12, 2007.

[7] Jayanta K. Chandra and Asit K. Datta, "Detection of defects in fabrics using subimage-based singular value decomposition," *Journal of the Textile Institute*, vol. 104, no. 3, pp. 295–304, 2013.

[8] Soo Chang Kim and Tae Jin Kang, "Texture classification and segmentation using wavelet packet frame and Gaussian mixture model," *Pattern Recognition*, vol. 40, no. 4, pp. 1207 – 1221, 2007.

[9] Ajay Kumar, "Neural network based detection of local textile defects," *Pattern Recognition*, vol. 36, no. 7, pp. 1645 – 1659, 2003.

[10] Yigang Peng, Arvind Ganesh, John Wright, Wenli Xu, and Yi Ma, "RASL: robust alignment by sparse and low-rank decomposition for linearly correlated images," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 34, no. 11, pp. 2233–2246, 2012.

[11] Tianzhu Zhang, Si Liu, Narendra Ahuja, Ming-Hsuan Yang, and Bernard Ghanem, "Robust visual tracking via consistent low-rank sparse learning," *International Journal of Computer Vision*, vol. 111, no. 2, pp. 171–190, 2015.

[12] Chunjie Zhang, Jing Liu, Qi Tian, Changsheng Xu, Hanqing Lu, and Songde Ma, "Image classification by non-negative sparse coding, low-rank and sparse decomposition," in *Computer Vision and Pattern Recognition. IEEE*, 2011, pp. 1673–1680.

[13] Tianyi Zhou and Dacheng Tao, "GoDec: Randomized low-rank & sparse matrix decomposition in noisy case," in *Proc. 28th International Conference on Machine Learning*, 2011, pp. 33–40.

[14] Emmanuel J. Candès, Xiaodong Li, Yi Ma, and John Wright, "Robust principal component analysis?," *Journal of the ACM*, vol. 58, no. 3, 2009.

[15] Hongyan Zhang, Wei He, Liangpei Zhang, Huanfeng Shen, and Qiangqiang Yuan, "Hyperspectral image restoration using low-rank matrix recovery," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 52, no. 8, pp. 4729–4743, 2014.

[16] Wei He, Hongyan Zhang, Liangpei Zhang, and Huanfeng Shen, "Hyperspectral image denoising via noise-adjusted iterative low-rank matrix approximation," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 8, no. 6, pp. 1–12, 2015.

[17] Svetlana Lazebnik, Cordelia Schmid, and Jean Ponce, "Beyond bags of features: Spatial pyramid matching for recognizing natural scene categories," in *Computer Vision and Pattern Recognition. IEEE*, 2006, pp. 2169–2178.

[18] Nobuyuki Otsu, "A threshold selection method from gray-level histograms," *IEEE Transactions on Systems Man and Cybernetics*, vol. 9, no. 1, pp. 62–66, 1979.

[19] Henry Y.T. Ngan, Grantham K.H. Pang, S. P. Yung, and Michael K. Ng, "Defect detection on patterned jacquard fabric," in *Proc. IEEE Int. Workshop on 32nd Applied Imagery Pattern Recognition*, 2003, pp. 163–168.

[20] Junjie Cao, Jie Zhang, Zhijie Wen, Nannan Wang, and Xiuping Liu, "Fabric defect inspection using prior knowledge guided least squares regression," *Multimedia Tools and Applications*, pp. 1–17, 2015.

[21] Junjie Cao, Nannan Wang, Jie Zhang, Zhijie Wen, Bo Li, and Xiuping Liu, "Detection of varied defects in diverse fabric images via modified RPCA with noise term and defect prior," *International Journal of Clothing Science and Technology*, vol. 28, no. 4, pp. 516–529, 2016.