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Stiffness Analysis of Wearing Fabrics Based on Singular Value Decomposition Method

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Abstract
To address the issues of high cost and low accuracy in the manual detection method, an improved singular value decomposition (SVD)-based fabric defect detection method was proposed in this study. The method first performed noise reduction by wavelet transform; then the image was segmented. Finally, SVD was applied to remove background texture information and improve detection accuracy. The results for the detection of different types of fabric defects showed that the improved SVD method for stiffness detection of fabrics was highly efficient and accurate. The computational complexity, data redundancy and detection results of different sub-image sizes of pixels were all significant. The area under the curve (AUC) value of the star and check fabric was inferior to the defect fabric. The method is highly accurate for different fabric types and can be subsequently applied to the detection of stiffness in apparel fabrics, providing a reference for textile manufacturing production.

Keywords
ROI, Stiffness, SVD, Taking Fabric, Wavelet Transform

1. Introduction

The stiffness of the apparel fabric is different from the color performance of the apparel fabric, which is called rigid and soft together with the softness. The stiffness of the fabric can be obtained by the fabric stiffness meter, the greater the resistance to bending length, the more stiff the fabric. The factors affecting stiffness include fiber stiffness, yarn structure, and fabric weave structure [1–3]. In the background of the maturing image processing technology, the defect detection method of wearing fabrics has been developed rapidly.

The defect detection methods for clothing fabrics can be divided into plain fabrics and patterned fabrics according to different fabric types. The detection methods include statistical method, spectral method, model method, and so on. Each detection method has ideal detection results, but these detection methods are easy to be affected by external environment, making their detection accuracy unstable [4,5]. The singular value decomposition (SVD) of a matrix is a factorization of that matrix into three matrices, which owns some interesting algebraic properties and conveys important geometrical and theoretical insights about linear transformations. Aamir et al. [6,7] used SVD to obtain singular value matrices (SVMs), U_A

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and V_A, which contained high-frequency elements of an input image. Currently, a few scholars pointed out that SVD had an excellent detection effect in the process of taking fabric inspection. In view of this, this study uses SVD technology to compress and reduce the dimensionality of fabric images, and enhances SVD technology through region of interest (ROI) image segmentation method. An in-depth analysis is carried out with the aim of achieving defect detection in wearing fabrics. During the process of introducing ROI, the interference of fabric texture background energy information in the ROI area is removed. The purpose of this study is to propose a more efficient and accurate identification technology for clothing fabrics. It is expected that this method can provide a reference for textile manufacturing production. In this study, an improved fabric defect detection method based on SVD is proposed. The first part of this study is the introduction, mainly describing the background and research objectives. The second part is the literature review, analyzing the existing achievements of fabric defect recognition technology. The third part is the main research method, which analyzes the application of SVD in fabric detection. The fourth part conducts experiments to verify the effectiveness of the method. Last, a summary is conducted for this study.

2. Review of the Literature

To improve the accuracy of fabric defect detection, reduce the complexity of the computational process and data imbalance, Huang et al. [8] proposed an effective convolutional neural network for the detection of fabric defects. Jun et al. [9] addressed the current increase in automation and labor costs in the textile industry and presented a two-stage strategy for applying deep convolutional neural networks for defect point detection. The strategy included local defect prediction and global defect identification. The dataset test results showed that the given method had superior performance in detecting fabric defect points. A hybrid supervised fabric defect point detection method based on a Gaussian mixture model and a variational autoencoder were given by Zhou et al. [10]. To improve the spatial resolution of spatial resolution hyperspectral images, Dian and Li [11] proposed a new low-tensor multi-rank regularization fusion method based on subspace. This method used SVD to learn the spectral subspace of low spatial resolution hyperspectral images. Tests on two datasets verified the superiority of this method. Guo and Hesthaven [12] presented a data-driven base reduction method for parametric time-varying problems. This method utilized the natural tensor grid between time and parameters in the database, and extracted the principal components of the projection coefficient data through SVD. Zhang et al. [13] designed a static output feedback controller for a nonlinear switching system, taking into account the possible transmission barriers between the actuator and the controller, drawing on the advantages of SVD. The method was non-invasive and fully decoupled between the offline and online phases, providing a reliable and effective tool for approximating parametric time-varying problems.

Combined with the research status of scholars at home and abroad, the SVD method has ideal effects in the fields of image quality enhancement and detection of mechanical condition. However, deep learning methods require a large number of labeled defect samples for training, which is tough to implement in practice. Based on this, the study provides an in-depth analysis of SVD theory and applies it to the detection of fabric stiffness, aiming to contribute technology to textile quality enhancement.

3. Stiffness Testing of Wearing Fabrics with Improved SVD

3.1 SVD Theory and Core Principles

SVD is widely used in dimensionality reduction, data compression, recommendation systems, etc. A matrix of the form $M \times N$ is represented by B and the rank of the matrix is r. M and N refer to the corresponding rows and columns of the matrix, respectively. Normally, $M \geq N$ and N are equal to or greater than r. The SVD of the matrix B is given in Eq. (1):

$$B = USV^T = U \begin{bmatrix} S_{k\times k} & 0 \\ 0 & 0 \end{bmatrix} B^T \tag{1}$$

In Eq. (1), the $M \times M$ matrix of order is U; The matrix of order $N \times N$ is V^T; The diagonal array of order $M \times N$ is S. When $i \neq j$, j and i represent the columns and rows of the diagonal array S, respectively; Then $S_{ij} = 0$; when $i = j$, then $S_{ij} = S_{ii} = S_i \geq 0$. The matrices U and V are two orthogonal matrices, a left singular matrix and a right singular matrix, respectively. Fig. 1 is a schematic diagram referring to the SVD. The diagonal matrix S is arranged in a decreasing form on the diagonal S_k and the corresponding diagonal elements represent the eigenvectors of the left and right singular matrices.

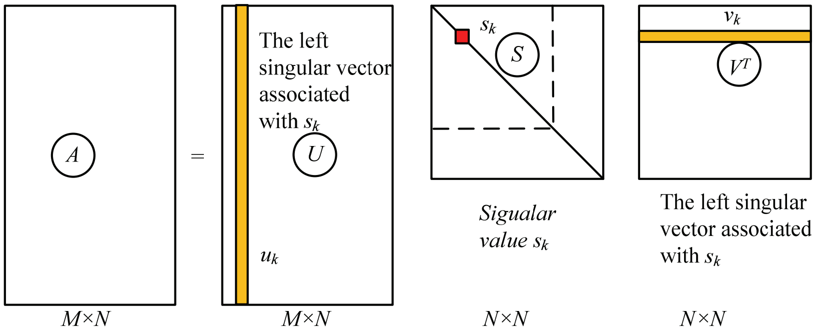

Fig. 1. Schematic diagram of SVD.

The expression for calculating the decomposition of the diagonal matrix S is Eq. (2). The matrix B can be considered as a sum of the rank-matrices $u_i s_i {v_i}^T$.

$$S^2 = \begin{bmatrix} S_1 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{bmatrix} \times \begin{bmatrix} 0 & 0 & \cdots & 0 \\ 0 & S_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{bmatrix} \tag{2}$$

In Eq. (2), the composition matrix of the matrix B is $u_k s_k {v_k}^T$. The optimal approximation matrix of the diagonal array S can be obtained by processing the first few values with larger singular values and the corresponding eigenvectors. The eigenvectors of u_k and v_k can be determined directly. Firstly, V^T is found and the diagonal array S is diagonalized to $B^T B$, as shown in Eq. (3):

$$BB^T = VS^2V^T \tag{3}$$

The matrix of order U is then calculated and the expression is given in Eq. (4):

$$U = XVS^{-1} \tag{4}$$

In Eq. (4), the eigenvectors of the U and V matrices are obtained by the Gram-Schmidt transformation. Next, the optimal approximation array for the matrix B rank r is calculated, see Eq. (5):

$$B^{(r)} = \textstyle\sum_{i=1}^{r} u_k s_k v_k^T. \tag{5}$$

The optimal approximation array for the matrix B in Eq. (5) is $B^{(r)}$. $B^{(r)}$ and B matrices both have the smallest mean squared difference MMSE, as shown in Eq. (6):

$$MMSE = (1/MN)\sum_{i=1}^{N}\sum_{j=1}^{M}\left|a_{ij} - a_{ij}^{(r)}\right|^2. \tag{6}$$

In Eq. (6), the singular value of the matrix decreases rapidly as the row and column values increase, i.e., the image matrix obtained after the rank reduction process is, which has the same order as the original image matrix. The retention of the basic features of the original image needs to satisfy Eq. (7):

$$\sum_{i=1}^{m}\sum_{j=1}^{n} f_{i,j}^2 \Big/ \sum_{i=1}^{m}\sum_{j=1}^{n}\left(\sum_{k=p+1}^{r} U_{r,i,k}\sigma_k V_{rik}\right)^2 \le SNR_M, \qquad p < r. \tag{7}$$

In Eq. (7), the signal-to-noise ratio of the image is referred to by SNR_M. An element of the original textile image is $f_{i,j}$; m and n, respectively represent the length and width of the image filtering area. k denotes the variance proportional coefficient. The number of singular values of the original matrix after the rank reduction is p.

3.2 Applying SVD to Remove Background Texture Information from Fabric Taking Images

In the field of matrix decomposition, SVD has the advantage of good robustness and high accuracy. In the defective fabric image, defects only occupy a part of the entire fabric image, and the gray level changes between the advanced defect area and the defect area are more obvious. Therefore, the fabric image is first automatically segmented to identify the ROI part containing defects, which is automatically set by comparing it with the defect free template fabric image. The more interwoven points in the fabric, the stiffer the fabric, with satin being the softest, followed by twill and smooth being the stiffest.

The study identifies defective and non-defective regions by removing singular values that contain information about the background texture of the fabric. The size of the fabric image is set to $L \times K$. When both are the same, the image is considered to be referred by the L^2 feature values. The number of feature values available after SVD is $2L^2 + L$, which increases the complexity of the operation. As the size of the image changes, the number of singular values used to obtain fabric background information also changes. Therefore, the number of singular values of the fabric background information is the type of background information that can be sadly removed, which can be obtained by comparing the template image with the defective point image. The template image needs to be split into several sub-images to reduce the computational effort. Assuming a window image of size $(l \times k)$, the expression for the number of non-overlapping sub-images D is calculated as Eq. (8):

$$D = (L/l \times K/k) \tag{8}$$

The first singular value of the image without defective sub-windows is normalized to obtain the average value, as shown in Eq. (9):

$$\bar{\sigma}_i^H(x,y) = \frac{1}{D}\sum_{x=1}^{L/L}\sum_{y=1}^{K/L}\sigma_i^H(x,y). \tag{9}$$

In Eq. (9), the normalized singular value of the subgraph i of the subgraph (x,y) of the template fabric image is $\bar{\sigma}_i^H(x,y)$. The formula for calculating is Eq. (10):

$$\sigma_i^H(x,y) = \frac{\sigma_i^H(a,b) - u_i^H(x,y)}{\delta_i^H(x,y)}. \tag{10}$$

In Eq. (10), the mean of all the singular values of the subwindow i of the (x,y) subgraph is $u_i^H(x,y)$. The standard deviation is $\delta_i^H(x,y)$. The $\delta_i^H(x,y)$ is the normalized singular value of the subgraph of the $i(a,b)$ subgraph. Setting the singular value of the *i*-th subwindow of the (x,y)-th subgraph of the defect image to $\sigma_i(x,y)$, as shown in Eq. (11):

$$\sigma_i^B(x,y) = abs[\sigma_i(x,y) - \bar{\sigma}_i^H(x,y)] \tag{11}$$

In Eq. (11), when the background information of the fabric is obscured or masked, the subgraph needs to be complemented by a 0 process to obtain the matrix $B^B(x,y)$. The subgraph needs to be reconstructed, calculated as Eq. (12):

$$S^B(x,y) = \mathrm{diag}\,[\sigma_1^B(x,y), \sigma_2^B(x,y), \dots, \sigma_P^B(x,y)] \tag{12}$$

In Eq. (12), the fabric sub image with suppressed energy information in the second background is reconstructed according to Eq. (13), as follows:

$$f^B \mid rec\ (x,y) = U(x,y)S^B(x,y)V(x,y)^T \tag{13}$$

In Eq. (13), the left singularity matrix and the right singularity matrix of the (x,y) subgraph of the defective point image of the fabric are $U(x,y)$ and $V(x,y)$, respectively.

3.3 Application of Improved SVD for Fabric Stiffness Testing

In this study, Haar wavelet threshold is utilized to remove noise. This method first sets the threshold parameter, which is set to be lower than the wavelet coefficients of the original signal. The image to be measured is decomposed by one or two layers of wavelet, and the threshold parameters are obtained by soft threshold function. Meanwhile, each layer needs to be processed by threshold. Then the ROI covering the defect points of the clothing fabric is determined, which can greatly reduce the amount of calculation and also reduce the calculation time. The schematic diagram of ROI area acquisition block diagram is shown in Fig. 2. When the segmentation coefficient takes different values, the number of segmented sub-images is different, and the number of sub-images is determined by L and K of the original image. The image of the fabric to be taken for the study is 256 × 256 pixels. After segmentation, the image size of the smallest sub-window is set to 2 × 2 pixels; The initial segmentation factor is set to 2. This average value is used as an assessment of the similarity between the fabric to be tested and the defect-free fabric image. Before testing the image, the study needs to train the images of the same texture in advance and set the maximum average value as the threshold parameter.

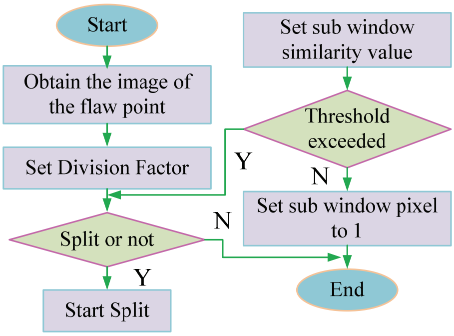

Fig. 2. Schematic diagram of ROI area acquisition block diagram.

The recognition of fabric defect images in this study is completed through SVD combined with ROI technology. After determining ROI in adaptive image segmentation, the texture background energy of the fabric is expelled and binary threshold processing is performed to determine the shape and position of the defect.

4. Application of Improved SVD to Take Fabric Stiffness Test Results

The fabric image samples used in this experiment were sourced from the industrial automation research laboratory of a chemical enterprise. The comparisons were for computational complexity, data redundancy, and detection results. Table 1 refers to flaw point detection results under different sub image sizes. Overall, the best detection results for taking fabric image defect points were obtained when the sub-image size was 32 × 32 pixels. In this case, not only the complete information of the reconstructed image was guaranteed, but also the calculation process and data redundancy in singular value calculation were reduced.

Table 1. Flaw point detection results under different sub-image sizes

Pixels	Average recognition accuracy	Number of original feature points in the image	Preserve feature points after dimensionality reduction
4 × 4	0.141	4	3
8 × 8	0.317	57	35
16 × 16	0.641	157	109
32 × 32	0.796	371	370
64 × 64	0.788	1,029	943

The study set up different taking fabric types for fabric stiffness detection, namely point, star and lattice. The defective point types were classified as hemp fibre, wool, fine yarn, and roving. Four detection methods—modified SVD, K-singular value decomposition (K-SVD), empirical mode decomposition (EMD) and singular value decomposition (EMD-SVD), and low rank sparse matrix factorization (MF)—were set and compared. Fig. 3 shows the results of the different defective point detection methods for point-like fabrics. Fig. 3 refers to each of the four types. Compared to the other three methods, the method given in the study had an outstanding advantage in the detection of the four defective point types. The area under curve (AUC) for the improved SVD method was 0.778, 0.767, 0.753, and 0.772 for the four defect types of hemp, wool, fines, and roving, respectively. The method given in the study had an excellent detection accuracy in the detection of defective spots in fabrics.

The test images used in this method were from an automation laboratory of a textile enterprise. Fig. 4 shows some fabric defect images and corresponding defect detection results. It was not difficult to find that for a defect fabric image, the result of a small window operation was better than that of a larger window image. This was because for larger windows, defects with relatively small defect areas contained very few pixels, so their projection values were also small and difficult to distinguish from normal background textures. When operating on small windows, this impact can be reduced, but meanwhile, it would lead to an increase in false detection rate, which meant that the detection results were unstable, and compared to processing on larger windows, noise and system changes would cause more errors.

In this study, fabric images with large and small windows in the laboratory were used as samples to detect and analyze the performance of different algorithms for fabric hardness detection. The specific experimental results are shown in Table 2.

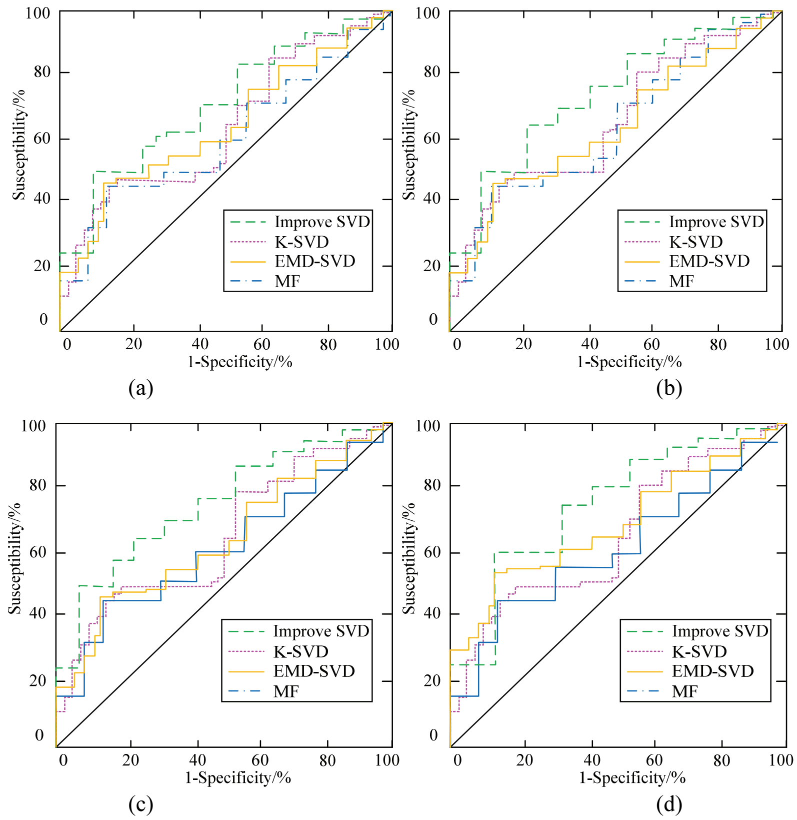

Fig. 3. Testing results of dotted fabrics by different flaw detection methods: (a) flax fibre, (b) wool, (c) spun yarn, and (d) roving.

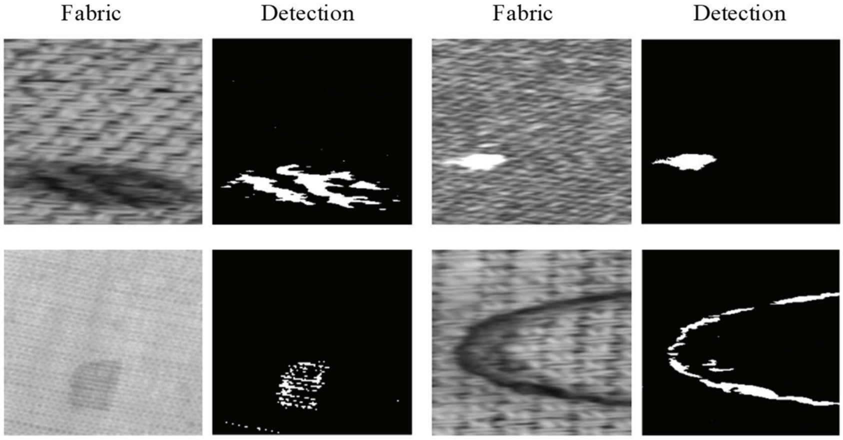

Fig. 4. Fabric testing results.

As shown in Table 2, the improved SVD algorithm proposed in this study had higher performance in detecting large and small window images of fabrics than the other two algorithms. In the case of hole-shaped defects, the recognition accuracy of the SVD algorithm was 87.2% and 93.17%, respectively. The recognition accuracy of the SVD algorithm for linear defects was 71.54% and 80.44%, respectively.

Table 2. Detection performance of non-algorithm in fabric images with large and small windows

Algorithm	Large window image			Small window image		
	Accuracy (%)		Mean time to detect (s)	Accuracy (%)		Mean time to detect (s)
	Hole-shaped defect detection	Linear defect detection		Hole-shaped defect detection	Linear defect detection	
Improved SVD algorithm	87.20	71.54	0.54	93.17	80.44	0.31
K-means	80.41	34.53	0.82	84.60	67.11	0.52
Window skip morphological method	76.34	27.59	0.41	81.36	48.63	0.11

5. Conclusion

To achieve real time and high accuracy in the stiffness detection method for wearing fabrics, a defect point detection technique applying improved SVD was constructed, which in turn reduced the computational complexity of the image processing by means of SVD. The best detection results for taking fabric images with defect points were obtained when the sub-image size was 32 pixels×32 pixels. For the four defect types of hemp fibre, wool, fine yarn, and roving, the AUC values of the four detection methods, improved SVD, K-SVD, EMD-SVD and MF, were lower compared to those of star and dotted fabrics. The corresponding AUC values for the improved SVD detection method were 0.778, 0.767, 0.753 and 0.772, respectively. The stiffness detection method for wearing fabrics given in the study had a low complexity and good performance, which was of reference value in practical applications. The limitation of this study is incomplete information extraction, which can be optimized in the future.

Conflict of Interest

The authors declare that they have no competing interests.

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References

[1] K. Rahimunnisa, "Textile fabric defect detection," *Journal of Innovative Image Processing*, vol. 4, no. 3, pp. 165-172, 2022.

[2] P. P. Patil, "A regional futures and options pattern and Gabor filter approach to fabric defect detection," *Webology*, vol. 18, no. 5, pp. 3474-3481, 2021. https://doi.org/10.29121/WEB/V18I5/93

[3] D. He, J. Wen, and Z. Lai, "Textile fabric defect detection based on improved faster R-CNN," *AATCC Journal of Research*, vol. 8, no. 1(suppl), pp. 82-90, 2021. https://doi.org/10.14504/ajr.8.S1.11

[4] G. Hu, J. Huang, Q. Wang, J. Li, Z. Xu, and X. Huang, "Unsupervised fabric defect detection based on a deep convolutional generative adversarial network," *Textile Research Journal*, vol. 90, no. 3-4, pp. 247-270, 2020. https://doi.org/10.1177/0040517519862880

[5] S. Dlamini, C. Y. Kao, S. L. Su, and C. F. Jeffrey Kuo, "Development of a real-time machine vision system for functional textile fabric defect detection using a deep YOLOv4 model," *Textile Research Journal*, vol. 92, no. 5-6, pp. 675-690, 2022. https://doi.org/10.1177/00405175211034241

[6] M. Aamir, Z. Rahman, Y. F. Pu, W. A. Abro, and K. Gulzar, "Satellite image enhancement using wavelet-domain based on singular value decomposition," *International Journal of Advanced Computer Science and Applications*, vol. 10, no. 6, pp. 514-519, 2019. https://doi.org/10.14569/IJACSA.2019.0100667

[7] M. Aamir, Y. F. Pu, Z. Rahman, M. Tahir, H. Naeem, and Q. Dai, "A framework for automatic building detection from low-contrast satellite images," *Symmetry*, vol. 11, no. 1, article no. 3, 2018. https://doi.org/10.3390/sym11010003

[8] Y. Huang, J. Jing, and Z. Wang, "Fabric defect segmentation method based on deep learning," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, article no. 5005715, 2021. https://doi.org/10.1109/TIM.2020.3047190

[9] X. Jun, J. Wang, J. Zhou, S. Meng, R. Pan, and W. Gao, "Fabric defect detection based on a deep convolutional neural network using a two-stage strategy," *Textile Research Journal*, vol. 91, no. 1-2, pp. 130-142, 2021. https://doi.org/10.1177/0040517520935984

[10] Q. Zhou, J. Mei, Q. Zhang, S. Wang, and G. Chen, "Semi-supervised fabric defect detection based on image reconstruction and density estimation," *Textile Research Journal*, vol. 91, no. 9-10, pp. 962-972, 2021. https://doi.org/10.1177/0040517520966733

[11] R. Dian and S. Li, "Hyperspectral image super-resolution via subspace-based low tensor multi-rank regularization," *IEEE Transactions on Image Processing*, vol. 28, no. 10, pp. 5135-5146, 2019. https://doi.org/10.1109/TIP.2019.2916734

[12] M. Guo and J. S. Hesthaven, “Data-driven reduced order modeling for time-dependent problems,” *Computer Methods in Applied Mechanics and Engineering*, vol. 345, pp. 75-99, 2019. https://doi.org/10.1016/j.cma.2018.10.029

[13] M. Zhang, P. Shi, C. Shen, and Z. G. Wu, “Static output feedback control of switched nonlinear systems with actuator faults,” *IEEE Transactions on Fuzzy Systems*, vol. 28, no. 8, pp. 1600-1609, 2020. https://doi.org/10.1109/TFUZZ.2019.2917177

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