International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 14, No.1 (Sep-2023)

http://dx.doi.org/10.12785/ijcds/140159

Dictionary Learning Based Adaptive Defect Detection In Complex Fabric Textures

Subashini R[1], Hemalatha R[2] and Muthumeenakshi K[3]

[1, 2, 3] *Department of ECE, Sri Sivasubramaniya Nadar College of Engineering, Chennai, India*

Received 10 Oct. 2022, Revised 13 Jul. 2023, Accepted 31 Jul. 2023, Published 01 Sep. 2023

Abstract: Textile industry is one of the noticeable contributors to our nation's growth. The quality control procedures in textile production primarily involves the defect detection process. For detecting the defects in complex fabric textures, proper construction of sparse representation is needed. Existing fabric defect detection methods are incapable of detecting defects in more than one type of fabric and have increased detection time while missing few defects. In this paper, dictionary learning is proposed which is used to learn the sparse representation of complex data. Three types of greedy algorithms OMP, ROMP and STOMP are used for sparse representation and the results are compared based on computational speed and accuracy. The experimental results indicate that the STOMP algorithm gives accurate and precise results with lesser time consumption. STOMP achieves 99.3% reduction in time consumption compared to OMP and 97.7% reduction in time consumption compared to ROMP. Also, if ROMP and STOMP are used for signal recovery, the formulation of joint matrix is not essential resulting in reduced computational complexity.

Keywords: Dictionary Learning, K-SVD, OMP, ROMP, STOMP, Sparse Representation, Image Joint Matrix

1. Introduction

In today's modern industrial world, discovery of defects in fabrics is a challenging task. Defects in fabric are a primary concern that would lead to considerable loss in profit and reduces the export revenue. It can also affect the quality of the product, due to which large amount of resource will be wasted. Existing fabric defect detection methods are incapable of detecting defects in more than one type of fabric and have increased detection time while missing few defects. In textile industry, automatic defect detection is very essential to ensure the textile quality to increase productivity with lesser investment.

2. Literature Survey

Quality of textile is one of the important aspects of the textile industry. Automated inspection system is required to maintain the quality of fabric. The detection system can be implemented through deep learning [1], [2], [3], [4], [5], [6], [7], [8], spectral estimation [9], vision [10], [11], [12], [13], and dictionary, [14] [15] based learning strategies. Boshan Shi et al. proposed a decomposition model with gradient information and noise regularization (G-NLR) to determine the edge position of the image[16]. It is designed to control the smoothing factors in different image regions, identify and highlight the edges. Huosheng Xie et al. proposed an image pyramid and direction template based defect detection method based on [17]. The direction template is introduced to reduce the false detection rate of defective image blocks. Hong Wei Zhang et al. proposed a method based on YOLOV2 for yarn-dyed fabric defect automatic localization and classification to reduce the labour cost involved in the manual extraction of image features[18].Efficient fabric defect detection was proposed using YOLOV5 with squeeze and excitation module [19]. Diazhong Peng et al. proposed a method to detect the defect to grab a cloth image in a weaving circle machine[20]. It can detect spots, holes and line defects. Jingmiao Zhang et al. proposed the digital image recognition technology to identify the fabric defect for textile industries[21]. Le Tong et al. proposed, a fabric inspection model, which comprises of image pre-processing techniques, image restoration and thresholding processes[22]. Wenming Gui et al. proposed a method of defect detection using learned dictionary by K-SVD. The process is divided into three stages: pre-processing, reduction and peak-picking. Sparse representation is used based on matching pursuit (MP) algorithm[23]. Hemant S.Goklani et al. proposed an image reconstruction using orthogonal matching pursuit (OMP) algorithm in the presence of noise[24]. In each iteration the column that is most strongly correlated with the residue is chosen and the least square method is used to reduce the error involved. G. Sun et al. proposed K-SVD based multiple description image coding (MDC)[25]. It partitioned the source into multiple bit streams and transmitted them through different channels respectively. Z. Liu et al. proposed an image in painting algorithm based on K-SVD and improved curvature

E-mail address: subashini2020016@ssn.edu.in, hemalathar@ssn.edu.in, muthumeenakshik@ssn.edu.in

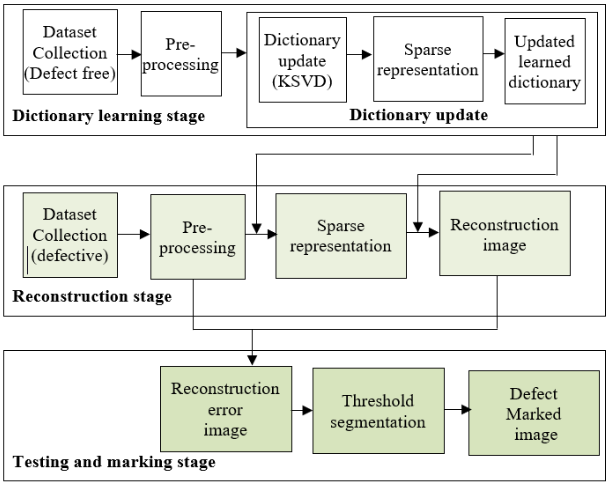


Figure 1. Adaptive Defect Detection Framework

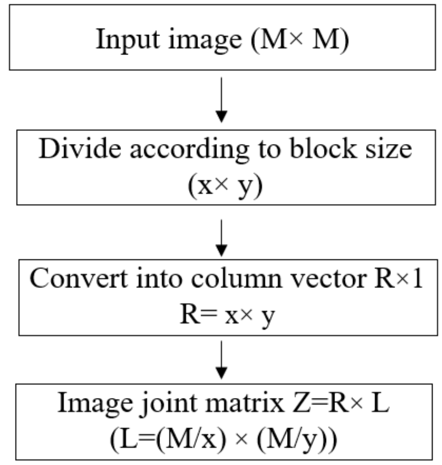


Figure 2. Image Joint Matrix

driven diffusion (CDD) technology[26]. It enhanced the visual coherence of the restored area. N. Karami et. al. proposed a method for detection of diabetic retinopathy in colour fundus images by K-SVD[27]. Yuanyuan Xiang et al. proposed a new tire defect detection algorithm based on dictionary representation[28]. Defect regions were detected by comparing the distributions of representation coefficients of it with the defect free ones.

All the methods used in the existing system generally fail to detect different types of defect for various types of fabric textures. Hence, the dictionary learning based detection is proposed, which shows good universality and adaptability and it can overcome the drawbacks faced in the existing system.

3. Dictionary Learning Based Adaptive Fabric Defect Detection

An adaptive fabric defect detection is proposed to detect various categories of defects of different fabric textures. This framework is developed using a dictionary learning algorithm. This framework of defect detection algorithm involves three stages as described below:

1) Dictionary learning stage - defect free sample images are used in this stage to learn a dictionary.
2) Reconstruction stage - sparse coefficients of the defective image are generated using the dictionary learnt in the previous stage, which is followed by constructing a reconstruction error matrix for the defective image.
3) Testing and Marking stage - difference between the defective and the reconstructed image is determined.

Segmentation thresholding is used to obtain the defective window sequence. The defective part of the image is marked finally. The methodology of the whole process is shown in Fig 1.

Algorithm 1: OMP Algorithm

Input: Original image (X), Dictionary (D)

Procedure:

- Initialization

Residue (R)=X, Iteration (t), No. of dictionary atoms (K), Index set I_0.

- Identification

Identify the maximum projection of residue on dictionary. Append one atom at each iteration.

$P_t = \max|D' \times R|$

- Augmentation

Intensify the index set.

Append one atom at each iteration.

$I_t = I_{t-1} \cup \{P_t\}$

Form the matrix of chosen atoms at each iteration.

$I_{mat(t)} = [\, I_{mat(t)} .\ X_{P_t}]$

- Least square method (sparse representation)

$S = (I_{mat(t)})^+ .\ X$

$(I_t)^+$ = pseudoinverse of I_t

$(I_t)^+ = (I_{mat(t)} .\ I_{mat(t)}{}^T)^{-1} .\ I_{mat(t)}{}^T\ X$

- Updation

Update the residue as,

$R = X - I_{mat(t)} .\ S$

Output: Sparse representation (S), Updated residue (R)

A. *Dictionary learning stage*

Pre-processing

The defect-free images have to be pre-processed before dictionary learning to improve the accuracy of defect detection. Averaged image is obtained by taking the average values for each pixel. After averaging, the image is reshaped, and mean filtering is applied.

Image joint matrix

It is important to obtain a more balanced image and to enhance the accuracy of the detection as the complexity of fabric texture and the degree of brightness/darkness of the background varies. Thus, the defect free image is segmented in accordance with a certain size and an image joint matrix is obtained. The work flow to obtain the image joint matrix is shown in Fig 2.

Sparse representation

Sparse representation matrix needs a special algorithm to implement it. It represents the image in matrix format which is used to reduce the unwanted processing of the pixel values. For obtaining the sparse representation three types of greedy algorithms namely, Orthogonal Matching Pursuit (OMP), Stagewise Orthogonal Matching Pursuit (STOMP) and Rapid Orthogonal Matching Pursuit (ROMP) are compared based on its performances[29].

Algorithm 2: ROMP Algorithm

Input: Original image (X), Dictionary(D)
Procedure: • Initialization Residue (R)=X, Iteration (t), No. of dictionary atoms (K), Index set I_0, maximum no. of columns selected at each iteration (C) • Identification Identify the absolute value of residue on dictionary. Selects multiple predefined atoms at each iteration. Pt = $\lvert D' \times R \rvert$ < C • Atom selection Pt=Unique (Pt) Returns a binary Boolean value for t atoms. • Augmentation Intensify the index set. Append multiple atom at each iteration. It= It-1 U {Pt} Form the matrix of chosen atoms at each iteration. $I_{mat(t)}$=[$I_{mat(t)}$. X P_t] • Least square method S=($I_{mat(t)}$)$^+$. X (It)$^+$ = pseudoinverse of It (It)$^+$ =($I_{mat(t)}$. $I_{mat(t)}^T$)$^{-1}$. $I_{mat(t)}^T$ X • Updation Update the residue as, R= X - $I_{mat(t)}$ .S
Output: Sparse representation (S), Updated residue (R)

In OMP, the corresponding column from the measurement matrix is taken to calculate sparse signal. The largest correlation magnitude with the residual signal is chosen at each iteration. Then, the generated columns are appended, and the sub-matrix is formulated in each iteration. The pseudo inverse of matrix is calculated to obtain the sparse signal representation. Then finally the residue is updated. The process of OMP algorithm is shown in Algorithm 1.

In ROMP, multiple predefined number of columns from the measurement matrix is taken at each iteration. The resultant correlated value returns binary Boolean values. The value 1 represents the atom selected and the value 0 represents the atom not selected for representation. The process of ROMP algorithm is shown in Algorithm 2.

STOMP selects multiple atoms simultaneously at each iteration. The product values in the sensor matrix which exceed the threshold value are selected as a support set. To obtain the sparse representation, the least square problem is solved. The process of STOMP algorithm is shown in Algorithm 3.

Algorithm 3: STOMP Algorithm

Input: Original image (X), Dictionary (D)
Procedure: • Initialization Residue (R)=X, Iteration (t), No. of dictionary atoms (K), Index set I_0, Threshold (T) • Identification Identify the absolute value of residue on dictionary. Simultaneously selects multiple atoms at each iteration. Pt = $\lvert D' \times R \rvert$ for all K atoms • Set threshold T=N . W Here, N = normalization of residue (R), W is the threshold parameter selected empirically, range between 2 to 3., W=2.5 (default) Select the atoms which is greater than T. Pt =Pt > T • Augmentation Intensify the index set. Append multiple atom at each iteration. It= It-1 U {Pt} Form the matrix of chosen atoms at each iteration. $I_{mat(t)}$=[$I_{mat(t)}$. X P_t] • Least square method S=($I_{mat(t)}$)$^+$. X (It)$^+$ = pseudoinverse of It (It)$^+$ =($I_{mat(t)}$. $I_{mat(t)}^T$)$^{-1}$. $I_{mat(t)}^T$ X
Output: Sparse representation (S), Updated residue (R)

Dictionary learning

The dictionary updation framework is shown in Fig 3. K-SVD is a dictionary learning algorithm used to create

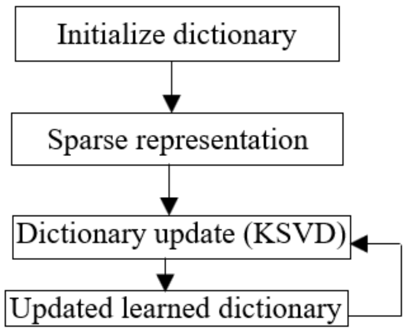


Figure 3. Dictionary update - Frame

a dictionary for sparse representation through SVD[30]. It is a generalization of K-means clustering method. It is an unsupervised learning algorithm. It needs less number of iterations than other methods. The process of KSVD Algorithm is shown in Algorithm 4 which is used for dictionary learning.

Algorithm 4: Process of dictionary learning KSVD Algorithm

Input: Original image (X), Dictionary (D), Sparse representation (S)

Step 1: Sparse coding
Find best coefficient 'S' using sparse coding
Step 2: Dictionary update
Fix all column in D except one, i.e.. D_p
D_p is selected column for updation
E_p is the representation error of all atoms except the updating atom D_p.
E=X-DS
E=X $-\sum dj\, Sj'$ j=1,2..K
E=X- $\sum dj\, Sj'$=Ep j=1, j≠p
E $=Ep - dpSp'$
Ep=SVD (Ep) $\longrightarrow$ [U S V]
U=de
$S \times V' = Se'$
E is the overall error
E= $deSe'$- $dpSp'$
By updating one atom at a time will reduce the overall error which speeds up the whole process.

Output: updated learned dictionary (D), updated sparse representation (S)

B. Reconstruction stage

Reconstruction stage helps to increase the accuracy of defect detection. Testing images are pre-processed and reshaped. Updated dictionary from previous stage is used to get sparse coefficient of test image. By using this sparse representation of the test image and the updated dictionary, reconstruction matrix is obtained [31].

TABLE I. Type of Fabrics and Defects

Fabric Types	Defect Types	Defect	Defect free
Raw Fabric	Holes	20	50
Yarn-dyed Fabric	Object on the surface error	20	50
Patterned Fabric (Box)	Holes	20	50
Patterned Fabric (Star)	Holes	20	50

TABLE II. Parameters Used

Input	Dimensions/Values
Training image (P×Q)	512×768
Pre-processed training image (M×M)	256×256
Test image (P×Q)	512×768
Pre-processed test image (M×M)	256×256
No. of dictionary atom (K)(for raw and yarn fabric)	8
No. of dictionary atom (K)(for star and box fabric)	20
Dictionary (M×K)	256×8, 256×20
No of iterations(t)	100
Block size(x×y)	32×32
Image joint matrix(R×L)	1024×64

C. Testing and Marking stage

The texture and background information are obtained from the reconstructed image of the second stage. However, it cannot fully represent the defective area of the tested image. Therefore reconstruction error image is generated to improve the effect of defect detection significantly by enhancing the abnormal points. A reconstructed error image is generated by subtracting the reconstruction matrix from the test image. Then by the use of threshold segmentation the defective part of image is marked appropriately.

4. Experimental Results And Discussion

The TILDA database, which contains 8 different textile types of fabric with 7 error classes is used for simulation. Each error class contains 50 TIF images (512 ×768). The type of fabric and the defect types considered for this are shown in Table. I

The parameters used for the defect detection process is shown in Table II.

The parameters used for the evaluation of the defect detection process are as follows,

Detection success rate (DSR): It is given by the ratio of correct predictions over the total number of instances evaluated.

$$Detection\ Success\ Rate = \frac{TP + TN}{TP + FP + TN + FN}$$

Precision: Considering a positive class, it measures the positive patterns that are correctly predicted among the total predicted patterns.

$$Precision = \frac{TP}{TP + FP}$$

Recall: Considering all classes, it measures the fraction of positive patterns that are correctly classified.

$$Recall = \frac{TP}{TP + FN}$$

F1-measure: Metric represents the harmonic mean between precision and recall.

$$Precision = \frac{2 * Precision * Recall}{Precision + Recall}$$

Timetaken: Time taken for updating the dictionary.

where TP is true positive, which is the accuracy of the defect detection, FP is false positive, which is the prediction of normal texture erroneously as defect, TN is true negative, which is normal texture detected rightly, and FN is false negative, which is predicted as no defect thus missing the defect in fabric part.

A. *Results obtained for Raw fabric*

After defect detection, the binary form of the test image is compared with the corresponding ground truth. By using the values of FP TP, FN and TN, the metrics such as precision, recall, F1-measure, and accuracy are tabulated for raw fabric in Table III.

Averaged results of raw fabric are shown in Table IV. STOMP gives better performance in defect detection than OMP and ROMP with lesser time consumption. STOMP without image joint matrix shows superior results than STOMP with image joint matrix.

The resultant graph for raw fabric for various sparse representation algorithms is shown in Fig 4.

B. *Results obtained for Yarn fabric*

In raw fabric very minute defect is taken and processed. In yarn fabric big size defects are taken and processed for tabulation to make it evident that the proposed algorithm can work well for all the types of defects with varying size and different defect types. The evaluation metrics are tabulated for Yarn fabric in Table V.

TABLE III. Results of Raw Fabric

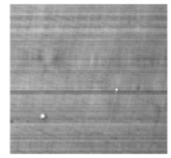
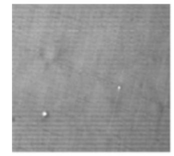
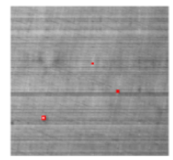
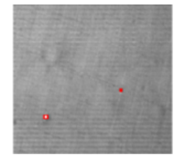
Type	Without image joint matrix	With image joint matrix
Defective Image		
Defect marked image		
Ground truth image		
Accuracy	99	99
Precision	88	94
Recall	60	80
F1-measure	75	85
Time Taken (s)	0.0250	0.0200

TABLE IV. Averaged Result for Raw Fabric

Raw Fabric	Accu - racy	Preci - sion	Recall	F1-meas - ure	Time Taken (s)
OMP without image joint matrix	99	81.85	35	45.25	0.0236
OMP with image joint matrix	99	82.45	48.5	54.65	0.0201
R-OMP without image joint matrix	97.1	81.85	51.3	60.35	0.0061
R-OMP with image joint matrix	99	84.65	46.25	55	0.0149
STOMP without image joint matrix	99	95.45	55.85	65.6	0.0004
STOMP with image joint matrix	99	95.35	54.45	65.4	0.0004

Figure 4. Time taken by various sparse representation algorithms for raw fabric

TABLE V. Results of Yarn Fabric

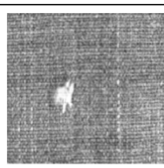
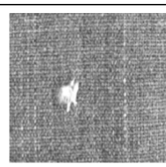
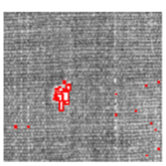
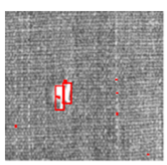
Type	Without image joint matrix	With image joint matrix
Defective Image		
Defect marked image		
Ground truth image		
Accuracy	99	99
Precision	93	96
Recall	25	41
F1-measure	39	57
Time Taken (s)	0.0336	0.0264

TABLE VI. Averaged Result for Yarn Fabric

Raw Fabric	Accu - racy	Preci - sion	Recall	F1-meas - ure	Time Taken (s)
OMP without image joint matrix	99	92.25	42.1	58.5	0.0286
OMP with image joint matrix	99	96.5	53.1	66.05	0.0257
R-OMP without image joint matrix	99	94.25	58.6	67.05	0.0072
R-OMP with image joint matrix	99	90.7	56.6	69.95	0.0146
STOMP without image joint matrix	99	93.8	67.05	76.75	0.0002
STOMP with image joint matrix	99	90.65	66.8	75.05	0.0002

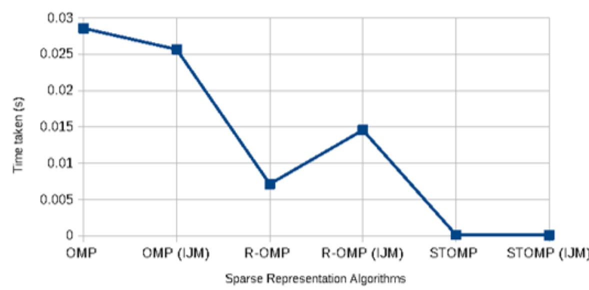


Figure 5. Time taken by various sparse representation algorithms for yarn fabric

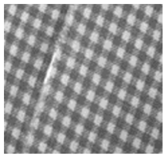
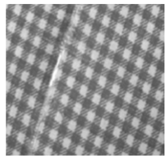
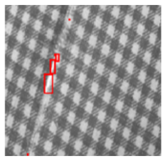
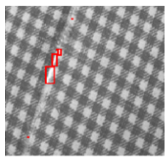
Averaged results of yarn fabric are shown in Table VI. STOMP gives better performance in defect detection than OMP and ROMP with lesser time consumption. STOMP without image joint matrix shows superior results than STOMP with image joint matrix.

The resultant graph for yarn fabric for various sparse representation algorithms is shown in Fig 5. For yarn fabric, by comparing all the algorithm STOMP without image joint matrix gives overall better performance. The time taken for raw fabric shows STOMP has less time consumption with high accuracy. Both with and without image joint matrix perform the same result.

C. Results obtained for Box Patterned fabric

Patterned fabric are more complex than raw fabric and yarn fabric. Due to its complexity, it is very difficult to distinguish the defect from the background. In patterned

TABLE VII. Results of Box Fabric

Type	Without image joint matrix	With image joint matrix
Defective Image		
Defect marked image		
Ground truth image		
Accuracy	99	99
Precision	85	85
Recall	55	55
F1-measure	67	67
Time Taken (s)	0.0002	0.0001

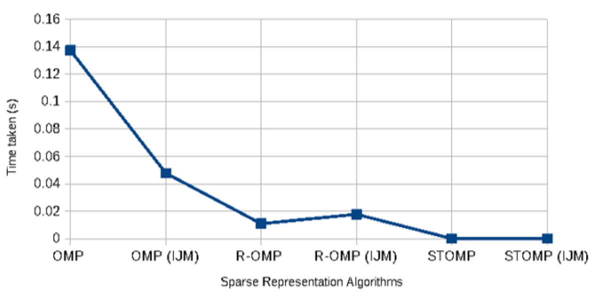


Figure 6. Time taken by various sparse representation algorithms for box fabric

fabric two types of fabric are tested here. It includes box patterned fabric and star patterned fabric. After defect detection, a comparison is made between the binary form of test image and the ground truth image, and the evaluation metrics are obtained and tabulated for box fabric in Table VII.

Averaged results of box fabric are shown in Table VIII. STOMP gives better performance in defect detection than OMP and ROMP with less time consumption. STOMP without image joint matrix shows superior results than STOMP with image joint matrix. The time taken by various sparse representation algorithms for box fabric is shown in Fig 6. For box fabric, by comparing all these algorithm

TABLE VIII. Averaged Result for Box Patterened Fabric

Raw Fabric	Accu - racy	Preci - sion	Recall	F1-meas - ure	Time Taken (s)
OMP without image joint matrix	99	53.75	20.5	28	0.1373
OMP with image joint matrix	99	79.35	26.3	38.15	0.0480
R-OMP without image joint matrix	99	81.4	30.9	41.5	0.0111
R-OMP with image joint matrix	99	60.85	21.15	29.45	0.0179
STOMP without image joint matrix	99	77.7	37.75	45.1	0.0002
STOMP with image joint matrix	99	77.65	37.35	44.8	0.0002

STOMP without image joint matrix gives overall better performance. The time taken for box fabric shows STOMP has lesser time consumption with high accuracy. Both with and without image joint matrix produces similar result. For box fabric, ROMP without image joint matrix performs well which is nearer to STOMP but lower than STOMP.

D. Results obtained for Star Patterned fabric

After defect detection, the binary form of test image is matched with the ground truth image and the performance metrics are evaluated for star fabric, which is shown in Table IX.

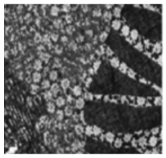
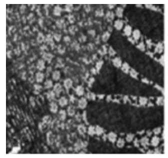
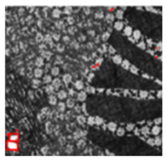
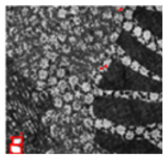
Averaged results of star fabric are shown in Table X. STOMP gives better performance in defect detection than OMP and ROMP with less time consumption. STOMP without image joint matrix shows superior results than STOMP with image joint matrix.

The time taken by various sparse representation algorithms for star fabric is shown in Fig 7. For star fabric, by comparing all these algorithm STOMP without image joint matrix gives overall better performance. The time taken for raw fabric shows STOMP has less time consumption with high accuracy. Both with and without image joint matrix produce similar results.

The differences between OMP, ROMP & STOMP are shown in Table XI.

The difference between all the methods showed that the computation time of STOMP is lesser with high accuracy.

TABLE IX. Results of Star Fabric

Type	Without image joint matrix	With image joint matrix
Defective Image		
Defect marked image		
Ground truth image		
Accuracy	99	99
Precision	99	99
Recall	59	58
F1-measure	74	74
Time Taken (s)	0.0002	0.0001

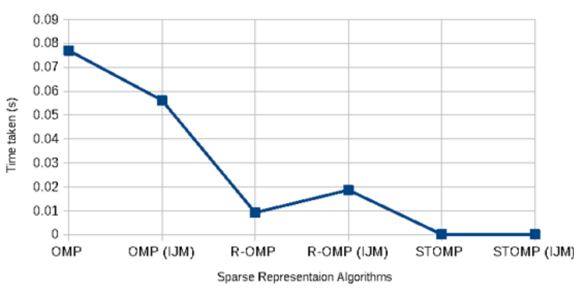


Figure 7. Time taken by various sparse representation algorithms for star fabric

STOMP achieves 99.3% reduction in time consumption compared to OMP and 97.7% reduction in time consumption compared to ROMP. Inclusion of image joint matrix improves the detection result of OMP but still less than ROMP and STOMP. In ROMP, image joint matrix degrades the detection result however it is higher than OMP. STOMP is not affected by image joint matrix. It is superior to other methods. Also, if ROMP and STOMP are used for signal recovery, the formulation of joint matrix is not essential as in [13] which used only OMP as the recovery algorithm. This would reduce the computational complexity involved.

TABLE X. Averaged Result for Star Patterened Fabric

Raw Fabric	Accur - acy	Preci - sion	Recall	F1-meas - ure	Time Taken (s)
OMP without image joint matrix	99	75.8	30.95	41.8	0.0770
OMP with image joint matrix	99	89.65	36.45	53.75	0.0562
R-OMP without image joint matrix	99	91.2	37.85	52.65	0.0093
R-OMP with image joint matrix	99	77.5	29.85	42.1	0.0187
STOMP without image joint matrix	99	96.85	43.85	58.65	0.0002
STOMP with image joint matrix	99	96.8	43.8	58.65	0.0002

TABLE XI. Comparison of OMP, ROMP and STOMP

Parameter	OMP	ROMP	STOMP
Computation time	Slower	Fast	Very Fast
Average time taken (s)	0.01 to 0.02	0.003 to 0.006	0.0003 to 0.0001
Accuracy	Low	High	Very High
Image joint Matrix [13]	Achieves improvement but still lesser than ROMP & STOMP	Works well even without image joint matrix, better result than OMP, but still slower than STOMP	Achieves accurate and fast result than OMP and ROMP even without image joint matrix

5. Conclusion

The proposed defect detection framework developed using dictionary learning approach makes the image more balanced, which can detect the defective portion of the image accurately. Compared to other methods the size of dictionary used for defect detection is much smaller which can also be the reason for saving the detection time and in addition it can also improve the adaptability by detecting various types of defects of different fabric types. K-SVD algorithm is used to update the dictionary. This updated dictionary is used to reconstruct the test image to form the reconstruction matrix. The reconstruction error image is generated in which the abnormal points are enhanced, and the effect of defect detection improves effectively. By threshold segmentation the defective part of the image is marked. The results show that STOMP is superior to other algorithms with lesser time consumption.

6. Acknowledgement

This work is part of the project funded by SSN Trust under the IFFP-2018. The authors wish to thank the management for their support.

References

[1] L. Z. M. An, S. Wang and X. Liu, "Fabric defect detection using deep learning: An improved faster r-approach," *International Conference on Computer Vision, Image and Deep Learning (CVIDL)*, pp. 319–324, 2020.

[2] Z. D. M. Li and L. Wang, "Defect detection of patterned fabric by spectral estimation technique and rough set classifier," *Fourth Global Congress on Intelligent Systems*, pp. 190–194, 2013.

[3] A. S. H. M. A. Aziz and M. S. Sayed, "Fabric defect detection algorithm using morphological processing and dct," *1st International Conference on Communications, Signal Processing, and their Applications (ICCSPA)*, pp. 1–4, 2013.

[4] S. J. C. K. H. Liu and T. J. Liu, "Unsupervised unet for fabric defect detection," *2022 IEEE International Conference on Consumer Electronics - Taiwan*, pp. 205–206, 2022.

[5] H. L. W. Yu, D. Lai and Z. Li, "Research on cnn algorithm for monochromatic fabric defect detection," *6th International Conference on Image, Vision and Computing (ICIVC), Qingdao, China*, pp. 20–25, 2021.

[6] Z. Y. D. Xia and X. Deng, "A real-time unsupervised two-stage framework for fabric defect detection," *3rd International Academic Exchange Conference on Science and Technology Innovation (IAECST), Guangzhou, China*, pp. 535–538, 2021.

[7] N. Sajitha and S. P. Priya, "Artificial intelligence based optimization with extreme gradient boosting for fabric defect detection and classification model," *International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), Erode, India*, pp. 509–515, 2023.

[8] R. T. X. Luo, Q. Ni and Y. Shi, "A lightweight detector based on attention mechanism for fabric defect detection," *IEEE Access*, vol. 11, pp. 33 554–33 569, 2023.

[9] J. Z. N. Li and P. Jiang, "Fabric defects detection via visual attention mechanism," *Chinese Automation Congress (CAC)*, pp. 2956–2960, 2017.

[10] R. E. S. Y. R. A. Lizarraga-Morales, F. E. Correa-Tome and J. CepedaNegrete, "On the use of binary features in a rule-based approach for defect detection on patterned textiles," *IEEE Access*, vol. 7, pp. 18 042– 18 049, 2019.

[11] S. L. R. Wang, Q. Guo and C. Zhang, "Tire defect detection using fully convolutional network," *IEEE Access*, vol. 7, pp. 43 502–43 510, 2019.

[12] M. H. W. Jianxia, Z. Guang and Q. Min, "Feature extraction of the fabric defects image," *Eighth International Conference on Electronic Measurement and Instruments*, pp. 2714–2717, 2019.

[13] X. Kang and E. Zhang, "A universal and adaptive fabric defect detection algorithm based on sparse dictionary learning," *IEEE Access*, vol. 8, pp. 221 808–221 830, 2020.

[14] Z. Wang and J. Jing, "Pixel-wise fabric defect detection by cnns without labeled training data," *IEEE Access*, vol. 8, pp. 161 317–161 325, 2020.

[15] B. Liu and Q. Ling, "Edge-guided depth image super-resolution based on ksvd," *IEEE Access*, vol. 8, pp. 41 108–41 115, 2020.

[16] L. D. C. C. B. Shi, J. Liang and Z. Hou, "Fabric defect detection via low-rank decomposition with gradient information," *IEEE Access*, vol. 7, pp. 130 423–130 437, 2019.

[17] Y. Z. H. Xie and Z. Wu, "Fabric defect detection method combing image pyramid and direction template," *IEEE Access*, vol. 7, pp. 182 320–182 334, 2019.

[18] P. F. L. H. W. Zhang, L. J. Zhang and D. Gu, "Yarn-dyed fabric defect detection with yolov2 based on deep convolution neural networks," *IEEE Seventh Data Driven Control and Learning Systems Conference (DDCLS)*, pp. 170–174, 2018.

[19] Q. W. S. W. L. Zheng, X. Wang and X. Liu, "A fabric defect detection method based on improved yolov5," *7th International Conference on Computer and Communications (ICCC), Chengdu, China*, vol. 7, pp. 620–624, 2021.

[20] Z. R. T. S. Y. C. D. Peng, G. Zhong and M. Wang, "A fast detection scheme for original fabric based on blob, canny and rotating integral algorithm," *IEEE Third International Conference on Image, Vision and Computing (ICIVC)*, pp. 113–118, 2018.

[21] J. Zhang and X. Meng, "A fabric defect detection system based on image recognition," *Second International Workshop on Intelligent Systems and Applications,*, pp. 1–4, 2010.

[22] W. K. W. L. Tong and C. K. Kwong, "Fabric defect detection for apparel industry: A nonlocal sparse representation approach," *IEEE Access*, vol. 5, pp. 5947–5964, 2017.

[23] W. Gui and X. Shao, "Onset detection using learned dictionary by k-svd," *IEEE Workshop on Advanced Research and Technology in Industry Applications (WARTIA)*, pp. 406–409, 2014.

[24] J. N. S. H. S. Goklani and A. M. Fahad, "Image reconstruction using orthogonal matching pursuit (omp) algorithm," *Second International Conference on Emerging Technology Trends in Electronics, Communication and Networking*, pp. 1–5, 2014.

[25] L. L. Y. T. J. Z. G. Sun, L. Meng and H. Zhang, "Ksvd- based multiple description image coding," *IEEE Access*, vol. 7, pp. 1962–1972, 2019.

[26] Z. Liu and W. Wan, "Image inpainting algorithm based on ksvd and improved cdd," *International Conference on Audio, Language and Image Processing (ICALIP)*, pp. 413–417, 2018.

[27] N. Karami and H. Rabbani, "A dictionary learning based method for detection of diabetic retinopathy in color fundus images," *Tenth Iranian Conference on Machine Vision and Image Processing (MVIP)*, pp. 119–122, 2017.

[28] C. Z. Y. Xiang and Q. Guo, "A dictionary-based method for tire defect detection," *IEEE International Conference on Information and Automation (CIA)*, pp. 519–523, 2014.

[29] P. Goyal and B. Singh, "Comparative analysis of omp and romp for sparse recovery of temporally correlated data in wsns," *Fourteenth IEEE India Council International Conference (INDICON)*, pp. 1–5, 2017.

[30] P. K. B. J. K. Chandra and A. K. Datta, "Singular value decomposition method for the detection of defects in woven fabric refined by morphological operation," *IEEE Recent Advances in Intelligent Computational Systems*, pp. 541–544, 2011.

[31] A. S. J. Zhou, D. Semenovich and J. Wang, "Sparse dictionary reconstruction for textile defect detection," *Eleventh International Conference on Machine Learning and Applications*, pp. 21–26, 2012.

R.Subhashini has received her B.E. degree in Electronics and Communication Engineering (ECE) from MNM Jain Engineering College affiliated to Anna University and M.E. degree in Communication Systems (ECE) from Sri Sivasubramaniya Nadar College of engineering. Her research interests include Wireless network and Image Processing.

R.Hemalatha Associate Professor in the department of ECE, Sri Sivasubramaniya Nadar College of Engineering has received her B.E. in Electronics and Communication Engineering from Periyar University, M.E. in Communication Systems from Anna University and Ph.D. from Anna University for her research work on Image transmission in WMSN. Her research interests include Wireless Sensor Networks, IoT, Compressive Sampling applications and Image Processing.

K.Muthumeenakshi serves as an Associate Professor in the Department of Electronics and Communication Engineering, Sri Sivasubramaniya Nadar College of Engineering. She received her B.E. in Electronics and Communication Engineering in 1999, M.E. in Applied Electronics in 2004 and Ph.D. in 2015. Her research interests include works on Signal processing, Machine Learning, Cognitive radios, and RF Energy Harvesting techniques.