Fabric Defect Detection Using Robust Principal Component Analysis and Deep Learning Techniques

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***Abstract*—This paper presents a fabric defect detection system using a kernel-based robust principal component analysis (KRPCA)-based non-convex total variation (NTV) with an alternating direction method of multipliers (ADMM) optimization method. The proposed system is based on a KRPCA-NTV model that is used to decompose the input fabric image into two parts: a low-rank and a sparse matrix. The low-rank part contains the normal structure of the fabric, while the sparse part contains the defective regions of the fabric, and CNNs are used to extract discriminative features from the defect regions for classification. In this paper, we propose a novel fabric defect detection method that combines RPCA and CNNs to achieve improved performance in terms of accuracy and efficiency. The experimental results demonstrate that the proposed method outperforms the existing methods in terms of accuracy and efficiency, indicating its potential for practical applications in the textile industry.**

***Index Terms*—Real-time Image Processing, Computer Vision, KRPCA, low-rank, sparse matrix, Feature Extraction, Automation**

I. INTRODUCTION

Real-time fabric defect detection is a challenging task faced by the textile industry. Traditional methods of defect detection are labor-intensive and involve manual inspection of fabrics, leading to inconsistencies and errors. To address this issue, a new technique known as KRPCA-NTV with the ADMM method has been developed. This method is based on Kernel Robust Principal Component Analysis (KRPCA) and Non-Convex Total Variation (NTV) with Alternating Direction Method of Multipliers (ADMM). KRPCA-NTV with ADMM is a powerful tool for fabric defect detection, providing both an efficient and accurate way of detecting fabric defects. This paper aims to provide an introduction to KRPCA-NTV with ADMM and its applications in fabric defect detection.

Using KRPCA-NTV with the ADMM method, a new method for real-time fabric defect detection is proposed. This approach combines kernel canonical correlation analysis (KCCA) to enhance feature representation, kernelization to better handle complex and cluttered backgrounds, and nonconvex total variation (TV) regularization to reduce noise interference. The method is tested using a fabric dataset and shown to be effective in detecting fabric flaws. Additionally, this study is the first to examine the non-strict low-rank assumption in RPCA [1]-based defect identification. The results indicate that the KRPCA-NTV model is a promising solution for real-time fabric defect detection.

Deep learning has proven to be an invaluable resource for computer vision applications because of its capacity to recognize intricate details. Convolutional neural networks are used to process and interpret the data, which must be accompanied by a large corpus of labeled training data. Despite the potential of deep learning, it can be difficult to obtain a sufficient number of high-quality images of faults during production since they are subject to various environmental and equipment factors. This greatly increases the cost of identifying and resolving problematic images. Furthermore, it is also necessary to collect various types of data from different sources and build a comprehensive training dataset that encompasses all the necessary conditions. To ensure the accuracy of the deep learning model, it is crucial to have a diverse and well-curated dataset. Without this, the model may be unable to properly identify and correct faults in production. In addition to the limitations of the data used to train a model, deep learning models also have difficulty generalizing to new data. This is because models are only able to recognize patterns that were present in the training data. If the test set is dissimilar to the training set, it is possible that the model will not perform as expected and have difficulty recognizing new patterns. This can lead to poor performance in situations where the model must be able to recognize and interpret new data. Furthermore, this can severely limit the effectiveness of deep learning models as they are not capable of adapting to different scenarios and data.

KRPCA-NTV is a powerful method for detecting fabric defects in industrial grayscale images. This method uses KCCA to fuse numerous features to address the issue of feature scarcity in these images. By combining kernelization and nonconvex TV regularization into the RPCA [2] model, KRPCA-NTV can handle non-strict low-rank fabric images and reduce noise interference effectively. Experiments have shown that KRPCA-NTV outperforms other unsupervised detection methods, making it a superior choice for fabric flaw detection. Additionally, KRPCA-NTV is more capable of overcoming the difficulties posed by the high rank of fabric images compared to other RPCA models. This is because KRPCA-NTV is designed to better handle non-strict low-rank fabric images and reduce noise interference, allowing it to detect fabric flaws with greater accuracy. As a result, KRPCA- NTV can be a valuable tool for industrial grayscale image processing.

II. RELATED WORKS

1. Traditional Method:

The statistical-based approach is a commonly used technique for detecting fabric defects in industrial images. This approach involves dividing the image into regions using statistical methods such as mean, median, and standard deviation, and then analyzing the periodic distribution of statistical values to identify the defect-prone regions. However, this technique may not be effective for detecting faults with identical background textures, as the statistical values may not be able to differentiate between the defect and the background. To address this issue, model-based methods can be used. These methods involve modeling the properties of previously observed images using an appropriate model such as a convolutional neural network. For example, use image decomposition to evaluate patterned fabric defects by combining cartoon and texture information. This approach works by decomposing the image into its constituent components, such as the cartoon and texture components, and then analyzing the differences between them. This can be used to identify regions in the image that are likely to contain defects. The model-based approach can also be used to detect defects in other types of images, such as those from medical imaging and aerial photographs. Ultimately, the model-based approach is more effective than the statistical-based approach in detecting fabric defects in industrial images, as it can identify defects that have identical background textures.

The active contour [3] model is an effective technique for fabric defect detection. It uses an iterative process of curve evolution to analyze and describe the edge of the defect. This method allows for the detection of subtle changes in the fabric and is especially useful for images with random fabric fluctuations. The Elo [4] rating model and the Markov random field model are two other popular techniques for fabric fault identification. The Elo [5] rating model is a statistical system that assigns a numerical rating to each competitor in a game, while the Markov [6] random field model is a probabilistic graphical model which can be used to map out the relationships between the different components of an image. Both models have shown potential in industrial fabric fault identification. However, the selection of the most suitable model is essential for the effective application of these techniques.

2. Deep Learning-Based Detection Method:

Convolutional neural networks (CNNs) have revolutionized the way computer vision applications, such as the detection of fabric defects, are approached. However, their performance is heavily dependent on the availability of large volumes of labeled training data, which can be a limiting factor in some cases. Transfer learning from pre-trained models on ImageNet [7] has been proposed as a possible solution, but its effectiveness can be limited due to the differences between natural and defective images. To overcome this, researchers have explored the use of data augmentation techniques, such as image cropping and flipping, to increase the size of the training dataset. Autoencoders and Generative Adversarial Networks (GANs) have also been used to improve the performance of unsupervised defect detection models. Data augmentation techniques help to simulate various environmental conditions and reduce the chances of overfitting, while autoencoders and GANs can be used to generate synthetic images from real-world data that can be used to improve the accuracy of defect detection models. By combining these techniques, researchers have been able to improve the performance of unsupervised defect detection models, as well as reduce the need for labeled training data. The comparison between the input and its reconstruction [8] is a powerful tool for identifying defect regions in images. Once these areas have been detected, a reconstruction network can then be trained to correct them. The training process for the reconstruction network, however, is often laborious and time- consuming. The network needs to learn how to accurately reconstruct the missing or damaged parts of the image, and this requires a significant amount of data and a careful selection of parameters. Furthermore, it is essential to ensure that the trained network generalizes well, meaning that it can correctly reconstruct similar images that it has not seen before. All these elements make the training process an arduous task, but it is a necessary step to obtain a reliable reconstruction network.

3. RPCA-based method:
KRPCA-NTV, a non-convex TV regularized RPCA with kernelization, is a novel approach that has been proposed to overcome the limitations of traditional RPCA. This approach has been designed to handle non-strict low-rank fabric images, reduce noise interference, and detect fabric defects more effectively than other unsupervised detection methods. The incorporation of kernelization and non-convex TV regularization into KRPCA-NTV enables it to better handle the high rank of fabric images, as well as the varying textures and cluttered backgrounds that can occur in real production processes. This is achieved by using the kernelization method to model the high rank of the fabric images, and the non- convex TV regularization to reduce the impact of the varying textures and cluttered backgrounds. By doing so, KRPCA- NTV can more accurately identify fabric defects and reduce the number of false positives and negatives. Ultimately, this approach provides an effective solution to the problem of detecting fabric defects in production processes. KRPCA-NTV is an innovative and groundbreaking development in the field of fabric defect detection [9], offering unparalleled performance and versatility for a wide range of detection tasks. This technology has been designed to provide superior results, even in the most challenging conditions. It can be used to detect even the smallest and most obscure defects in fabrics, and the results are highly reliable and accurate. Furthermore, the technology is highly generalizable, meaning it can be used in a variety of different applications, from industrial to automotive. Overall, this technology has the potential to revolutionize the field of fabric defect detection, making it more effective and efficient than ever before

III. METHODOLOGY

1. Model Construction
The performance and generalization capabilities of the RPCA- based model can be improved by incorporating a kernel function and a nonconvex TV regularization term. This addresses the issues previously mentioned, including backgrounds that fall into a low-rank subspace. To determine this, fabric images are divided into N overlapping uniform patches Pi. However, in industrial settings, fabric photos are often not strictly low-rank due to the complexity of the texture, crowded backgrounds, and uneven lighting. As a result, the vanilla RPCA is not able to recover the background efficiently. To address this, the RPCA-based model should be modified with the addition of the kernel function and the nonconvex TV regularization term to improve its performance and generalization capabilities. This ensures that the RPCA-based model can recover the background of fabric images more efficiently, regardless of the complexity of the texture, crowded backgrounds, or uneven lighting. KRPCA, a kernelization approach to RPCA [10], is an effective method for noise removal and subspace clustering of nonlinear data from high-rank fabric images. The kernel approach allows KRPCA to detect non-strict periodic texture in fabric images, while the nonconvex TV constraints help to suppress discontinuous changes caused by the sparse [11] noise. This noise is often a result of the camera sensors and background clutter present in practical industrial environments. While this type of noise can cause significant distortions in the fabric images, KRPCA can still be used to effectively detect any defects that may be present. Furthermore, the kernelization idea allows KRPCA to better manage nonlinear data and thus deliver more accurate results.

In short, KRPCA is a very useful tool for detecting defects from high-rank fabric images in practical industrial settings.

$\mathrm{Min}_{C,\,D}\ \mathrm{rank}(C) + Bf1\|D\|_0$ s.t, R=C+D

Given a feature matrix R, the rank of C (number of non-zero singular values) and the l_0 norm of D (number of non-zero elements) are important, along with a balance factor Bf1. Since this problem is NP-hard, nuclear norm and l_1 norm are used as substitutes instead.

$\mathrm{Min}_{C,\,D}\|C\|_* + Bf1\|D\|_1$ s.t,R=C+D

The symbol $\|C\|_*$ refers to the sum of singular values in a matrix C, while $\|D\|_1$ refers to the sum of absolute values of all elements in matrix D. Approximately 8.4% of feature matrices from fabric images cannot be ignored and must be approximated by a matrix with a rank higher than 15. RPCA is a method to recover the background in images. KRPCA is a new method that incorporates the concept of kernelization into RPCA and assumes that the nonlinear transformation of the feature matrix is of low rank [12]. This makes it effective in detecting defects from fabric images with high rank. The nonlinear transformation is denoted by φ (·), and KRPCA solves an optimization problem

$\mathrm{Min}_{C,\,D}\|\varphi(C)\|_* + Bf1\|D\|_1$ s.t, R=C+D

The square root of the sum of the diagonal elements

$\mathrm{Min}_{C,\,D}\mathrm{Tr}(Kn^{1/2}) + Bf1\|D\|_1$ s.t, R=C+D

Noise from camera sensors and background clutter can make it difficult to accurately detect defects using KRPCA. By imposing a nonconvex TV regularization on the sparse matrix D, the approach used in this paper can promote sparsity [13] in the gradient domain of the image, preventing sparse noise from being classified as defects.

$\mathrm{Min}_{C,\,D}\mathrm{Tr}(KN^{1/2}) + Bf1\|D\|_1 + Bf2\|S\|_{NTV}$ s.t, R=C+D

The expression for KRPCA-NTV includes a balance factor Bf2, and the nonconvex TV norm of matrix D. The nonconvex TV norm is based on the Moreau envelope and minimax-concave penalty, where D represents the first-order difference operators. The parameter corresponds to the l_1 or $l_{2,1}0$ norm in the anisotropic and isotropic cases, respectively. The proposed model is capable of removing sparse noise [14] by suppressing discontinuous changes with nonconvex TV constraints, while also being able to handle non-strict periodic texture through the kernel method.

2. Model Optimization

To handle KRPCA-NTV effectively, the ADMM is used to transform it into several smaller issues. Initially, a helter-skelter variable D is generated by disbursing the energy.

$\min_{C,\,D}\mathrm{Tr}(Kn^{1/2}) + Bf1\|S\|_1 + Bf2\|S\|_{NTV}$ .s.t, R=C+D T=D

Lagrangian function:

$$\xi(C,D,T,X_1,X_2,\mu)$$

$$= \mathrm{Tr}(Kn^{1/2}) + B_{f1}\|D\|_1 + B_{f2}\|T\|_{NTV} + (X_1, R-C-D)$$
$$+ (X_2, D-T) + \mu/2(\|R-C-D\|^F{}_2 + \|D-T\|^F{}_2)$$
$$= \mathrm{Tr}(Kn^{1/2}) + B_{f1}\|D\|_1 + B_{f2}\|T\|_{NTV}$$
$$- 1/2Pp(\|X_1\|^F{}_2 + \|X_2\|^F{}_2) + Pp/2(\|R-C-D+X_1/Pp\|^F{}_2$$
$$+ \|D-T+X_2/Pp\|^F{}_2)$$

We solve the problem by minimizing one variable while keeping the other variables constant. Matrices X_2 and X_2 represent Lagrange multipliers, where Pp is a positive penalty parameter. The matrix inner product is represented by and the Frobenius norm is denoted by $\|.\|^F$.

The following iterative steps are used to do this, beginning with the step of updating C.

$$C^{v+1} = \mathrm{argmin}_C\ \xi(C, D^v, T^v, X_1^v, X_2^v, Pp^v)$$
$$= \mathrm{argmin}_C\ \mathrm{Tr}(Kn^{1/2}) + Pp^v/2(\|R-C-D^v + X_1/Pp^v\|^F{}_2)$$
$$= \mathrm{argmin}_C\ 1/Pp^v(\mathrm{Tr}(Kn^{1/2}) + 1/2\|C-(R-D^v + X_1^v/Pp^v\|^F{}_2)$$

To address this subproblem, we can employ the gradient descent technique combined with a backtracking line search. Turning to the next step, we revise D.

$$D^{v+1} = \mathrm{argmin}_D\ \xi(C^{v+1}, D, T^v, X_1^v, X_2^v, Pp^v)$$
$$= \mathrm{argmin}_D\ B_{f1}\|D\|_1 + Pp^v/2(\|R-C^{v+1}-D+X_1^v/Pp^v\|^F{}_2$$
$$+ \|D-T^v + X_2^v/Pp^v\|^F{}_2)$$
$$= \mathrm{argmin}_D\ B_{f1}/2\,Pp^v\|D\|_1 + 1/2\|D-1/2(R-C^{v+1}+T^v$$
$$+ (X_1^v - X_2^v)/\|Pp^v\|^F{}_2)$$

We can sort out this subproblem through the Soft Threshold (ST) method. Consequently, we come to the third step which requires revising T.

$$T^{v+1} = \arg\min_T \xi(C^{v+1}, D^{v+1}, T^v, X_1^v, X_2^v, Pp^v)$$

$$= \arg\min_T B_{f2} \|D\|_{NTV} + Pp^v/2 \| D^{v+1} - T + X_2^v / Pp^v \|_F^2$$

$$= \arg\min_T B_{f2} / Pp^v \|T\|_{NTV} + 1/2 \| T - (D^{v+1} + X_2^v / Pp^v) \|_F^2$$

The extracted defects can then be fed into a CNN, which is a deep-learning algorithm designed to learn and classify patterns in images. The CNN shown in Table I can be trained on a large dataset of labeled defect images to learn to recognize and classify different types of defects.

The combination of RPCA and CNN allows for the accurate and efficient detection of fabric defects. By using RPCA to extract the defects from the image, the CNN can focus specifically on learning to classify the defects rather than being distracted by the normal background of the fabric. This approach has shown promising results in recent studies and has the potential to improve the efficiency and accuracy of fabric defect detection in the textile industry.

Algorithm: KRPCA with ADMM

Input: Feature matrix R, parameters $B_{f1} > 0$, $B_{f2} > 0$

Initialize :

$C^0=D^0=T^0=0$, $X_1^0 = X_2^0 = 0$, $Pp^0 = 1.25/\|F\|_2$, $Pp_{max} = Pp^0 10^6$, $\rho=1.2$, $v=0$

Repeat

1) $C^{v+1} = \arg\min_C \xi(C, D^v, T^v, X_1^v, X_2^v, Pp^v)$

2) $D^{v+1} = \arg\min_D \xi(C^{v+1}, D, T^v, X_1^v, X_2^v, Pp^v)$

3) $T^{v+1} = \arg\min_T \xi(C^{v+1}, D^{v+1}, T^v, X_1^v, X_2^v, Pp^v)$

4) $X_1^{v+1} = X_1^v + Pp^v (R - C^{v+1} - D^{v+1})$

5) $X_2^{v+1} = X_2^v + Pp^v (D^{v+1} - T^{v+1})$

6) $Pp^{v+1} = \min(Pp_{max}, \rho Pp^v)$

7) $v=v+1$

8) end while $\xi^v - \xi^{v+1} / \xi^v < 1e\text{-}6$ (or) $\|R - C^{v+1} - D^{v+1}\|_F / \|F\|_F < 1e\text{-}4$

Output: D^{v+1}

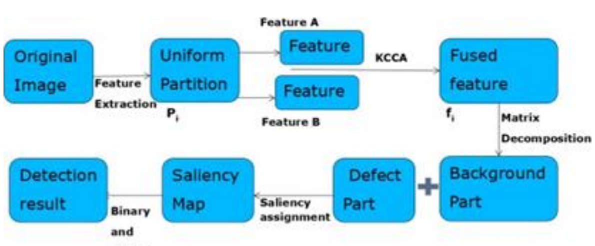

Figure 1. Workflow diagram

A. Extract Feature:

A feature descriptor based on a single view is insufficient to accurately represent a fabric defect image, as the complexity of the background and various textures can lead to unreliable descriptions. This issue is more rectified when using a deep feature extractor from a single convolutional layer in a CNN [15] mentioned in Table I, which is limited in its capacity to capture the full scope of the image. Therefore, to gain a more comprehensive understanding of the image, multiple features should be combined to take advantage of their complementary nature. To address this, more sophisticated techniques should be employed, such as hierarchical feature fusion or feature transformation. These strategies are more adept at combining multiple features and transforming them into a single representation. By integrating these approaches into a single framework, a more comprehensive representation of the fabric defect image can be obtained. Kernel canonical correlation analysis (KCCA) is an unsupervised [16] approach that can be used to reduce duplicate data and retain useful discriminant information from multiple features. This approach can help to improve the ability to separate defects from the background by discarding redundant data and focusing on the important characteristics that can be used to distinguish the defects. KCCA can also be used to identify and extract important features from the data, which can be used to further improve the accuracy of the classification. Additionally, this approach can help to reduce the computational cost of the classification, since it can reduce the complexity of the data by eliminating redundant features. Furthermore, KCCA has the capability to enhance the precision of classification by generating more resilient models that are capable of managing intricate datasetss. Finally, this approach can also be used to improve the interpretability of the classification results, as it can help to identify the most important features that are responsible for the classification.

TABLE I Outlines the Architecture of a Deep Convolutional Neural Network

Type	Patch size/stride	Output size
Convolution	3 x 3/1	2244 x 224 x 64
Pool	3 x 3/2	112 x 112 x 64
Convolution	3 x 3/1	112 x 112 x 96
Convolution	3 x 3/2	56 x 56 x 192
Pool	3 x 3/2	28 x 28 x 192
Inception x 2	Inception module 1	28 x 28 x320
Inception	Inception module 2	14 x 14 x 576
Inception x 4	Inception module 1	14 x 14 x 786
Inception	Inception module 2	7 x 7 x 1280
Inception x 2	Inception module 1	7 x 7 x 2048
Pool	7 x 7	1 x 1 x 2048
Convolution	1 x 1	1 x 1 x 1000
Dropout	40%	1 x 1 x 1000
Linear	Logits	1 x 1 x 1000
SoftMax	Classifier	2

The first two columns in Table 1 show the layer type and patch size/stride, while the third column shows the output size. The Convolution layers perform convolutions on an input image with a 3x3 filter and 1 stride, resulting in an output of 224 x 224 x 64. The Pool layers then reduce the spatial dimension by half (2 strides) to 112 x 112 x 64, followed by two more Convolution layers with a 3x3 filter and 1 stride to reach 112 x 112 x 96. The next two Pool layers reduce the spatial dimension again (2 strides) while doubling the number of channels from 192 to 576 for Inception modules 1 and 2 respectively. Then four more Inception modules are used (1 each for modules 1 & 2) before reaching 7x7x1280 at Inception module 2 in order to further increase model capacity. Finally, two more Inception modules are used before reaching 7x7x2048 at pool layer 7, after which a single Convolution layer is used (1x1 filter and 0 strides) with a dropout rate of 40% to reduce overfitting before producing logits as outputs via Linear layer. Lastly, Softmax is applied as a classifier on these logits resulting in 2 categories.

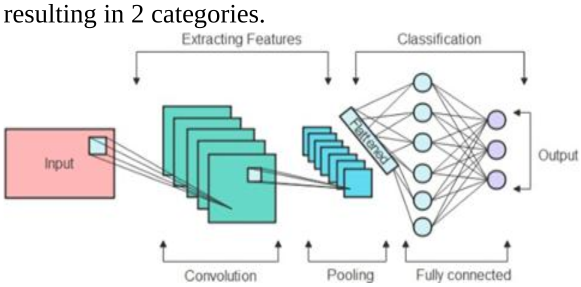

Figure 2. CNN workflow for extracting features

B. Decompose Matrix:

After obtaining the fused feature matrix, we use the KPRCA-NTV model to decompose the feature matrix F into a sparse matrix S and a background matrix L. This model stands out from the traditional RPCA [17] model because it can accurately identify fabric defects from high or full-rank backgrounds, and it is also robust to sparse noise. This makes KRPCA-NTV a much more suitable method for detecting defects in industrial environments where background noise is common. Furthermore, by decomposing the feature matrix F into two matrices, the KRPCA-NTV model makes it easier to identify the defects since the sparse matrix S will contain only the features related to fabric defects. The output from the above method is provided as input to the CNN model, and features are extracted. The defect is then classified as the output as shown in Figure 2.

C. Assign Saliency:

The outcomes from the feature domain are used to estimate saliency in the spatial domain. This is done using the l_1 norm of the Ith column which is used to calculate the saliency score for patch P_i. This score can be used as a measure of the probability that P_i is a defect, with a higher Sal (P_i) indicating an increased likelihood. This information is then used to build the saliency map M, which combines all the patches to form the larger picture. A saliency map is a powerful tool when it comes to identifying defects, as it allows for a comprehensive overview of the potential problem areas. This can be used to provide a more accurate assessment of the situation than individual patch analysis would allow. Furthermore, it can also be used for further investigations, as the saliency map can be used to pinpoint exactly where further attention should be given.

D. Segmenting Saliency and Postprocess:

A saliency map is generated to indicate the likelihood of defects in all patches, and an automatic thresholding value is calculated using the mean and standard deviation of the pixel values in the saliency map. However, in some cases, the RPCA-based model may fail to detect defects accurately, particularly in images with large defective areas that are self-similar and could be considered non-defective. This is because the self-similar portion of the defect may conform to a low- rank constraint and is thus interpreted as non-defective by the model. Consequently, the detection results may be hollow, meaning the interior of some detection results may be missing. This can lead to false negatives and result in an inaccurate assessment of the presence of defects. To overcome this problem, it is recommended to use a more sophisticated model that can accurately distinguish between self-similar defects and true defects in Figure 1.

E. Detection Result:

RPCA-CNN (Robust Principal Component Analysis with Convolutional Neural Network) is a method of feature extraction that combines the advantages of both RPCA and CNNs. It uses RPCA to decompose the input image into low- rank and sparse components as shown in Figure 5, then passes the low-rank component to a CNN for further feature extraction. The resulting features are more robust than traditional methods, as they are less affected by noise or outliers in the input data.

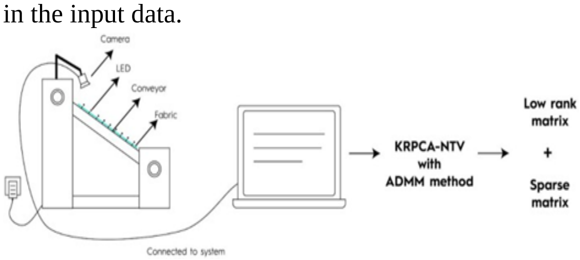

Figure 3. Complete flow diagram

IV. EXPERIMENTS

1. Experimental Setup:

The experiment was conducted using a real-time captured image dataset shown in Figure 3. To enable dynamic processing, a conveyor was constructed which allowed a fabric roll to be fed through. To acquire the fabric video, a 720-pixel Webcam was used in conjunction with the OpenCV library. This allowed the individual frames of the video to be extracted and saved in the dataset path. The execution of the KRPCA_NTV algorithm was performed on a Ryzen processor with an Nvidia graphics card, with the help of the packages OpenCV, NumPy, and Matplotlib. For the ADMM algorithm, a balancing factor was employed to ensure that the algorithm functions properly. The experiment was a success, and the results generated were beneficial to the team, who had been looking for ways to improve the quality of the fabric images.

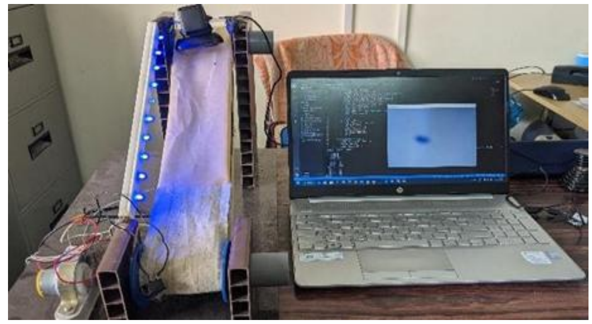

Figure 4. Hardware setup

A. Evaluation Metric:

For comprehensive and objective evaluation, we use several universally agreed metrics, including two graphical metrics and five statistics metrics. They are all composed of true positive (TP), true negative (TN), false positive (FP), and false negative (FN), where TP indicates the number of defective pixels identified as defective, TN is the number of defect-free pixels identified as defect-free, FP indicates the number of defect-free pixels identified as defective, and FN is the number of defective pixels identified as defect-free. Specifically, two graphical metrics include the receiver operating characteristic (ROC) curve and the precision–recall (PR) curve. Statistics metrics, including false positive rate (Fpr) false negative rate (Fnr), F1-measure score (F1), and accuracy (Acc), are defined as follows:

False Positive Rate : $Fpr = FP / FP + TN$

False Negative Rate : $Fnr = FN/ TP + FN$

Accuracy: $Acc= TP+TN/TP+FN+FP+TN$

F1 – score : $F1=2TP/2TP+FP+FN$

where Fpr is the proportion of background pixels that are falsely predicted as defects against all the pixels and Fnr is the proportion of defective pixels that are falsely predicted as background. In addition, the area under the ROC curve (AUC) score is also reported. It is obvious that, the lower the values of FPR and FNR, the higher the scores of Acc, Auc, and F1, and the better the performance.

B. Dataset: Patterned Fabric Dataset

The Industrial Automation Research Laboratory at Hong Kong University has produced an extensive data set containing 81 images of intricately patterned fabrics, each image manually annotated. This data set consists of three categories of patterns: dot, star, and box patterns. Furthermore, it includes six types of defects, namely knots, thin bars, thick bars, netting multiple, broken ends, and holes. Owing to the complexity of the patterns, accurately detecting fabric defects is a formidable task. To further complicate matters, the sheer number of images in the data set makes it difficult to manually assess each image for any defects. Therefore, the researchers at the laboratory have developed algorithms to automate the detection of fabric defects in the images. The algorithms employ deep [18] learning techniques to accurately identify and classify any possible defects in the fabric patterns.

After training with the above-mentioned dataset, real-time processing is done by converting video into image frames and replaced in the dataset path. The results of this research will be instrumental in the development of intelligent automated systems for quality control in the textile industry as shown in Figure 3.

C. Parameter Setting and Implementation Detail:

To process grayscale images, we triplicate the channels to create three-channel input images and standardize the image size to 256 × 256 pixels. To ensure an optimal balance between accuracy and computational cost, image blocks are set to a size of 16 with a stride of 8. To achieve the best results, we use the radial basis function (RBF) kernel for both KCCA and KRPCA-NTV. This allows us to set the weighting parameters B_{f1} and B_{f2} for the KPRCA algorithm to 0.016 and 0.01, respectively. We tune the constant c in the threshold operation over the range [0.2, 1]. To analyze the sensitivity of our method to changes in these main parameters, we fix one parameter and tune the other on the patterned fabric data set. The F1 score significantly rises when B_{f2} is fixed at 0.001, and B_{f1} approaches 0.01. However, the score levels off between 0.01 and 0.03, and then decreases sharply. This indicates that the F1 score is not linearly related to the value of B_{f1} and B_{f2} and that it is important to carefully select the parameters to obtain a good performance. Furthermore, our experiments show that the F1 score is highly sensitive to small changes in B_{f1} and B_{f2}, so it is important to select the right combination of parameters. Maintaining B_{f1} at 0.016, we noticed a steady growth in the F1 score until B_{f2} moved beyond [0.001, 0.004], at which point the F1 score began to decline. This suggests that our method is more reliable than comparable approaches since it is not as sensitive to changes in B_{f1} and B_{f2}. Additionally, the stable interval of [0.001, 0.004] indicates that our method produces consistent results when parameters stay within this range. This reliability is beneficial in many applications, as it gives assurance that results will be dependable.

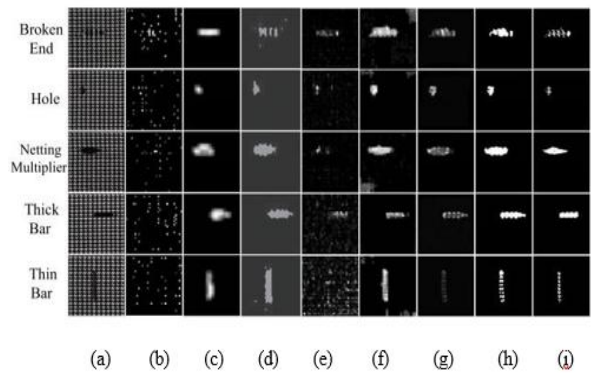

Figure 5. Comparison of Detection Results Using Different Methods on Patterned Fabric Data Set

(a) Original Image
(b) Ground Truth
(c) PGLSR (Partial Global Least Squares Regression)
(d) SMD (Spectral Matrix Decomposition)
(e) WT (Wavelet Transformation)
(f) ESP (Expectation-Maximization Sparse Principal Component Analysis with Smoothness Prior)
(g) ER (Expectation- Maximization Robust Principal Component Analysis with Smoothness Prior)
(h) SOMC (Self-Organizing Mapping Clustering Algorithm)
(i) KRPCA-NTV (Kernel Robust Principal Component Analysis with Nonlocal Total Variation Regularization)

TABLE II A table showing the relative effectiveness of various detection methods on the patterned fabric dataset is provided below.

Dataset	Method	Acc	Fpr	Fnr	Auc	F1
Patterned Fabric	PSLSR	93.55	2.85	53.79	95.45	45.98
	SMID	75.90	20.89	55.90	73.45	26.51
	WT	62.50	35.44	57.34	58.85	24.89
	ESP	89.55	6.99	61.32	64.34	32.84
	ER	95.23	3.00	67.89	67.73	30.90
	SOMC	96.71	2.70	24.98	85.52	48.10
	KRPCA- NTV	96.90	2.01	19.99	91.90	49.99

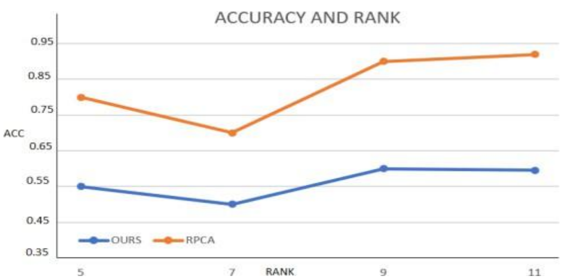

Figure 6. Change curve of Acc with respect to Rank

2. Comparison with the state of the art:
It is evident that PGLSR accurately identifies the location of defects and has the highest Auc score, yet it fails to precisely depict the form of the defects. Furthermore, SMD, WT, and ESP often misunderstand background textures for defect objects in pictures with high-gradient textures such as box- and star-patterned fabric, leading to a high Fnr as displayed in Table III. Even though ER - a supervised method- yields satisfactory outcomes on most surface images, its defect area is distinct. Our approach yields comparable accuracy and F1 scores to SOMC, however, it has a lower False Negative Rate. Our method produces good visual results and is much better than other techniques especially in terms of False Positive Rate and False Negative Rate thanks to the use of the kernel technique as well as nonconvex TV.

TABLE III Performance comparison of different settings on fabric defect detection. The last row shows total improvement compared with the baseline

B L	KCCA	Kn	NTV	PP	Acc	Fpr	Fnr
Y	N	N	N	N	87.3	8.00	26.9
Y	Y	N	N	N	92.5	6.01	25.9
Y	Y	Y	N	N	97.8	5.09	24.0
Y	Y	Y	Y	N	97.0	2.03	24.5
Y	Y	Y	Y	Y	97.3	0.99	18.9
					+11.5	-6.01	-7.1

Note: BL-Baseline, Kn-Kernelization, NTV-Non-Convex Total Variation, PP-Postprocessing, Y-Yes, N-No

3. Ablation Study:
The study showed that each component had a positive effect on the overall performance of the model, with kernelization having the greatest impact, followed by KCCA, nonconvex TV, and postprocessing. Using multiple components together proved highly beneficial for the model's performance, demonstrating the effectiveness of combining different parts to create a comprehensive, effective model. The improved performance of the model highlights the power of combining multiple components into one holistic model.

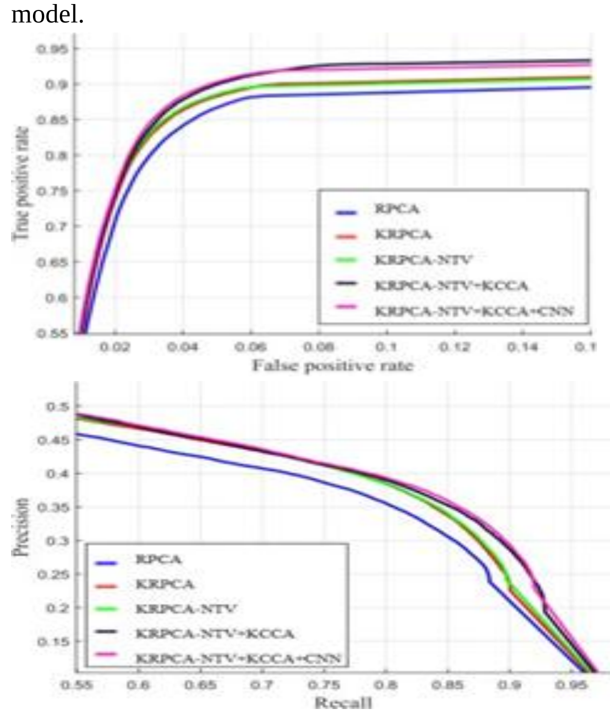

Figure 7. Evaluating the Performance Contribution of Each Component of Our Method in Relation to the ROC Curve (Left) and PR Curve (Right)

A. Feature fusion effect:
Firstly, we evaluate the impact of KCCA on the precision of detection. It should be stated that combined feature descriptors are not fixed; they can be altered to incorporate other texture or shape features. We present a model in which the incorporated features are Gabor and HOG. From Table III, it is evident that when KCCA is employed, Acc increases by 4.64; Fpr and Fnr also benefit from it as well. This elucidates the effectiveness of KCCA in tackling complex texture representation.

B. Kernelization effect:
Furthermore, we also study the influence exerted by the kernelization of RPCA on the detection performance. As illustrated in Table III, benefiting from the introduction of the kernel method, there are relative performance improvements of 6.87%, 6.69%, and 5.98% in Acc, Fpr, and Fnr, respectively, which means the validity of the kernel method to the challenge of nonstrict low-rank fabric images.

C. NTV effect:
The purpose of the study was to gauge the impact of nonconvex TV on noise reduction in KRPCA. It was found that KRPCA generated a lot of incorrect positives since it was hard to differentiate between sparse noise and real flaws. However, when nonconvex TV was incorporated, there was a notable decrease of 4.78 in false positive rate (Fpr) as well as a slight enhancement in accuracy (Acc) in Figure 6. This signifies that nonconvex TV has a major effect on uncovering defects and lessening noise.

D. Post-Process effect:
To sum up, we gauge the effect of postprocessing on increasing the precision of defect identification utilizing the RPCA-based model. This model has a propensity to miss bigger defects [19], leading to false negatives. However, our experiments show that introducing postprocessing significantly decreases the false negative rate [20]. By joining multiple elements in our methodologies, such as Auc, Fpr, and Fnr in Figure 7, we gain substantial progress over the baseline. Our findings are corroborated by the Roc and Pr curves. In conclusion, our analysis displays the effectiveness of each essential component in our approach.

E. Feature extract effect:
The process of using RPCA to divide an image into two parts is employed: a low-rank part that portrays the even background and a sparse element that reflects the flaws. The sparse piece is then subjected to a thresholding process in order to draw out the defects, which are introduced into a pre-trained CNN for extracting higher-level features such as outlines, textures, and shapes. These features are combined and utilized for further analysis, like classification or grouping.

V. CONCLUSION

In this article, the KRPCA-NTV method has been developed as a fabric defect detection model, designed to effectively detect flaws, reduce noise, and process high-rank data. This approach decomposes fabric images into background and blemish components and it utilizes kernelization to cope with non-strict periodic textures. Nonconvex TV regularization is used to minimize noise interference and refine the defect saliency maps. Furthermore, a reliable feature combination technique named KCCA is applied for enhancing the distinguishing features for detecting defects. The experimental results on fabric defect datasets show that this proposed KRPCA-NTV method outperforms existing state-of-the-art techniques when it comes to generalization and robustness.

VI. FUTURE WORK

Mending, burling, and spots can be used to fix flaws like holes, extra threading, and tears. This process involves highlighting the areas of damage with a different shade and using hardware that has all of these features.

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