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# Fabric Defect Detection for Apparel Industry: A Nonlocal Sparse Representation Approach

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**ABSTRACT** With the increasing customer demand on fabric variety in fashion markets, fabric texture becomes much more diverse, which brings great challenges to accurate fabric defect detection. In this paper, a fabric inspection model, consisting of image preprocessing, image restoration, and thresholding operation, is developed to address the woven fabric defect detection problem in the apparel industry, especially for fabric with complex texture and tiny defects. The image preprocessing first improves the image contrast in order to make the details of defects more salient. Based on the learned sub-dictionaries, a non-locally centralized sparse representation model is adopted to estimate the non-defective version of the input images, so that the possible defects can be easily segmented from the residual images of the estimated images and the inputs by thresholding operation. The performance of the proposed defect detection model was evaluated through extensive experiments with various types of real fabric samples. The proposed detection model was proved to be effective and robust, and superior to some representative detection models in terms of the detection accuracy and false alarms.

**INDEX TERMS** Fabric inspection, image restoration, sparse representation, nonlocal similarity.

## I. INTRODUCTION

In the textile and apparel industry, fabric quality inspection plays an important role, as defects on the fabric surface can significantly influence the quality of garments, and thereby impact the benefits of companies. Traditionally, fabric inspection is accomplished by human visual checking, which suffers from high labour cost and low efficiency. Their performance is also unreliable due to human error caused by fatigue and the fact that very small defects are difficult to be identified. Applications of artificial intelligence techniques can offer an efficient and low-cost approach for decision-making in fashion industry [1]–[4]. As a result, automated fabric inspection techniques which can be integrated into the existing inspection machine are in increasing demand. Moreover, with the fast development of textile industry, fabric texture becomes more and more diverse and complex. Due to the improvement of weaving techniques, defects are much smaller on such fabric surface, which makes the fabric inspection task much harder. Therefore, it is of paramount significance to develop new automated fabric inspection models which are of higher detection accuracy and efficiency. This paper presents a novel defect detection model using dictionary learning and image restoration techniques.

Fabric defects are regarded as the aberrant points that appear on the regular fabric texture which exhibits a high periodicity of sub-patterns. Basically, these defects can be divided into three groups: 1) defects in the warp direction (e.g., missing warp and stop mark); 2) defects in the weft direction (e.g., missing weft and double weft); and 3) defects with no directional characteristics (e.g., stain spot and knotted yarn). From the view of computer vision, these defects are considered as anomalous arrayed pixels in the image, comparing with non-defective area. In the case of small defects like stain spots, there is a possibility that the defect occupies only one or two pixels in the image. The aim of automatic detection is to acquire the shapes and locations of any possible fabric defects without human interventions. Generally, the performance of the automatic defect detection model is evaluated by three criteria: 1) detection rate, which reflects the sensitivity of the detection model; 2) false alarm rate, which represents the robustness of the detection model; and 3) model efficiency, which denotes the feasibility of the detection model for industrial application.

In the previous researches, with the utilization of computer vision and pattern recognition techniques, numerous approaches have been proposed for fabric defect detection [5], [6]. Gray-level co-occurrence matrix [7], [8] was able to identify defects through analyzing the gray-level relationship among image pixels. Taking advantage of the fact that textile texture is essentially repeated by sub-patterns, template matching approaches [9], [10] provided simple solutions, which were easy to be implemented, for fabric inspection. Fourier transformation [11], wavelet transform coefficients [12], [13] and Gabor filters [14], [15] addressed fabric inspection problem in the spectral domain. However, since these approaches identify defects through extracting the features of normal or abnormal fabric texture, the sensitivity of the detection model will be influenced when the defects are very small and of low contrast.

Since the fabric defects which appear as anomalous areas could also be regarded as noise in the image, with the utilization of image de-noising techniques, some defect detection models have been presented [16]–[20]. By means of sparse representation with a dictionary, the corresponding normal fabric texture could be estimated from the input defective samples. Hence, the defective area could be enhanced in the residual image which is the result of subtracting the estimated image from the input image. These methods rely on the restoration of non-defective fabric texture but not the feature extraction of defects. Therefore, the detection results would not be affected by the size and contrast of defects, which makes them more applicable to various types of defects and fabric textures. Moreover, because image restoration is a pixel-based operation, which is sensitive to small aberration, these methods are much more effective in detecting small defects. Nevertheless, the selection of dictionary influences the accuracy of normal fabric texture restoration, which in turn will impact the false alarm rate of the detection model. Moreover, the detection rate is affected by the sparse coding model, since small defects are very difficult to be eliminated by some classical model, like regression model. Therefore, it is of great importance to design the appropriate sparse coding model and dictionary to increase the sensitivity and robustness of the detection model.

In this paper, a novel detection model, which is based on non-locally centralized sparse representation, is developed for fabric inspection. Considered as stochastically distributed noise, fabric defects can be detected by restoring the testing fabric images with the utilization of de-nosing techniques. The proposed detection model includes four main parts: preprocessing, dictionary learning, sparse coding and defect segmentation. In the detection model, gray-level transformation is first applied as a preprocessing step in order to reduce the embedded noise caused by the digital imaging device and enhance the contrast between fabric defects and the background. As the training data, non-defective image patches are divided into $K$ clusters by $K$-means clustering in the dictionary learning. In each cluster, a compact sub-dictionary will be obtained through principal component analysis (PCA). Based on the conventional regression model, the sparse representation accuracy is improved by exploiting the rich amount of non-local feature redundancies of the images. Finally, defects can be successfully segmented from the residual image of the testing image and the corresponding restored image.

Based on the discussion above, the main contributions of this paper are concluded as follows:

(1) Since the fabric texture is of high periodicity and refined, in the proposed model, the compact sub-dictionary, which is learned from each cluster of image patches, is able to reduce the instability which is caused by sparse coding over an over-complete dictionary.

(2) In the sparse representation of fabric texture, the sub-dictionary with atoms of the most relevant structural features can be adaptively selected in order to increase the accuracy of normal fabric texture restoration, which is beneficial for the robustness of the detection model.

(3) By adopting non-locally centralized sparse representation in the detection model, non-local similarities of fabric structural are introduced into the sparse coding model, which enables image restoration through the non-defective area of the input image itself so as to increase the detection rate on small defects. Meanwhile, the utilization of non-local image patches makes the proposed detection model immune to uneven illumination.

The remainder of this paper is organized as follows. In Section II, literature review on fabric defect detection approaches is presented. In Section III, the framework of the proposed defect detection model is introduced. In Section IV, extensive experiments are conducted; meanwhile, experimental results and related analysis are provided. Conclusion is given in Section V.

## II. RELATED WORKS

Automatic defect detection has gained increasing attention in engineering research. It has been widely appreciated that improving the effectiveness of fabric defect detection is a common demand in the apparel industry. Referring to the related surveys [5], [6], the most common methods for fabric defect detection can be classified into four groups: statistical, structural, model-based and spectral approaches. Subsequently, with the development of image de-noising techniques, models based on sparse representation have emerged to address the problem of fabric inspection. In this section, we firstly review related works in classical fabric defect detection. Then, we will review recent progress in image restoration-based fabric defect detection in detail.

Statistical methods tend to distinguish defects through feature analysis of standard textile texture. First-order statistics (e.g., mean and variance), and second-order statistics (e.g., auto-correlation function and co-occurrence matrices) were utilized to represent textural features in texture discrimination [7], [21]–[24]. However, it is very difficult to discriminate small and blurry defects which do not change the average grey-level value of an image. Recently, a directional Bollinger bands method was proposed for plain and twill fabric inspection [25]. Instead of global statistic features, moving average and standard deviation are used to extract features of defects. Nevertheless, the Bollinger band computation was applied in four directions for each testing image, which significantly increases the computational cost of the detection model.

Structural methods claim that texture can be decomposed into a set of textural primitives. Texture analysis is implemented by extracting the texture elements and inferring their replacement rules [9], [26]. Unfortunately, these approaches are only effective in segmenting defects from texture whose pattern is very regular. In [10], defect detection is accomplished by comparing the testing image with a Golden image which is subtracted from the non-defective reference image and refers to its pattern unit. However, the validation of this method only limits on fabric defects of holes and thick bars. Moreover, due to the weaving process, lots of stochastic variations appear in the real fabric samples. Hence, the detection accuracy largely depends on the choice of matching template and alignment render.

Model-based approaches stress that the relationship between pixels in a textural image can be modeled by a predictive model: the pixels intensities in an image largely depends on their neighboring pixels [27]–[29]. In [30], Gaussian Mixture Model was applied to acquire the dependencies between wavelet coefficients within each sub-band of wavelet decomposition. Similar to statistical approaches, model-based methods also do not perform effectively in detecting small defects with low contrast.

In spectral methods, regarding yarns as basic texture primitives, texture pattern can be extracted by analyzing the frequency spectrum of fabric sample images. In [11], fabric defects were extracted by detecting abnormal value in the three dimensional frequency spectrum. Fourier analysis is only suitable for detecting large and conspicuous defects because of the difficulty in quantifing the contribution of each spectral component of the infinite Fourier basis. In [12], wavelet shrinkage was utilized to highlight the defective area in the image, of which the normal fabric texture was eliminated by zero-masking dominant frequency components. Although wavelet transform, which consists of small waves of varying frequency and limited duration, is useful for detecting small defects, its massive computational cost would greatly affect the work efficiency in the real industry. Recently, [15] proposed a fabric inspection model based on optimized Gabor filters. In the model, Gabor filters are only optimized in horizontal and vertical by differential evolution [31], which significantly reduced the total computational cost. However, this method only focuses on the classical fabric defects which are normally in the shape of lines. The reliability of this model in detecting small defects was not validated. Moreover, the selection of appropriate parameters of both wavelet transform coefficients and Gabor filters becomes the most challenging task in defect detection issue.

Most of the above studies rely on feature extractions of normal fabric texture or fabric defects. The most challenging work in these methods is to find the appropriate features that can be adapted to different types of fabric texture and defects, which possibly influences the accuracy of the detection model [32]–[34]. For the fabric of low-density weaving structure, the external noise, which exists as stochastic variations in the image, will make the accurate extraction of fabric texture feature very difficult. On the other hand, high-density weaving structure makes the possible fabric defects too small to be distinguished in the image. To tackle the above aforementioned problems, several image restoration-based defect detection models were proposed. No matter structural or tonal fabric defects, they can be treated as singular points which do not belong to the normal fabric texture. Therefore, similar to image de-noising, image restoration-based defect detection models could segment the possible defects from the residual images of the inputs and their estimations which were restored through sparse coding.

In [16], based on sparse coding, an over-complete dictionary was trained from the testing image itself, believing that the fabric defect is small in size. For a specific type of fabric, each column of the image was taken as the training data of dictionary learning, which is beneficial for defects detection through finding abnormal pixels in one-dimensional signal. However, to adapt to linear defects, the algorithm was implemented on the original image and its rotated images, which would significantly boost the computation cost of the system. Moreover, the sparse representation was based on the basic regression model, which is not suitable for eliminating scattered noise (e.g., spot defects). Later, in [17], after image restoration by regression model, Euclidean distance and correlation coefficient between the original image and its approximation were selected as the features to train a support vector data description classifier which was adopted for discriminating novelty from normal samples. It requires huge amount of training data to ensure the accuracy of the classifier as it is known that there are more than 70 types of fabric defects. On the other hand, subtle fabric defects are usually too small to be discriminated just by the first and second order statistical features of the image. To overcome the computation problem, the projections of a fabric image on all vectors of a small scale dictionary which is trained from non-defective samples could be taken as the features in defect detection [18]. A Gabor filter, whose parameters were trained according to the features of normal fabric texture, is introduced as preprocessing in the detection model. Although the complexity of the input image signal and the influence of noise can be greatly reduced after preprocessing, the contrast between defects and fabric texture background will be reduced after Gabor filtering as well, when defects are very small and mixed with noise. Consequently, the defects detection rate will be greatly influenced.

In summary, very limited methods reported in the literature have achieved an overall good performance on detection sensitivity, robustness and efficiency. In this paper, a defect detection model based on non-locally centralized sparse representation is presented. Instead of over-complete dictionaries, compact sub-dictionaries, which are obtained from clustered image patches, is more effective in providing relevant structure information for image restoration and performs very well in reducing the overall computation cost and enhancing the restoration performance. By means of non-locally centralized sparse representation model, non-local structural information of the image is helpful to improve the de-noising effect, thereby increasing the detection rate of the detection model.

## III. DEFECT DETECTION MODEL BASED ON NON-LOCALLY CENTRALIZED SPARSE REPRESENTATION (NCSR)

In this paper, we propose a defect detection model based on non-locally centralized sparse representation. First, all images are preprocessed through gray-level transformation to enhance image contrast. Then, the approximation images of the input images are constructed based on adaptive compact sub-dictionaries which are obtained from non-defective samples. Finally, possible defects in the residual image of input images and its approximation are segmented through thresholding operations. The defects detection procedures are given in Figure 1. The entire detection model consists of two main modules, namely, dictionary learning, which is an off-line process, and defect detection, which can be executed in real time. Each operation of the proposed model will be introduced in detail in the following.

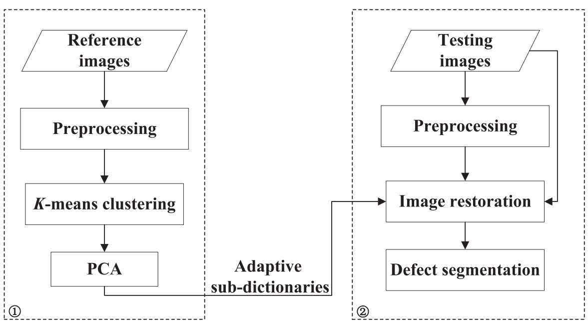


**FIGURE 1.** Flowchart of the defect detection process: ① dictionary learning; ② detection model.

### A. PREPROCESSING VIA GRAY-LEVEL TRANSFORMATION

Generally, fabric texture is synthetic and quite refined because of the fine raw materials and precise weaving structure. When the detail of the fabric texture is not well presented in the digital image, the contrast between small defect and the background will be minimal. As a result, the discrimination of defects and normal fabric texture is a very difficult task. As the textile material easily absorbs dust in the air, noise is hard to avoid in the image and is sometimes mixed with the defects, which could increase the omission ratio and the false alarm rate. To increase the contrast of the input images and highlight the possible fabric defects, we introduce preprocessing into the system before the detection operation.

Among all contrast enhancement operations, such as Log transformations, Gamma transformations, and contrast-stretching transformation, gray-level transformation is the simplest and most straightforward one. The preprocessing operation adopted in this paper is contrast-stretching transformation whose function is as follows:

$$\mathbf{s} = T(\mathbf{r}) = \frac{1}{1+(\frac{m}{\boldsymbol{r}})^{\varepsilon}}, \tag{1}$$

where $\boldsymbol{r}$ denotes the intensities of the input image; $\mathbf{s}$ is the corresponding intensities of the output; $\varepsilon$ and $m$ control the slope and the center of gravity of the transformation function respectively. The gray-level range under $m$ will be compressed. By contrast, the gray-level range under $m$ will expand. Therefore, the result of the transformation function is an image of higher contrast. Normally, the value of $m$ is set as the median value of the input gray-level intensities. In other words, the value could be adaptively selected according to different image samples, which increases the degree of freedom of preprocessing. The value of $\varepsilon$ depends on desired gray-level range $[LL, HL]$ of the output image:

$$\varepsilon_1 = \log_{\frac{m}{\min(\boldsymbol{r})}}\left(\frac{1}{LL-1}\right), \tag{2}$$

$$\varepsilon_2 = \log_{\frac{m}{\max(\boldsymbol{r})}}(\frac{1}{HL-1}), \tag{3}$$

$$\varepsilon = \lceil \min(\varepsilon_1, \varepsilon_2) \rceil . \tag{4}$$

Figure 2 shows several examples of the preprocessing results. Defects in the original images are too subtle to notice. However, after preprocessing, the dynamic range of the image is obviously expanded. The contrast between defects and texture background is thus greatly enhanced.

### B. IMAGE RESTORATION BASED ON SPARSE REPRESENTATION

Research on image de-noising revealed that two dimensional signal can be sparsely represented by a set of basis vectors (or called as dictionary), such as Discrete Cosine Transform (DCT) or wavelet basis. Mathematically, the sparse representation model assumes that, for a degraded image $\mathbf{y} \in \boldsymbol{R}^N$, we can have the corresponding high quality image $\boldsymbol{x} \approx \boldsymbol{\Phi\alpha}$, where $\boldsymbol{\Phi} \in \boldsymbol{R}^{N\times M}(N < M)$ denotes an over-complete dictionary, and most of the coefficients in $\boldsymbol{\alpha}$ are close to zero [35], [36]. The selection of dictionary plays an important role in sparse representation, since it provides the basic information of the restored image. In this paper, according to fabric structural information, patches of non-defective fabric images are divided into several classes by $K$-means clustering. The sub-dictionary learnt from each cluster is adaptively selected to provide the most relevant basis in the image restoration. With the learned dictionary, non-locally centralized sparse representation model is adopted to find a sparse vector $\boldsymbol{\alpha} = [\alpha_1; \alpha_2; \ldots; \alpha_m]$, such that $\hat{\boldsymbol{x}} = \boldsymbol{\Phi\alpha}$. Exploiting non-local redundancies in an image ensures that possible fabric defects could be successfully eliminated in the restored non-defective version of the input image. In the rest of this subsection,

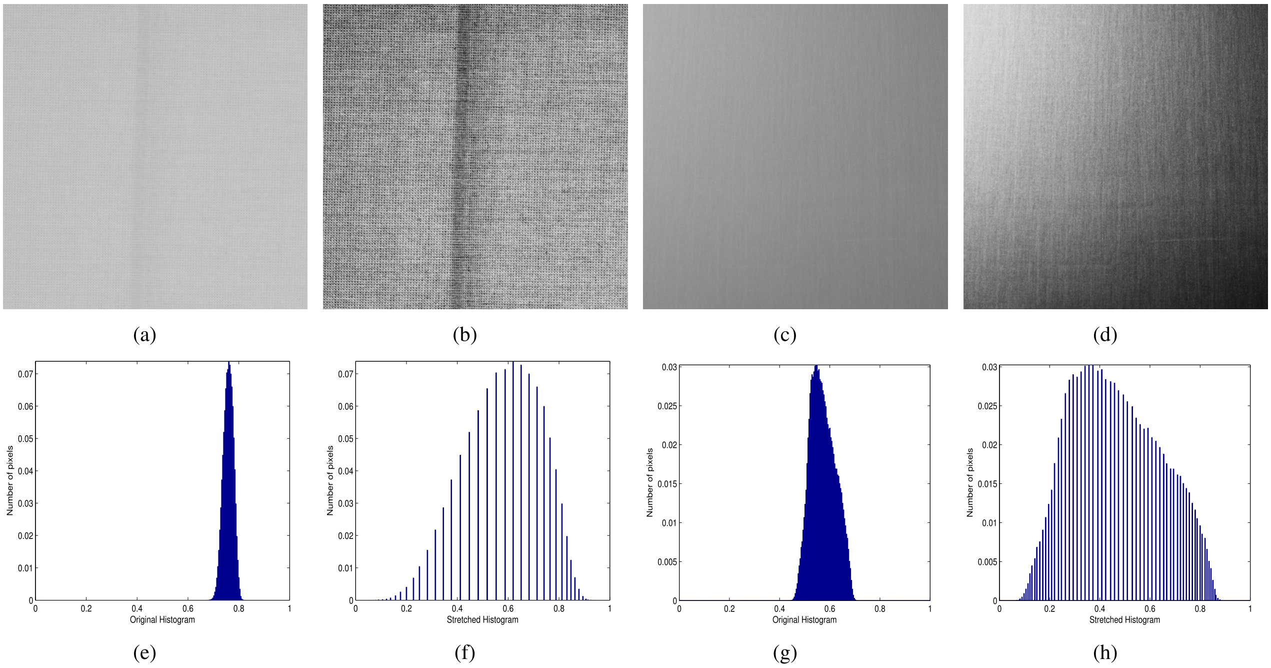


**FIGURE 2.** **Examples of preprocessing results. The first row shows the original and the corresponding preprocessed images. The second row shows the gray-level histogram of the original and preprocessed images.**

image restoration based on sparse representation is illustrated in detail.

*Remark 1:* Similar to template matching, defect detection based on image de-noising tends to find possible defects through comparing the original image with its corresponding estimated version which is restored from the most relevant basis. However, the reference image used in template matching is fixed one which can barely represent parts of the normal fabric texture. Consequently, the successful detection rate of the proposed model can be relatively higher than template matching method.

#### 1) ADAPTIVE SUB-DICTIONARY LEARNING

Nowadays, the appearance of textiles changes rapidly because of the development of fabric design. Even for a fabric in solid color, texture patterns could vary significantly across images, as shown in Figure 3. Nevertheless, the types of fabric texture elements are similar between two fabrics because the basic weaving methods of textile material are very similar. Therefore, in this paper, non-defective fabric images are divided into small patches which could be clustered according to their structural features. Each cluster of patches represents a kind of fabric texture element. The objective of sparse representation is to find a linear combination of a small number of basic atoms to restore the signal with minimal approximation error. Thus, an effective representation of testing patches over sub-dictionaries could be learned from each cluster of fabric image patches. Suppose that $\boldsymbol{x}_i = \boldsymbol{R}_i\boldsymbol{x}$, $i = 1, 2 \ldots, N$, is the $i^{th}$ patch vector of image $\boldsymbol{x}$, where $\boldsymbol{R}_i$ is a matrix extracting patch $\boldsymbol{x}_i$ from $\boldsymbol{x}$. The estimation of $\boldsymbol{x}$ could be denoted as the average of all restored patches $\hat{\boldsymbol{x}}_i$, which can be formulated as

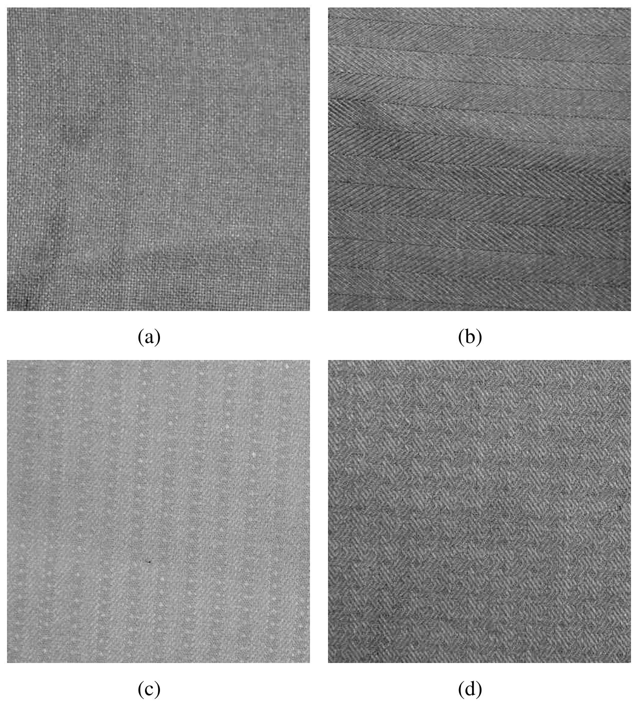


**FIGURE 3.** **Gray-level examples of different patterns of white woven fabric. (a) is plain weaving pattern; (b) is twill weaving pattern; (c) and (d) are jacquard weaving patterns.**

the following function [37]:

$$\hat{\boldsymbol{x}} = \boldsymbol{\Phi} \circ \boldsymbol{\alpha} = \left(\sum_{i=1}^{N} \boldsymbol{R}_i^T \boldsymbol{R}_i\right)^{-1} \sum_{i=1}^{N} (\boldsymbol{R}_i^T \boldsymbol{\Phi}_{k_i} \boldsymbol{\alpha}_i), \tag{5}$$

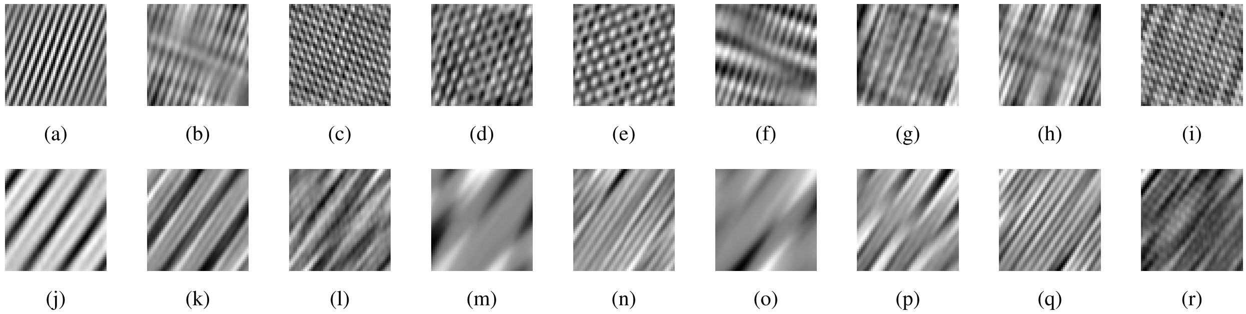


**FIGURE 4. Examples of learned sub-dictionaries. (a) and (j) demonstrate the centroids of two sub-dictionaries after K-means clustering. (b)-(i) show the nearest eight atoms to the centroid of the first cluster. (k)-(r) show the nearest eight atoms to the centroid of the second cluster.**

where operation "$\circ$" is defined for the convenience of expression; $\mathbf{\Phi}_{k_i}$ represents the $k^{th}$ sub-dictionary, which is selected to restore the $i^{th}$ image patch, and $\boldsymbol{\alpha}_i$ denotes the coefficient of the sparse representation of the $i^{th}$ image patch.

To better suppress noise and block artifacts [38], [39], $N$ overlapping image patches, denoted by $\mathbf{S} = [\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_N]$, are cropped from non-defective fabric samples that are selected as the reference images. Suppose that $K$ distinctive fabric texture elements are involved in all image patches. Hence, dataset $\boldsymbol{S}$ can be clustered into $K$ clusters, from each of which a sub-dictionary could be learned. Subsequently, for a given image patch, the most suitable structure basis could be selected from $\mathbf{\Phi}_k$. To obtain clusters that are associated with fabric structure texture, image clustering is conducted in the feature space. As shown in Figure 3, most of the semantic information of the fabric texture is conveyed by the edges in the image. High-pass filtering enhances the edges and structures in the image, as well as reduces the disturbance of pixel intensity variations between different image samples. Therefore, the outputs of high-pass filtering are utilized as the features for the classification of non-defective image patches. Given the low computational cost and easy implementation, $K$-means algorithm is adopted to divide $\mathbf{S}^h$, which denotes the high-pass filtered patch set, into $K$ sub-sets. The centroid of each cluster $\mathbf{S}_k^h$, $k = 1, 2, \ldots, K$ is denoted by $\boldsymbol{\mu}_k$. Consequently, the clustering result of the original image patches is denoted by $\mathbf{S}_k$, $k = 1, 2, \ldots, K$.

The next step of dictionary learning is to obtain a sub-dictionary $\mathbf{\Phi}_k$ from a cluster $\mathbf{S}_k$, such that $\hat{\mathbf{S}}_k = \Phi_k \boldsymbol{\alpha}_k$. As the representation coefficient is required to be as sparse as possible, the solution of $\mathbf{\Phi}_k$ is usually solved by iteratively minimizing $\mathbf{\Phi}_k$ and $\boldsymbol{\alpha}_k$ in the following function [40]:

$$(\hat{\mathbf{\Phi}}_k, \hat{\boldsymbol{\alpha}_k}) = \arg\min\{\| \mathbf{S}_k - \mathbf{\Phi}_k \boldsymbol{\alpha}_k \|_F^2 + \lambda \| \boldsymbol{\alpha}_k \|_1\}. \quad (6)$$

where $\| \|_F$ is the Frobenius norm.

However, the joint optimization problem of Eq. (6) is time consuming. Moreover, the solution of this function is normally an over-complete dictionary, which is unsuitable for our problem of fabric image representation. On the one hand, when representing a specific type of fabric structure element, only limited elements are involved in each sub-set $\boldsymbol{S}_k$. On the other hand, elements in one sub-set are highly correlated with each other, such that an over-complete dictionary will possibly cause data redundancy in the sparse coding. In [41], PCA, which is a signal de-correlation and dimensionality reduction technique, is found to be suitable for learning sub-dictionaries. PCA can extract the principal components of a set of possibly correlated data, which revealed the internal structure of the data. With regard to fabric image patches, the differences of weaving structure among a cluster are not large. Therefore, in the proposed model, PCA is applied on each cluster of image patches $\mathbf{S}_k$ to achieve a set of values of linearly uncorrelated variables which composes a compact dictionary $\mathbf{\Phi}_k$. A compact dictionary is sufficient for sparse representation of an image patch, and reduces the computation cost of the model. Figure 4 shows sub-dictionary examples learned from a training dataset. The centroids of some clusters are shown in the first column. The other columns show the first several atoms in the corresponding sub-dictionaries.

*Remark 2:* All sub-dictionaries together could be deemed as an over-complete dictionary that characterizes all the possible local structures of fabric images. Thus, instead of learning a universal and over-complete dictionary, sub-dictionary is beneficial for avoiding the visual artifacts and the considerable calculation cost that are generated by sparse coding over a redundant dictionary.

The sub-dictionaries learned from clustered image patches adaptively exploited the local structure information of images. Thus, for a given local image patch, the assignment of appropriate sub-dictionary could be adaptively accomplished in the online model. Normally, the input of natural images is unknown beforehand, and an estimation of the given patch is computed over wavelet basis. However, because of the characteristic of its fine structure texture, the noise level of fabric images is relatively low. Therefore, in this paper, the cluster attribute of a given image patch $\mathbf{y}_i$ is decided by the distance between its high-pass filtering output $\mathbf{y}_i^h$ and the centroid $\boldsymbol{\mu}_k$ of every cluster. In other words, the dictionary for image patch $\boldsymbol{x}_i$ is selected by the following function:

$$k_i = \arg\min_k \| \mathbf{y}_i^h - \boldsymbol{\mu}_k \|_2, \quad (7)$$

where $k_i$ represents the sequence number of sub-dictionary for the $i_t h$ image patch.

### 2) SPARSE REPRESENTATION MODEL BASED ON NONLOCAL SIMILARITIES

Generally, unlike uniform distributed and Gaussian distributed noise, the distribution of fabric defects in the image does not follow any specific rules or patterns. Moreover, defects usually occupy only a small proportion of area in the image, which could be treated as outliers in the image. This feature makes such singular point noise removal difficult. Approximating the high-quality image $\boldsymbol{x}$ from the observed image $\mathbf{y}$ barely by the $l_1$ norm constraint is difficult. The conventional regression model performs well only in removing Gaussian distributed noise. As discussed in [42], over a fixed dictionary, errors may occur between sparse codes of $\boldsymbol{x}$ and $\boldsymbol{y}$, which are defined as sparse coding noise (SCN) $\mathbf{v}_\alpha = \boldsymbol{\alpha}_y - \boldsymbol{\alpha}_x$, where $\boldsymbol{\alpha}_x = \arg\min_\alpha \parallel \boldsymbol{\alpha} \parallel_0$, s.t. $\parallel \boldsymbol{x} - \boldsymbol{\Phi\alpha} \parallel_2 \leq \varepsilon$. Obviously, restoration result could be significantly improved if suppressing the SCN is introduced into the sparse representation model. Therefore, in this paper, image restoration will be based on the non-locally centralized sparse representation model [42]:

$$\boldsymbol{\alpha}_y = \arg\min_{\boldsymbol{\alpha}} \{\parallel \boldsymbol{y} - \boldsymbol{\Phi} \circ \boldsymbol{\alpha} \parallel_2^2 + \lambda \sum_i \parallel \boldsymbol{\alpha}_i \parallel_1 + \gamma \sum_i \parallel \boldsymbol{\alpha}_i - \boldsymbol{\beta}_i \parallel_1\}, \tag{8}$$

where $\lambda$ denotes the regularization parameter that controls the balance between the sparse approximation of $\boldsymbol{x}$ and the sparsity of $\boldsymbol{\alpha}$, and $\boldsymbol{\beta}_i$ is some good estimation of $\boldsymbol{\alpha}_{x_i}$; $\gamma$ is the regularization parameter.

Generally, parameter $\boldsymbol{\beta}$ could be obtained from the sparse coding coefficients of images that are similar to the input image. Repetitive structures found in the fabric image for any local structure features lead it applicable to derive $\boldsymbol{\beta}$ from the input testing image itself. Moreover, in [42], it is shown that there are some correlations among the the sparse coding coefficients, instead of random distribution. Owing to the high structural periodicity of fabric texture, a lot of local and non-local redundancies appear in the images, which means that the spatially separated patches are still likely to have similar patterns. Thus, for a given $i_{th}$ patch, the nonlocal similar patches could be searched in a large widow centered at pixel $i$. Then, $\boldsymbol{\beta}_i$ is computed as the weighted average of the sparse coefficients associated with nonlocal similar patches to the $i_{th}$ patch:

$$\boldsymbol{\beta}_i = \sum_{q \in \boldsymbol{\Omega}_i} \omega_{i,q} \boldsymbol{\alpha}_{i,q}, \tag{9}$$

where $\boldsymbol{\Omega}_i$ denotes a set of image patches that are similar to the $i_{th}$ patch; $\boldsymbol{\alpha}_{i,q}$ represents the sparse coefficients of the $q_{th}$ patch within set $\boldsymbol{\Omega}_i$, and $\omega_{i,q}$ is the corresponding weight, which is inversely proportional to the distance between $\boldsymbol{x}_i$ and $\boldsymbol{x}_{i,q}$.

*Remark 3:* For eliminating fabric defects which are regarded as outliers in the image, non-locally centralized sparse representation model outperforms the conventional regression model. The former brings the structure information of non-defective areas in the testing image in the restoration of the estimated image. In other words, the estimation of the normal structure features of the testing image is not only based on the adaptively selected sub-dictionary but also on non-local feature redundancies in the testing image itself to increase image restoration accuracy and the defect detection rate.

As discussed in *Remark* 2, for the entire training dataset, the set of $K$ compact sub-dictionaries could still be regarded as an over-complete dictionary. When one sub-dictionary is adaptively chosen in the sparse coding, only a small number of atoms in the over-complete dictionary are selected. As a result, regularization constraint $\parallel \boldsymbol{\alpha}_i \parallel_1$ is satisfied. Hence, the non-locally centralized sparse representation model adopted in this paper is adjusted as follows:

$$\boldsymbol{\alpha}_y = \arg\min_{\alpha} \left\{ \parallel \mathbf{y} - \boldsymbol{\Phi} \circ \boldsymbol{\alpha} \parallel_2^2 + \gamma \sum_i \parallel \boldsymbol{\alpha}_i - \boldsymbol{\beta}_i \parallel_1 \right\}. \tag{10}$$

The surrogate algorithm, which is an iterative algorithm, is adopted to solve objective function in Eq. (10). $\boldsymbol{\beta}$ is first initialized as $\boldsymbol{\beta}^{(-1)} = 0$, in order to obtain the initial sparse coefficients $\boldsymbol{\alpha}_y^{(0)}$. Thus, the initial estimation of $\mathbf{x}$ is solved by $\boldsymbol{x}^{(0)} = \boldsymbol{\Phi} \circ \boldsymbol{\alpha}_y^{(0)}$. Thereafter, by searching similar patches from $\boldsymbol{x}^{(0)}$, the non-local estimation $\boldsymbol{\beta}^{(0)}$ can be updated through Eq. (9), which improved the accuracy of sparse representation coefficients in turn. This procedure is iterated until the convergence constraint is satisfied. With optimal sparse representation coefficients $\boldsymbol{\alpha}_y$, the estimation of the non-defective fabric image $\boldsymbol{x}$ could be represented as $\hat{\boldsymbol{x}} = \boldsymbol{\Phi} \circ \boldsymbol{\alpha}_y$, because only normal fabric structure information is admitted in the sub-dictionaries learned previously. Noise is greatly reduced in the restored image, and the defective areas would not be well presented.

## C. DEFECT SEGMENTATION

Similar to template matching, defect detection based on image restoration tends to segment possible defects through comparing the input image with a reference image. However, instead of a fixed template fabric image, the reference image used in this research is the restored non-defective image.

Ideally, in this paper, the possible fabric defects regarded as noise in the original image could be removed in the estimated version of the input image. In the residual image of the original image and its estimation, the gray-level intensity of the defective area will be greater than that of the background area. Thus, a simple statistic technique would distinguish defects pixels from the background in the residual image.

The thresholding limits are derived from the reference residual image of a standard non-defective sample and its estimation which is also restored by the procedures in Section III-B. Instead of setting a fixed parameter, the thresholding limits could be adaptively selected for each type of fabric to achieve good detection results as much as possible. Meanwhile, the adaptively selected parameter is beneficial to reduce false alarm rate, because the noise and blurry effects caused by dust will weaken in the restored image. Suppose that the gray-level values of the reference residual image is denoted as $\boldsymbol{R}(x, y)$. The upper and lower thresholding limits are:

$$\psi_{upper} = \max_{x,y \in W} |\boldsymbol{R}(x, y)|, \tag{11}$$

$$\psi_{lower} = \min_{x,y \in W} |\boldsymbol{R}(x, y)|, \tag{12}$$

where $W$ is a window centered at the feature image. The window size is chosen to avoid distortion effects caused by the borders of the image. In this paper, the window size is obtained by removing 10 pixels from each side of the image $\boldsymbol{R}(x, y)$. Then, the maximum and minimum values $\psi_{upper}$ and $\psi_{lower}$ of gray levels are obtained within a window "$W$" from the reference residual image. Hence, the binary feature image $\boldsymbol{B}(x, y)$ could be obtained by:

$$\boldsymbol{B}(x, y) = \begin{cases} 1, & \text{if } \boldsymbol{G}(x, y) > \psi_{upper} \text{ or } \boldsymbol{G}(x, y) < \psi_{lower}, \\ 0, & \text{otherwise,} \end{cases} \tag{13}$$

where $\boldsymbol{G}(x, y)$ denotes the gray-level of the testing residual image.

## IV. EXPERIMENTS AND RESULTS

In this section, the performance of the proposed fabric defect detection model is validated through two databases: the first one is TILDA which is created by a workshop on texture analysis of Deutsche Forschungsgemeinschaft Germany [43]; the second one is our own database which consists of 102 non-defective and 102 defective fabric samples acquired from an apparel factory in Mainland China and scanned from the fabric defect handbook [44]. These fabric samples contain the most common types of defects that always appear in the textile industry. In the following, first, the experimental setup is introduced in detail.The experiments are then conducted from two aspects: (1) the proposed detection model is applied on both fabric databases; (2) with the same fabric samples, the performance of the proposed defect detection model is compared with other four representative detection models: detection model based on optimal Gabor filters [15], detection model based on Gabor filters bank [14], sparse coding-based detection model [16], and detection model based on Fourier and wavelet shrinkage [12].

### A. EXPERIMENTAL SETUP

Four kinds of woven fabric in solid color with a relatively coarse texture are included in the TILDA database. Within each fabric type, four defect classes were defined. For each of the above classes, 50 images ($768 \times 512$ pixels) were acquired through relocation and rotation of the textile samples. In our own database, images of the real fabric samples were captured at $1050 \times 1050$ pixels by a digital camera Canon 600D. All detection models used in the experiments were realized and programmed under the image processing toolbox of MATLAB prototyping environment. Experiments were conducted on a personal computer under a Win10 operating system running on an Intel core i7 processor. The performance of the defect detection model was visually assessed by the binary feature images. In this paper, the following four measurements (expressed as percentages) are employed to judge the performance of defect detection models:

$$\text{Precision} = \frac{\text{TA}}{\text{TA+FA}}, \tag{14}$$

$$\text{Sensitivity} = \frac{\text{TA}}{\text{TA+FN}}, \tag{15}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FA}}, \tag{16}$$

$$\text{Accuracy} = \frac{\text{TA+TN}}{\text{TA+TN+FA+TN}}, \tag{17}$$

where true abnormal (TA), which means correct detection with good localization, is recorded when only the defect area in the original image is covered by white pixels in the binary feature image. False abnormal (FA) means that white pixels appear in the binary feature image of a non-defective sample. True normal (TN) is recorded when no white pixels appear in the binary feature image of a non-defective sample. False normal (FN) means that no white pixels appear in the binary image even though there is a defect in the original sample.

**TABLE 1. Performance evaluations of the proposed defect detection model on TILDA.**

| | Precision | Sensitivity | Specificity | Accuracy |
|---|---|---|---|---|
| Performance | 92.0% | 97.8% | 91.5% | 94.6% |

**TABLE 2. Performance evaluations of the proposed defect detection model on our own database.**

| | Precision | Sensitivity | Specificity | Accuracy |
|---|---|---|---|---|
| Performance | 92.5% | 96.1% | 92.2% | 94.1% |

### B. EXPERIMENTS AND RESULT ANALYSIS

#### 1) PERFORMANCE EVALUATION OF THE PROPOSED APPROACH

The inspection of woven fabric in solid color was done in accordance with the flowchart shown in Figure 1. Some typical detection results are shown in Figures 5-8. For each type of fabric, a set of non-defective image samples was collected as the training data in the dictionary learning. It can be seen that the proposed detection model can successfully segment the defects of various shapes, sizes and positions. Tables 1 and 2 summarize the overall testing results by using the proposed defect detection model on TILDA and our own database, respectively. The four measurements provide the evaluation of the detection model from different aspects. Precision

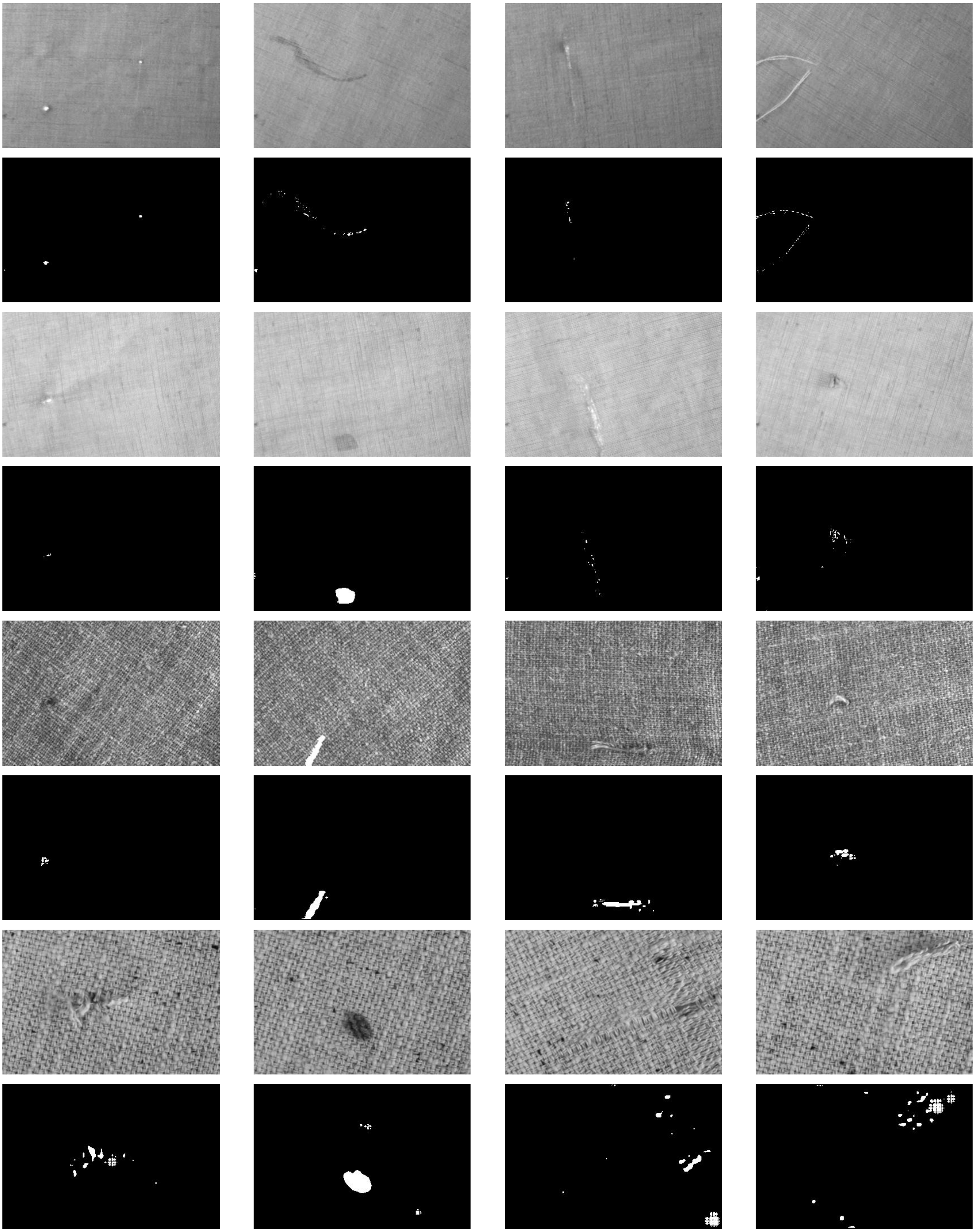

**FIGURE 5.** Detection results of TILDA database.

indicates the percentage of correct alarm during detection. Sensitivity indicates the percentage of defective samples that are correctly detected. Specificity manifests the percentage of non-defective samples that are correctly classified as normal. Accuracy indicates the percentage of correct classification of all testing samples.

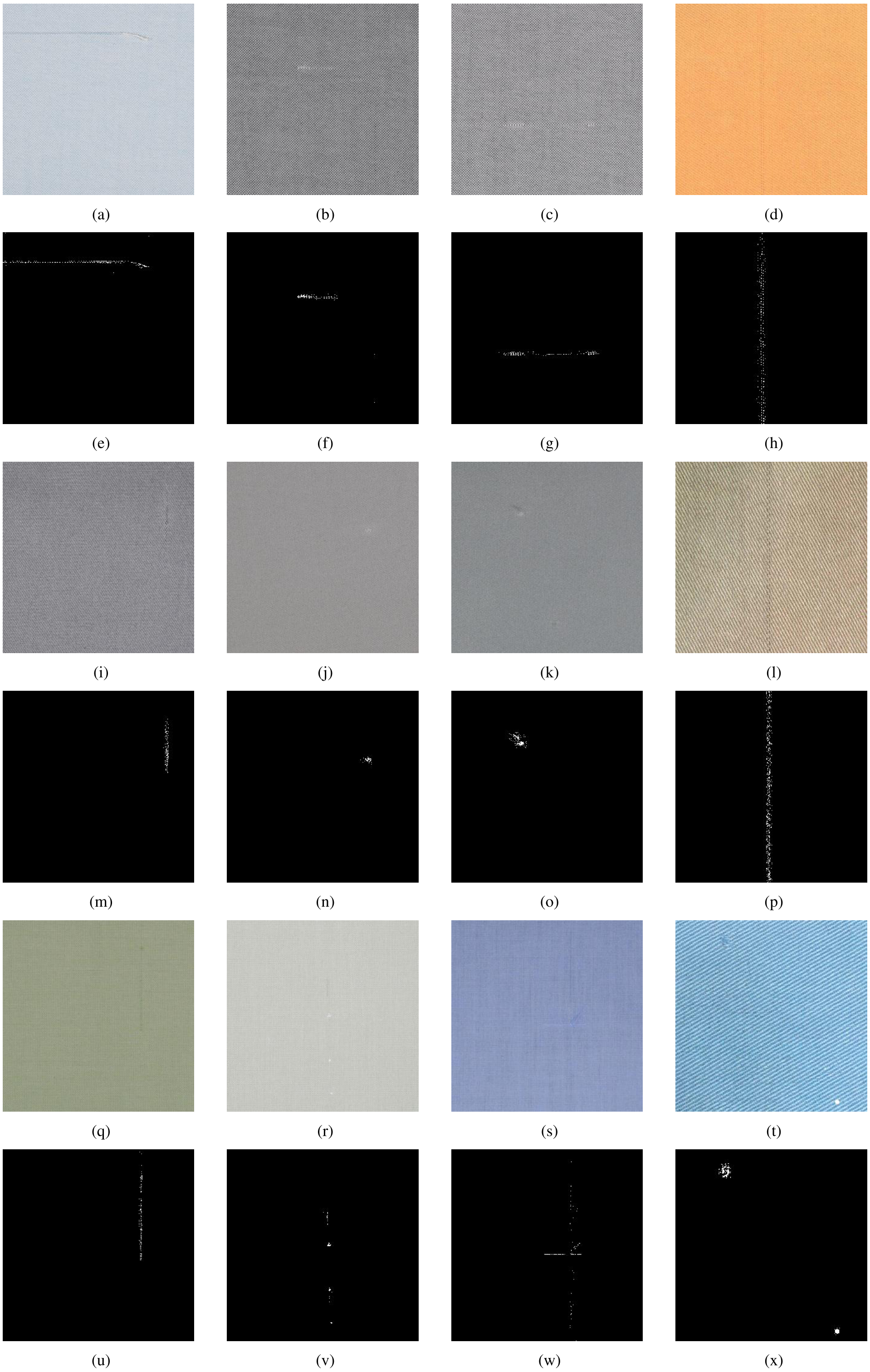


**FIGURE 6.** Detection results of missing yarn, thick-yarn and knots.

Figure 5 shows the detection results of four types of fabric in TILDA. For each type of defects, one representative sample was selected as demonstration. These defects are holes, stain, missing yarn and spot. From the detection results, it is noticed that most of the defects were well detected. For the first three types of fabric, the proposed detection model accurately located the defects and outlined their shapes. However, two defects on the fourth type of fabric were not well detected,

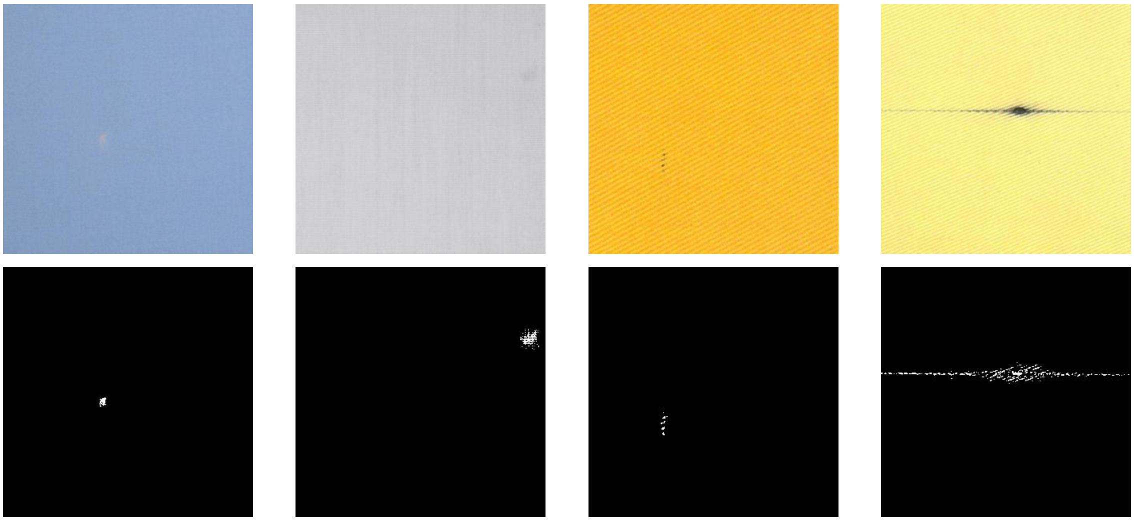

**FIGURE 7.** Detection results of stain defects.

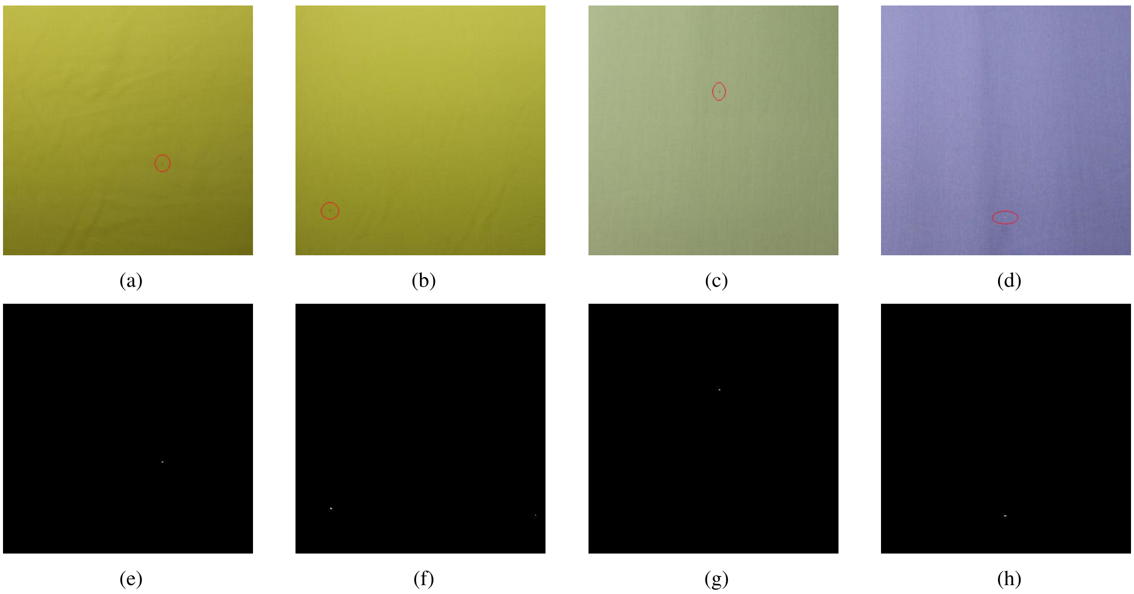

**FIGURE 8.** Detection results of tiny defects.

because the coarse fabric texture greatly influenced the image restoration accuracy and the thresholding selection. In all, the proposed detection model still achieved a rather high successful detection rate on TILDA. Moreover, as shown in Figure 5, nearly no false detection appear in the detection results, which reveals that the detection model is of high sensitivity and robustness.

As remarked in the database, an image of 768 × 512 in TILDA only covers an area of 37.5 square centimeter around, in which the defects occupy a large proportion area. Given that most of the fabric defects found in a real case might be much smaller than the samples in TILDA, more experiments were conducted on some real samples collected from an apparel company and scanned from the fabric defects handbook to verify the effectiveness of the proposed detection model for the apparel industry. The image samples collected from the real apparel factory is of 1050 × 1050 and covers about an A4 size area. The smallest defects on the fabric surface occupy only an area of one or two pixels approximately. Larger coverage of a testing image could result in a more efficient detection model. In accordance with the type of fabric defects, the defective samples are classified into three groups: defects caused by yarn arrangement such as missing yarn, thick-yarn and knots; tonal defects such as color mark and oil stain; subtle defects which are very small and of very low contrast with respect to the background. The detection results are presented in Figures 6-8.

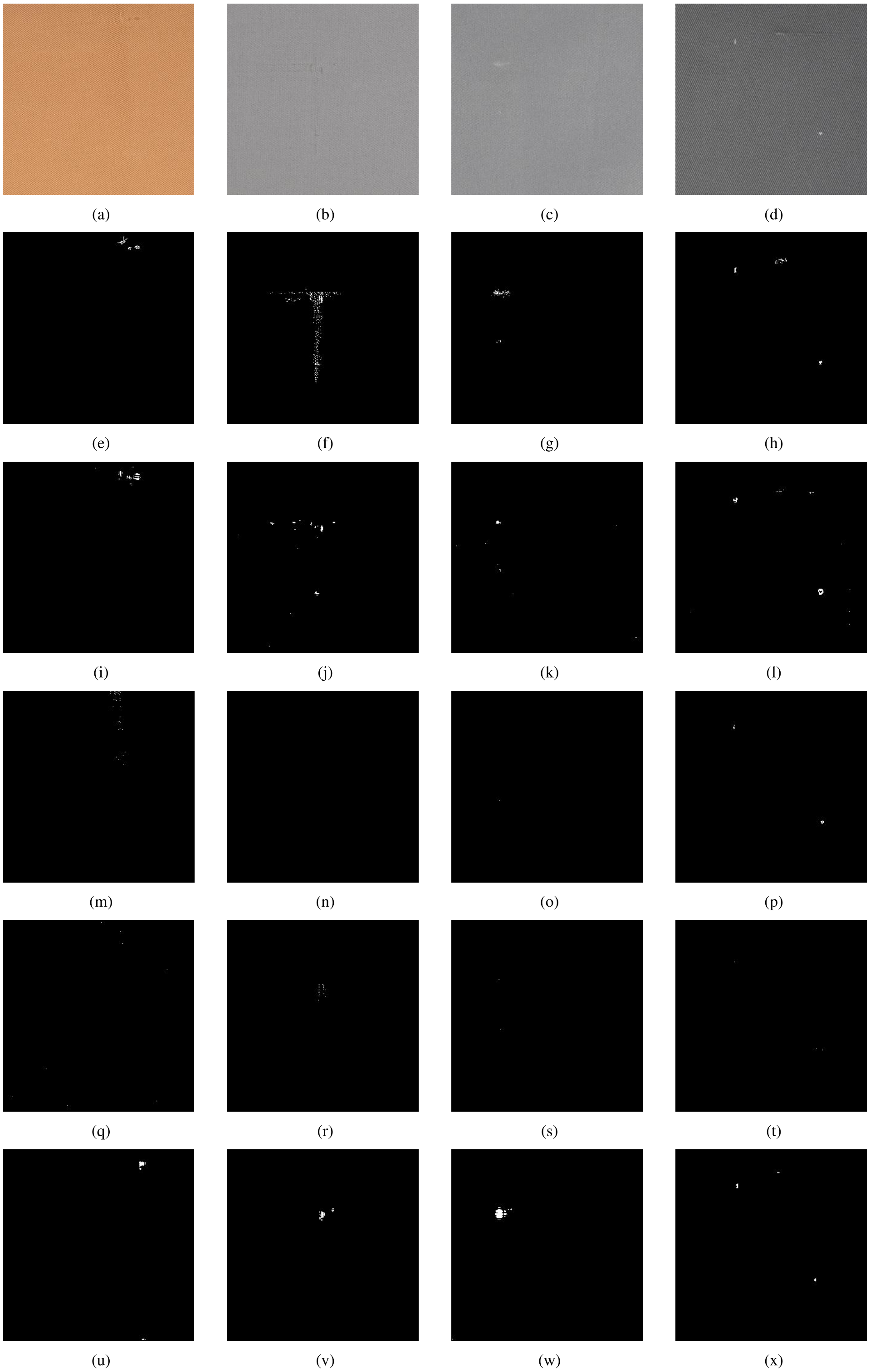


**FIGURE 9. Results of comparative experiment on twill fabric.**

Figure 6 shows examples of the detection results of defects related to yarn arrangement. Defects on the fabric whose weft and wrap yarns are of different color are more conspicuous than others, e.g., Figures 6(a)-6(c). The proposed detection model successfully located the defect and outlined their accurate shape. Since their fabric texture structure is slightly more complex than others, some false alarms appeared in their detection results, e.g., Figures 6(e) and 6(f). Due to the high

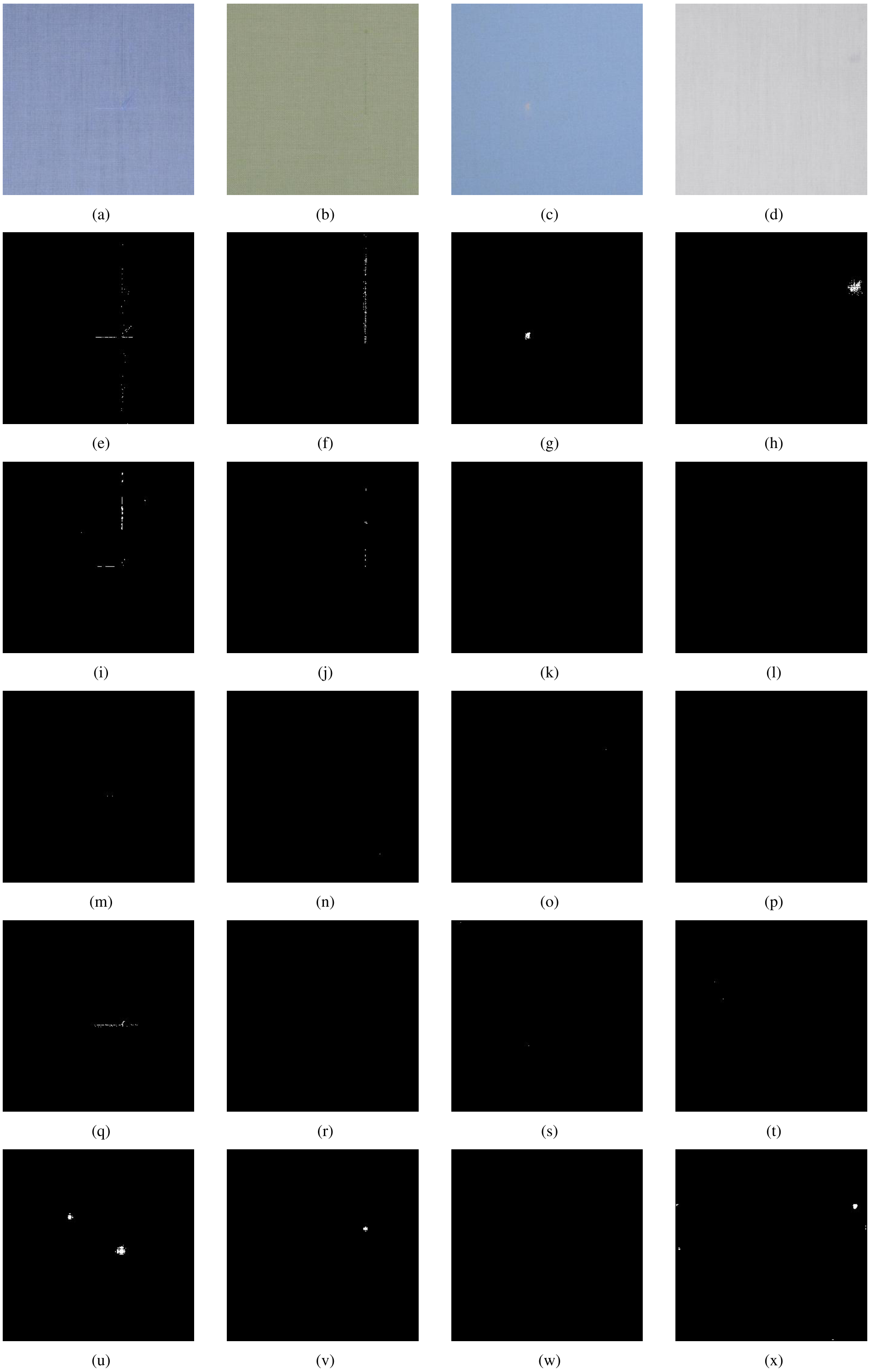


**FIGURE 10.** Results of comparative experiments on plain fabric.

density of yarn arrangement of twill fabric, the defects on such fabric are usually of low contrast, such as Figures 6(i) and 6(j). However, by using the proposed model, both of them were well detected in Figures 6(m) and 6(n).

Stain defects alter the color of fabric but not their structure, thus the contrast between these defects and the background is much higher. The proposed detection model achieved fairly good detection performance, as shown in Figure 7.

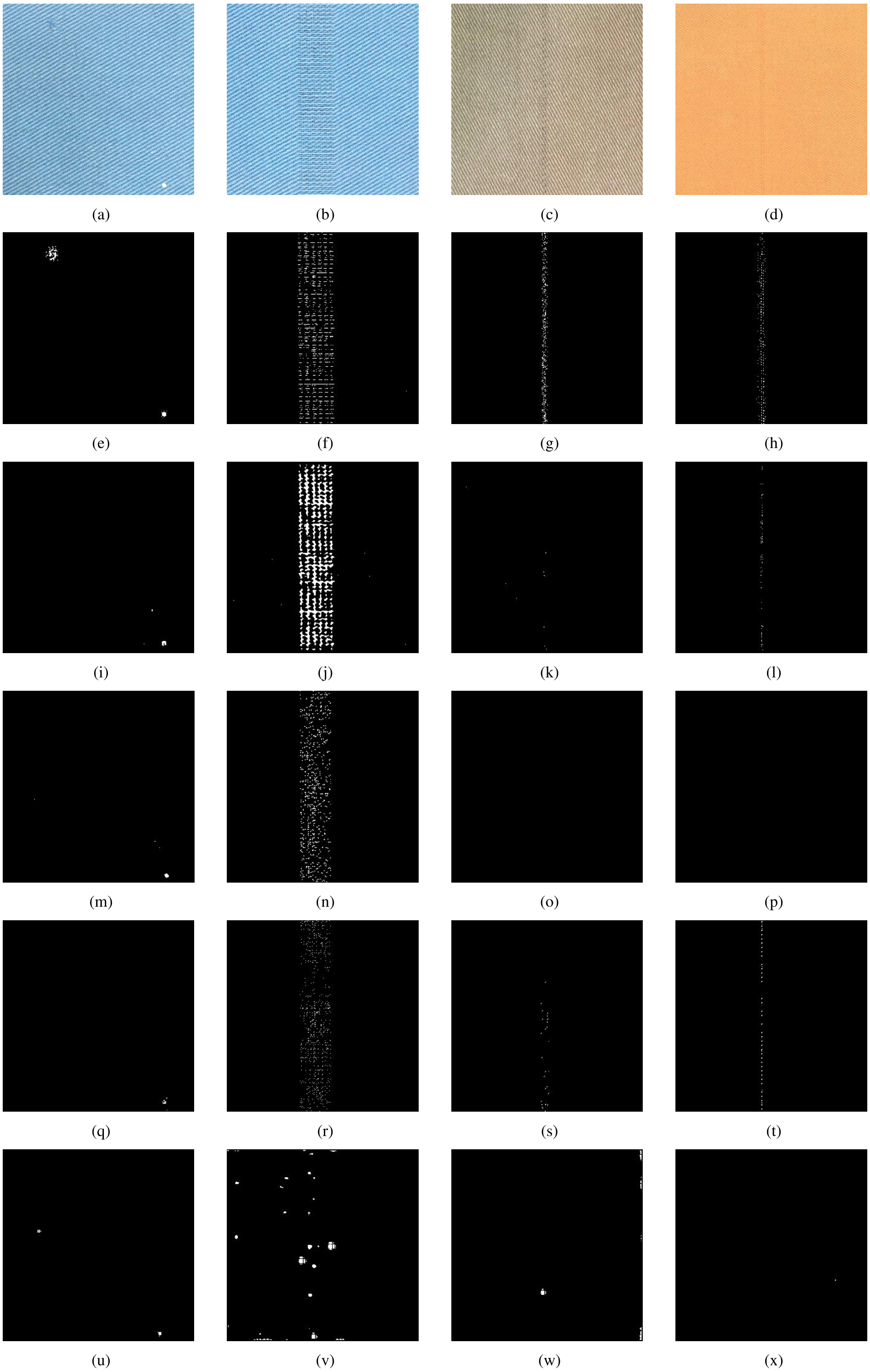


**FIGURE 11.** Results of comparative experiments on scanned images.

Figure 8 demonstrate the detection results of some tiny defect samples. For the sake of convenience for observation, the defects are labeled with red circle in the original images. All these defects are detected, even though they are as small as one or two pixels. Moreover, even in the condition of uneven illumination (e.g., Figures 8(a) and 8(b)), the proposed detection model can achieve an outstanding performance, which further verifies that the proposed defect

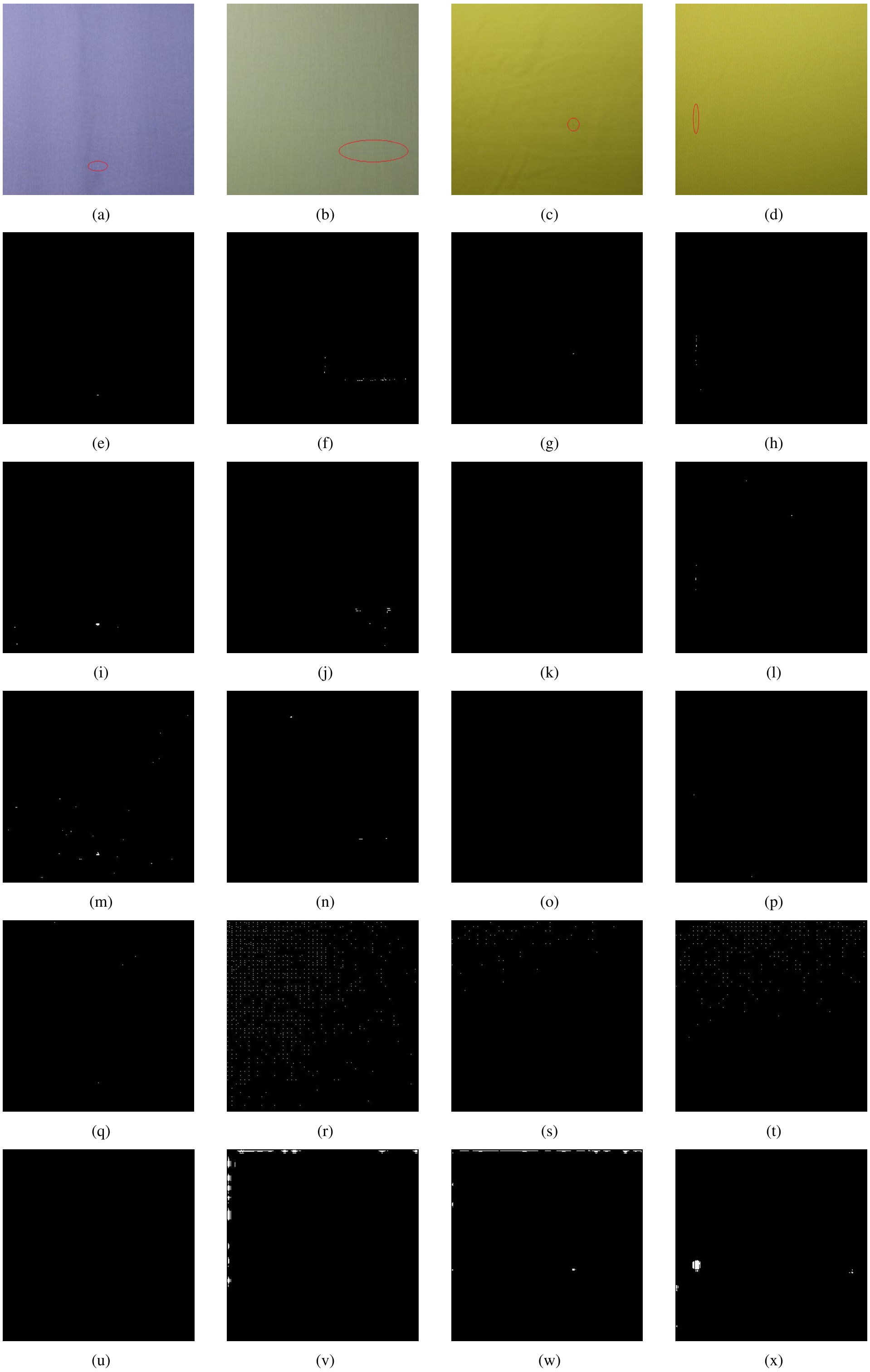


**FIGURE 12.** Results of comparative experiments on tiny defects.

detection model is very robust to the illumination variation. As stated in Table 2, the successful detection rate reached as high as 96.1% by utilizing the proposed defect detection model.

### 2) COMPARISON OF THE PROPOSED MODEL AND THE REPRESENTATIVE DETECTION MODELS

To further validate the effectiveness of the proposed model in fabric defect detection, its detection performance is compared with the other four representative defect detection approaches. The first one is differential evolution-based optimal Gabor filter model [15], which is one of the most popular approaches for fabric inspection and has shown the superior fabric inspection performance to some classical fabric detection models interns of detection accuracy computational cost. The second one is detection model based on Gabor filters bank [14], which is widely considered as a classical method for fabric defects detection. The third one is adaptive sparse representation-based detection model [16], which is a recently emerging detection method by utilizing image denosing techniques. The last one is a detection model based on Fourier and wavelet shrinkage [12], which is one of the latest spectral methods for fabric defect detection, and has shown its abilities in detecting small defects. Therefore, these four representative detection models are used in the comparative experiments to validate the superiority of the defect detection model proposed in this paper. The evaluations are conducted under the same environment on the basis of real fabric samples.

Figures 9-12 present the detection results of comparative experiments on our own database. The first row shows the original defective fabric samples. Figures in the second row are the detection results obtained by the proposed model. The last four rows show the detection results by using models in [12] and [14]–[16]. It is noticed that the proposed detection model segment all defect samples effectively and generally outperforms the other four methods.

Figures 9-11 show the comparative results of detection on various types of defects. As shown in Figures 9 and 11, detection model proposed in [15] performs well in detecting linear fabric defects, because Gabor filters optimized in horizontal and vertical are applied to extract features of defects. However, the detection model by using Gabor filters mainly depends on the feature extraction of defects in the joint spatial and frequency domain. Hence, the sensitivity of the detection model would not be satisfied when the defects contour are blurry and confused with normal fabric texture. Therefore, the model in [15] fails to outline the complete shape of the defects, as shown in Figures 9(j)-9(l).

The detection model in [14] is only applicable to limited types of defects, such as defects of high contrast (see in Figures 11(m) and 11(n)), because of the predefined parameters of Gabor filters bank. From the detection results, it is noticed that the detection model in [12] fails to provide precise test results. It is sensitive to some small texture variations, which leads to the problem of high false alarm rate as well.

Compared with the conventional regression-based model in [16], non-local similarities of the fabric structure information are utilized to reduce noise in the restored image in the proposed model, which in turn increases the detection rate. Therefore, even for small and subtle defects, the proposed detection model could achieve good performance, as shown in Figures 9(g), 10(g) and 10(h).

The comparative detection results on several tiny defects are demonstrated in Figure 12. It is noticed that the models

**TABLE 3. Performance comparison of defect detection models.**

| | Precision | Sensitivity | Specificity | Accuracy |
|---|---|---|---|---|
| The proposed model | 92.5% | **96.1%** | 92.2% | **94.1%** |
| Model in [15] | **94.7%** | 88.2% | **95.1%** | 91.7% |
| Model in [14] | 79.3% | 81.2% | 83.1% | 82.2% |
| Model in [16] | 93.3% | 82.3% | 94.1% | 88.2% |
| Model in [12] | 82.7% | 88.2% | 79.1% | 83.5% |

proposed in [16] fail to detect all the defects, when the defects are hard to visually distinguish. Moreover, uneven illumination in Figure 12(b)-12(d) resulted in lots of false alarms in the detection results. Other comparative methods cannot obtain the accurate recognition of defects. However, with the utilization of features of non-local image patches, the proposed defect detection model is effective in detecting tiny defects and immune to uneven illumination. In all, Table 3 summaries the performance comparison of the five detection models, which reveals that the detection rate is much higher by using the proposed detection model than the other four models.

## V. CONCLUSION

In this paper, an automated and efficient fabric defect detection model based on non-locally centralized sparse representation has been proposed. This model is mainly based on two modules: dictionary learning (off-line) and defect detection through image restoration (real-time). First, the compact sub-dictionaries learned from non-defective samples could be adaptively selected in sparse coding to provide the most relaxant fabric structure information for image restoration. Then, by adopting the non-locally centralized sparse representation model, nonlocal similarities of the fabric structure information are exploited to improve the image restoration effect, thereby increasing the defect detection rate.

Extensive experiments were conducted to validate the performance of the proposed model. The performance of the proposed defect detection model was evaluated on the basis of TILDA database and some more real fabric samples. A series of results demonstrates its effectiveness on the detection of defects of various shapes, sizes and locations. The results reveals that the proposed defects detection model achieves not only high successful detection rate but also low false alarm rate. Further, experiments that compared the proposed model with four representative detection models showed that the proposed defect detection model performs better than the other four detection models in terms of both detection accuracy and detection efficiency.

As noticed in the experiments, there are still four undetected fabric defects which are color marks on black fabric caused by weaving machine restart. Because the tonality of the defects and fabric background is almost the same, the color difference between them is too little to be distinguished. Moreover, the constraints of illumination and the imaging exposure time limited the contrast between color mark defects and standard fabric texture in the acquired images, since increasing the exposure time will influence the efficiency of the detection model. Therefore, finding suitable features of color marks for defect detection will be the main focus in the future work.

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## REFERENCES

[1] R. Stojanovic, P. Mitropulos, C. Koulamas, Y. Karayiannis, S. Koubias, and G. Papadopoulos, "Real-time vision-based system for textile fabric inspection," *Real-Time Imag.*, vol. 7, no. 6, pp. 507–518, 2001.

[2] C.-S. Cho, B.-M. Chung, and M.-J. Park, "Development of real-time vision-based fabric inspection system," *IEEE Trans. Ind. Electron.*, vol. 52, no. 4, pp. 1073–1079, Aug. 2005.

[3] J. L. Raheja, B. Ajay, and A. Chaudhary, "Real time fabric defect detection system on an embedded DSP platform," *Opt.-Int. J. Light Electron Opt.*, vol. 124, no. 21, pp. 5280–5284, 2013.

[4] W. Du, Y. Tang, S. Y. S. Leung, L. Tong, A. V. Vasilakos, and F. Qian, "Robust order scheduling in the discrete manufacturing industry: A multi-objective optimization approach," *IEEE Trans. Ind. Informat.*, to be published, doi: 10.1109/TII.2017.2664080.

[5] H. Y. T. Ngan, G. K. H. Pang, and N. H. C. Yung, "Automated fabric defect detection—A review," *Image Vis. Comput.*, vol. 29, no. 7, pp. 442–458, 2011.

[6] A. Kumar, "Computer-vision-based fabric defect detection: A survey," *IEEE Trans. Ind. Electron.*, vol. 55, no. 1, pp. 348–363, Feb. 2008.

[7] A. Latif-Amet and A. Ertüzün, and A. Erçil, "An efficient method for texture defect detection: Sub-band domain co-occurrence matrices," *Image Vis. Comput.*, vol. 18, no. 6, pp. 543–553, 2000.

[8] J. L. Raheja, S. Kumar, and A. Chaudhary, "Fabric defect detection based on GLCM and Gabor filter: A comparison," *Opt.-Int. J. Light Electron Opt.*, vol. 124, no. 23, pp. 6469–6474, Sep. 2013.

[9] M. F. Costa, F. Rodrigues, J. Guedes, and J. Lopes, "Automated evaluation of patterned fabrics for defect detection," in *Proc. Edu. Training Opt. Photon. (ETOP)*, 2000, pp. 403–407.

[10] H. Y. Ngan, G. K. Pang, S. Yung, and M. K. Ng, "Defect detection on patterned jacquard fabric," in *Proc. 32nd IEEE Appl. Imag. Pattern Recognit. Workshop*, Sep. 2003, pp. 163–168.

[11] C. H. Chan and G. K. H. Pang, "Fabric defect detection by Fourier analysis," *IEEE Trans. Ind. Appl.*, vol. 36, no. 5, pp. 1267–1276, May 2000.

[12] G. H. Hu, Q. H. Wang, and G. H. Zhang, "Unsupervised defect detection in textiles based on Fourier analysis and wavelet shrinkage," *Appl. Opt.*, vol. 54, no. 10, pp. 2963–2980, 2015.

[13] S.-D. Kim and S. Udpa, "Texture classification using rotated wavelet filters," *IEEE Trans. Syst., Man, A, Syst. Humans*, vol. 30, no. 6, pp. 847–852, Nov. 2000.

[14] A. Kumar and G. K. H. Pang, "Defect detection in textured materials using Gabor filters," *IEEE Trans. Ind. Appl.*, vol. 38, no. 2, pp. 425–440, Mar. 2002.

[15] L. Tong, W. Wong, and C. Kwong, "Differential evolution-based optimal Gabor filter model for fabric inspection," *Neurocomputing*, vol. 173, pp. 1386–1401, Jan. 2016.

[16] J. Zhou, and J. Wang, "Fabric defect detection using adaptive dictionaries," *Textile Res. J.*, vol. 83, no. 17, pp. 1846–1859, 2013.

[17] J. Zhou, D. Semenovich, A. Sowmya, and J. Wang, "Dictionary learning framework for fabric defect detection," *J. Textile Inst.*, vol. 105, no. 3, pp. 223–234, 2014.

[18] Q. Zhu, M. Wu, J. Li, and D. Deng, "Fabric defect detection via small scale over-complete basis set," *Textile Res. J.*, vol. 84, no. 15, pp. 1634–1649, 2014.

[19] T. Qu, L. Zou, Q. Zhang, X. Chen, and C. Fan, "Defect detection on the fabric with complex texture via dual-scale over-complete dictionary," *J. Textile Inst.*, vol. 107, no. 6, pp. 743–756, 2016.

[20] J. Zhou and J. Wang, "Unsupervised fabric defect segmentation using local patch approximation," *J. Textile Inst.*, vol. 107, no. 6, pp. 800–809, 2016.

[21] R. W. Conners, C. W. Mcmillin, K. Lin, and R. E. Vasquez-Espinosa, "Identifying and locating surface defects in wood: Part of an automated lumber processing system," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 5, no. 6, pp. 573–583, Sep. 1983.

[22] L. H. Siew, R. M. Hodgson, and E. J. Wood, "Texture measures for carpet wear assessment," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 10, no. 1, pp. 92–105, Jan. 1988.

[23] D. Chetverikov and A. Hanbury, "Finding defects in texture using regularity and local orientation," *Pattern Recognit.*, vol. 35, no. 10, pp. 2165–2180, 2002.

[24] D. Zhu, R. Pan, W. Gao, and J. Zhang, "Yarn-dyed fabric defect detection based on autocorrelation function and GLCM," *Autex Res. J.*, vol. 15, no. 3, pp. 226–232, 2015.

[25] H. Y. Ngan and G. K. Pang, "Robust defect detection in plain and twill fabric using directional Bollinger bands," *Opt. Eng.*, vol. 54, no. 7, pp. 073106.1–073106.13, 2015.

[26] D. Chetverikov, "Pattern regularity as a visual key," *Image Vis. Comput.*, vol. 18, no. 12, pp. 975–985, 2000.

[27] O. Alata and C. Ramananjarasoa, "Unsupervised textured image segmentation using 2-D quarter plan autoregressive model with four prediction supports," *Pattern Recognit. Lett.*, vol. 26, no. 8, pp. 1069–1081, 2005.

[28] S. Ozdemir and A. Ercil, "Markov random fields and Karhunen-cLoeve transform for defect inspection of textile products," in *Proc. IEEE Conf. Emerg. Technol. Factory Autom. (EFTA)*, vol. 2. 1996, pp. 697–703.

[29] G. H. Hu, G. H. Zhang, and Q. H. Wang, "Automated defect detection in textured materials using wavelet-domain hidden Markov models," *Opt. Eng.*, vol. 53, no. 9, p. 093107, 2014.

[30] S. C. Kim and T. J. Kang, "Texture classification and segmentation using wavelet packet frame and Gaussian mixture model," *Pattern Recognit.*, vol. 40, no. 4, pp. 1207–1221, Apr. 2007.

[31] W. Du, S. Y. S. Leung, Y. Tang, and A. V. Vasilakos, "Differential evolution with event-triggered impulsive control," *IEEE Trans. Cybern.*, vol. 47, no. 1, pp. 244–257, Jan. 2017.

[32] B. Zhang, W. Li, P. Qing, and D. Zhang, "Palm-print classification by global features," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 43, no. 2, pp. 370–378, Mar. 2013.

[33] W. Jia, R.-X. Hu, Y.-K. Lei, Y. Zhao, and J. Gui, "Histogram of oriented lines for palmprint recognition," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 44, no. 3, pp. 385–395, Mar. 2014.

[34] P. Henriquez, J. B. Alonso, M. A. Ferrer, and C. M. Travieso, "Review of automatic fault diagnosis systems using audio and vibration signals," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 44, no. 5, pp. 642–652, May 2014.

[35] Y.-Q. Zhao and J. Yang, "Hyperspectral image denoising via sparse representation and low-rank constraint," *IEEE Trans. Geosci. Remote Sens.*, vol. 53, no. 1, pp. 296–308, Jan. 2015.

[36] J. X. Yang, Y. Q. Zhao, J. C. W. Chan, and S. G. Kong, "Coupled sparse denoising and unmixing with low-rank constraint for hyperspectral image," *IEEE Trans. Geosci. Remote Sens.*, vol. 54, no. 3, pp. 1818–1833, Apr. 2016.

[37] M. Elad and M. Aharon, "Image denoising via sparse and redundant representations over learned dictionaries," *IEEE Trans. Image Process.*, vol. 15, no. 12, pp. 3736–3745, Dec. 2006.

[38] M. Lysaker and X.-C. Tai, "Iterative image restoration combining total variation minimization and a second-order functional," *Int. J. Comput. Vis.*, vol. 66, no. 1, pp. 5–18, 2006.

[39] J. Mairal, F. Bach, J. Ponce, G. Sapiro, and A. Zisserman, "Non-local sparse models for image restoration," in *Proc. IEEE 12th Int. Conf. Comput. Vis.*, Sep. 2009, pp. 2272–2279.

[40] J. A. Tropp and S. J. Wright, "Computational methods for sparse solution of linear inverse problems," *Proc. IEEE*, vol. 98, no. 6, pp. 948–958, Jun. 2010.

[41] W. Dong, L. Zhang, G. Shi, and X. Wu, "Image deblurring and super-resolution by adaptive sparse domain selection and adaptive regularization," *IEEE Trans. Image Process.*, vol. 20, no. 7, pp. 1838–1857, Jul. 2011.

[42] W. Dong, L. Zhang, G. Shi, and X. Li, "Nonlocally centralized sparse representation for image restoration," *IEEE Trans. Image Process.*, vol. 22, no. 4, pp. 1620–1630, Apr. 2013.

[43] D. F. Germany. (1996). *Tilda Textile Texture-Database*. [Online]. Available: http://lmb.informatik.uni-freiburg.de/resources/datasets/tilda.en.html,version1.0

[44] *Manual of Standard Fabric Defects in the Textile Industry*, Graniteville, SC, USA: Graniteville Company, 1975.

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