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Fabric Defect Detection and Classifier via Multi-Scale Dictionary Learning and an Adaptive Differential Evolution Optimized Regularization Extreme Learning Machine

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Abstract
To develop an automatic detection and classifier model for fabric defects, a novel detection and classifier technique based on multi-scale dictionary learning and the adaptive differential evolution algorithm optimised regularisation extreme learning machine (ADE-RELM) is proposed. Firstly in order to speed up dictionary updating under the condition of guaranteeing dictionary sparseness, k-means singular value decomposition (KSVD) dictionary learning is used. Then multi-scale KSVD dictionary learning is presented to extract texture features of textile images more accurately. Finally a unique ADE-RELM is designed to build a defect classifier model. In the training ADE-RELM classifier stage, a self-adaptive mutation operator is used to solve the parameter setting problem of the original differential evolution algorithm, then the adaptive differential evolution algorithm is utilised to calculate the optimal input weights and hidden bias of RELM. The method proposed is committed to detecting common defects like broken warp, broken weft, oil, and the declining warp of grey-level and pure colour fabrics. Experimental results show that compared with the traditional Gabor filter method, morphological operation and local binary pattern, the method proposed in this paper can locate defects precisely and achieve high detection efficiency.

Key words: *defect detection, multi-scale dictionary learning, regularisation extreme learning machine, adaptive differential evolution.*

Introduction

In the process of textile weaving, there will be a variety of defects on textile surfaces because of the harsh environment and weaving machine failure. Since the defects are generally localised, they can be regarded as local abnormal texture regions. The purpose of defect detection is to localise the local abnormal texture and visualise the defective region. Traditional fabric defect detection is done by humans with vast experience, but this is inefficient due to the visual fatigue and psychological factors of the human. Manual detection efficiency is only 40% to 50% when textile weaving speeds are beyond 30 m/min [1]. Moreover there are some types of defect that are difficult to detect with the naked eye. Thus fabric defect detection based on compute vision is emerging as the times require. In recent years, many fabric defect detection technologies based on computer vision have been proposed [2-4]. The most representative defect detection methods can be divided into two categories [5] based on the frequency domain and spatial domain.

Fabric defect detection based on the frequency domain can be defined as the original defective image being converted into a frequency domain to detect the defect. The most commonly used methods include the Fourier transform, wavelet transform and Gabor filter transform. Hu et al. [6] proposed an unsupervised defect detection method based on the Fourier transform and wavelet shrinkage. Firstly the main frequency component of the periodic pattern in the background is partially filtered with high-gradient values using the 0-mask method. Secondly the Fourier transform is used to repair the residual image. Finally wavelet threshold shrinkage is introduced to remove noise. Malek et al. [7] presented an automated online fabric inspection by means of the fast Fourier transform and cross-correlation. The key to the method is converting the image into a frequency domain by means of the fast Fourier transform to calculate the texture regularity of each image. Fabric defect detection based on Fourier transform has the disadvantage of lacking support in the spatial domain and is unable to detect a random patterned texture. Lucia et al. [8] put forward an automated defect detection method for structured fabrics using Gabor filters and principal component analysis. The Gabor filter bank and principal component analysis are used to extract texture features of the image, and then the Euclidean distance is used for evaluating feature differences. Finally the defective region will be located according to feature differences. Hu et al. [9] proposed texture defect detection based on the simulated annealing algorithm and optimisation of the Gabor filter. The key point of this method is the Gabor filter being converted to a specific frequency and direction to match the characteristics of a defect-free image. In fabric defect detection based on the Gabor filter, it is difficult to achieve a good result because of the parameters of the Gabor filter bank needing precise and meticulous calculation.

Fabric defect detection based on the spatial domain directly deals with the pixels of the original defective image in the spatial domain. The most commonly used methods include the mathematical morphology operator, gray level co-occurrence matrix, local binary pattern and dictionary learning method. Celik et al. [10] presented fabric defect detection based on linear filtering and the morphological operation. First of all, the captured images were denoised using a linear filter, and then the defective region was detected through the morphological closure operation. The normal texture regions were detected when using the morphological operation for defect detection because the threshold setting is sensitive and generalisation performance is poor. Raheja et al. [11] proposed fabric defect detection based on the gray level co-occurrence matrix and compared it with the Gabor filter method. In [11], experimental results show that the gray level co-occurrence matrix has better performance. Raheja also designed a real time fabric defect detection system on an embedded DSP platform in [12]. The gray level co-occurrence matrix is used to describe the texture features of textile images. Defect detection using the gray level co-occurrence matrix is a statistical method based on the texture feature statistic, which compares the texture features of standard normal fabric images with those of defective images. However, the gray level co-occurrence matrix needs intensive calculation and does not work well for texture fabric with large-size defects. Jing et al. [13] used a Gabor filter and the local binary pattern to detect fabric defects. The defective image is converted into a binary image via the Gabor filter and local binary pattern, and then the defective region is segmented. However, the binary problem of the local binary pattern is strongly dependent on the threshold setting, hence some normal texture regions are also detected as defective areas because the threshold setting is improper. Zhou et al. [14] proposed fabric defect detection using the complementary fractal feature vector and fuzzy c-means. Fabric defect detection based on dictionary learning is a relatively new detection method proposed in recent years. Qu et al. [15] used a dual-scale over-complete dictionary for fabric defect detection, where the detection efficiency is low due to the high complexity of the textured surface.

Inspired by fabric defect detection using dictionary learning, and to detect fabric defects more correctly, a novel method based on multi-scale k-means singular value decomposition (KSVD) dictionary learning combined with an optimised regularisation extreme learning machine (RELM) is proposed to establish a defect detection model in this paper. The main innovations in this paper are as follows:

(1) Due to the different sizes and types of defects on textiles surface, a multi-scale KSVD dictionary learning method is proposed. Different sizes of dictionaries can be learned from standard defect-free images, where the learned multi-scale dictionaries extract texture feature information from the image more clearly and improve the efficiency of defect recognition. The dictionaries only learn the normal texture, and using the learned multi-scale dictionary, they approximate the defective image, where the difference between the original image and approximate image is the defective region.

(2) A defect classifier model based on the adaptive differential evolution (ADE) algorithm to optimise RELM is proposed in the phase of training the ADE-RELM classifier, which improves detection efficiency by iteratively calculating the optimal input weights and hidden bias of the RELM. The adaptive mutation operator is used, which can prevent premature convergence in the initial iteration, prevent difficult convergence in the terminal iteration, and solve the problem of low efficiency and large workload in the original differential evolution algorithm. Adaptive differential evolution is introduced to obtain the weighted and hidden layer bias of RELM, which solves the problem that the original ELM randomly generates input weights and hidden layer bias, and that despite the training speed being fast, the classification accuracy is low.

The paper is organised as follows:

- The method proposed is provided in the next Section.
- The subsequent sections present detailed experiment results and discussions.
- The conclusions are given in the last section.

Proposed method

In this paper, we propose a novel image texture feature extraction method based on multi-scale dictionary learning. The linear summation of multi-scale dictionaries is used to approximate textile images and describe feature information of the image more clearly. Besides this, we propose an ADE-RELM algorithm to build defect detection and a classifier model. Not only does it solve the problem of low accuracy in RELM but also the limitation of parameter setting in the original differential evolution algorithm.

Feature extraction using multi-scale dictionary learning

In image sparse representation, an image can be represented as a linear summation of a set of basis vectors and coefficients, and the approximated image is highly similar to the original one. Generally speaking, finding this set of basis vectors is called the dictionary learning method [16]. Basically dictionary learning can be considered as an optimal solution to an approximated problem, that is, the difference between the approximated image and the original one is minimised [17]. Multiple scale dictionary learning is proposed for the single scale learning dictionary due to its lack of a multiple scale and multiple directionality in image processing. Moreover this method can express image information more sparsely and efficiently. The task of this paper is to find such a dictionary, where the D and matrix x coefficients are as sparse as possible, so that the original image can be approximated by the linear sum of the dictionary and coefficients. However, the method is complex and computationally expensive due to the calculation of the inverse matrix; hence the KSVD algorithm [18] is introduced in this paper. KSVD is divided into two steps: the first is sparse coding, and the second is dictionary updating. In the KSVD algorithm, the dictionary elements are updated with columns to reduce the complexity of the algorithm. Using 2-norm to solve dictionary D based on the KSVD algorithm is represented by:

$$\min_D \|Y - DX\|_2^2 = \min_D \left\| Y - \sum_{j=1}^{k} d_j x_j^T \right\|_2^2 =$$

$$= \min_D \left\| Y - \sum_{\substack{j=1 \\ j \neq j_u}}^{k} d_j x_j^T - d_{j_u} x_{j_u}^T \right\|_2^2 \qquad (1)$$

Where, d_j represents the j-th atom in dictionary D and x_j^T the row of the j-th coefficient. We can update d_{j_u} and x_{j_u} in every step. The updated dictionary atoms and sparse coefficients are obtained after each step of the update. Consequently we learn the dictionary and most sparse coefficient matrix when the update is complete. Until each column in the dictionary is updated, through repeating iterations, the optimal dictionary and corresponding sparse coefficients can be obtained. In this paper, for defects of the same piece of cloth surface, the dictionary learned by the standard image learning dictionary only contains the normal texture structure. However, the areas of defect indicate that its local texture is abnormal. By learning the dictionary to approximate the defect image, the defect area is implicitly covered; thus the difference between the two images is the defect area.

Considering defects of different types and sizes on a textile surface, we proposed a multi-scale dictionary to approximate fabric images to describe the texture features of a textile surface more precisely. A traditional single-scale dictionary is used to approximate images with linear summation of single-scale dictionaries to reconstruct images; however many details of the images are lost. Multi-scale dictionaries are learned through the dictionary learning algorithm, and then the dictionary elements learned contain almost all texture features of the textile images. Then the linear summation of the multi-scale dictionary is used to approximate the textile images, which retains detailed information of the original textile images under the condition of high approximation performance. Approximating the textile images using the multi-scale dictionary, elements can be computed as:

$$Y \approx D_s X_s + D_m X_m + D_l X_l \qquad (2)$$

Where, D_s, D_m and D_l represent the small scale dictionary, middle scale dictionary and large scale dictionary, respectively. X_s, X_m and X_l denote the coefficient matrix respectively.

In this paper, the size of fabric images is 200*200. The defect-free image is divided into image patches $p \times p$, which are non-overlapping, and each small patch is expanded into a column vector, which is combined into a feature matrix. The KSVD method is used to learn the dictionaries. Plain fabric and twill fabric are divided into three scale patches, respectively. Small-scale, middle-scale and large-scale dictionaries are learned from 20×20, 25×25, 40×40 patches, respectively. Note that all dictionary elements shown in ***Figure 1*** are reshaped back into image patches $p \times p$ for displaying.

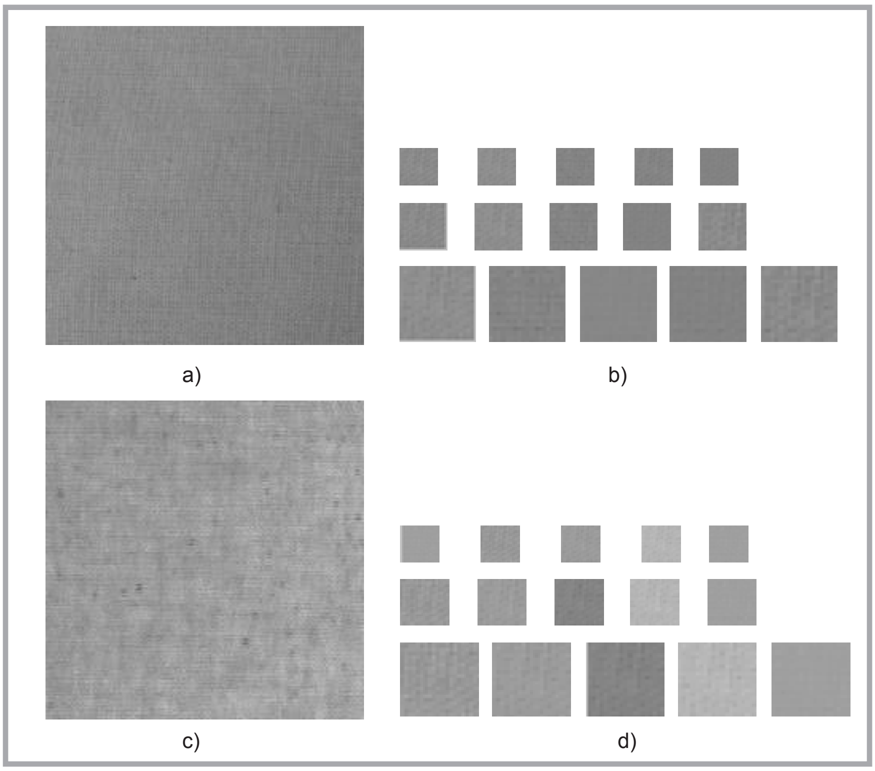

Figure 1. *Multi-scale dictionary elements learned from normal fabrics: a) and c) are the twill fabric image and plain fabric image; b) and d) are multi-scale dictionary elements learned from a) and c), respectively.*

The features that we learned using the single-scale dictionary are incomplete, and cannot describe detailed features on the surface of textile images; thus there is a large difference between the approximated image and original image. A linear combination of multi-scale dictionaries is used to approximate the original image, and the combination of information

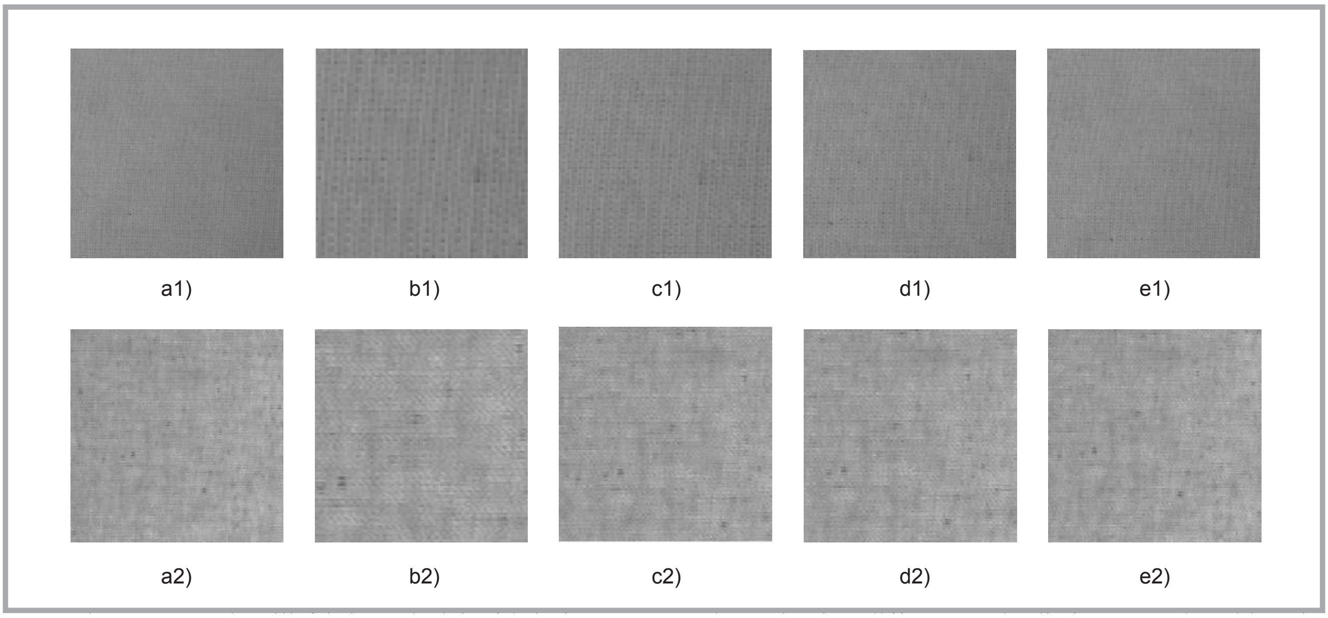

Figure 2. *Normal twill fabric and plain fabric image approximated using a different scale dictionary and multi-scale dictionary. a) Original defect-free images, b) approximated image using 40*40 dictionary, c) approximated image using 25*25 dictionary, d) approximated image using 20*20 dictionary, e) approximated image using multi-scale dictionary.*

Table 1. Comparison of the error degree of a single-scale dictionary and multi-scale dictionary.

	Error degree			
	20*20 dictionary	25*25 dictionary	40*40 dictionary	Multi-scale dictionary
2	90%	95%	95%	90%
4	75%	80%	80%	70%
8	50%	60%	75%	40%
12	35%	40%	55%	20%
16	20%	25%	30%	15%
20	10%	15%	25%	5%

from the different scale dictionaries is used to describe texture features of the textile image more clearly. For example, some features are learned by the small-scale dictionary, but none by the middle-scale dictionary and large-scale dictionary; then an amount of feature information will be lost if only the middle-scale and large-scale dictionaries are used to approximate the original image. There is complementation between the multi-scale dictionaries as much as possible to learn all features of fabric images, and then the difference between the approximate fabric images and original images is minimised. Defect-free images are approximated using different scale dictionary elements and a multi-scale dictionary, as shown in ***Figure 2***, with a defect-free image approximated using 20*20 scale dictionary elements, 25*25 scale dictionary elements, 40*40 scale dictionary elements and multi-scale dictionary elements, respectively. It can be clearly seen that the larger the dictionary size, the larger the distance between the approximated image and the original image, due to the fact that a great deal of feature information will be lost in the process of the large-scale dictionary learning stage. The difference between the approximated image and original image is smaller when using 20*20 dictionary elements, and the approximated image using a combination of multi-scale dictionary elements is nearly identical to the original normal texture image, with only the smallest difference.

In order to evaluate the approximate effect, we define ED as the error degree of the approximated images and original images:

$$ED = \frac{\sum_{i=1}^{N}(x_i - x_i^{'})}{N} \times 100\% \qquad (3)$$

Where, x_i represents original image patches, $x_i^{'}$ approximated image patches, and N is the total number of image patches. To evaluate the quality of approximated images, our idea is that because there are multiple original images and each single-scale dictionary and multiple scale dictionary must approximate multiple original images, the approximate average value of the multiple original image is taken. We calculated the error degree of approximated images and original images in the case of different single-scale and multi-scale dictionaries via different cardinality of dictionaries. As shown in ***Table 1***, the left column of the table represents the cardinality of dictionaries.

In ***Table 1***, the error degree is small under the condition of using a small-scale dictionary. Because small-scale dictionaries are learned from small-scale image patches, the small-scale image patches will learn more detailed feature information in the process of learning a dictionary. The middle-scale and large-scale dictionaries will lose some detailed features in the dictionary learning phase, due to the image patches being larger than in the small-scale dictionary. Through the complementarity of multi-scale dictionaries, we can learn as much as possible the feature information of the image, and minimize the difference between the approximated image and the original image. Also the error degree is smaller when the cardinality of dictionaries is 12 to 20, and it verifies the texture feature of the approximated image more clearly when more dictionaries are used. ***Figure 3*** shows the approximated defective images using different scale and cardinality dictionaries, where the first to third rows represent the approximated defective image using 20*20, 25*25 and 40*40 dictionaries with different cardinality, respectively. The last row represents the approximated fabric image using a multi-scale dictionary with different cardinality.

The size of the dictionary has a significant effect on the defect detection. This paper hopes to find a dictionary that approximates the normal texture region well, yet it cannot approximate the defect region well simultaneously. Thus the choice about K is extremely important for successfully detecting the defect area. It can be seen from ***Figure 3*** that the small-scale dictionary used to approximate a defective image has good performance with a small number of dictionaries. A large-scale dictionary cannot approximate a defective image very well when using the same number of dictionaries. The multi-scale dictionary used to approximate a defective image has very good performance with fewer dictionaries. In this paper, we selected K as accounting for around 15% of the error degree, which performed well for approximating the fabric image and robustness.

Adaptive mutation operator of a DE-based regularisation extreme learning machine

The defects on a textile surface are of different types and sizes, and hence it is difficult to extract all types of defect for training. In this paper, we propose a novel fabric defect classifier method called the single-class classifier, which means either normal texture or abnormal texture. The defective areas will be considered as local abnormal texture for the same textiles. Then we trained a classifier that only catches the normal texture and discards the abnormal texture. Generally speaking, textiles with defects are few and the defective areas are relatively small, and thus the method we propose in this paper is suitable for textiles that contain a large amount of normal texture and small amount of abnormal texture.

Researches show that the variation factor of the DE algorithm is generally selected as between 0 and 1 in the iterative optimisation process. The variation factor is used to amplify or reduce the difference. In general, the DE algorithm [19-21] randomly generates the initial amount of the mutation factor in practical application, and then according to the specific problem, the DE algorithm dynamically selects the optimal variation factor. If the variation factor is too large, the search efficiency is low, and it is difficult to converge to a global optimum. In contrast, if the variation factor is too small, premature convergence will occur, and the diversity of the population will be greatly reduced. Therefore the adaptive mutation operator is introduced. In the early stage of DE algorithm optimisation, premature convergence and the local optimum is prevented under the premise of ensuring

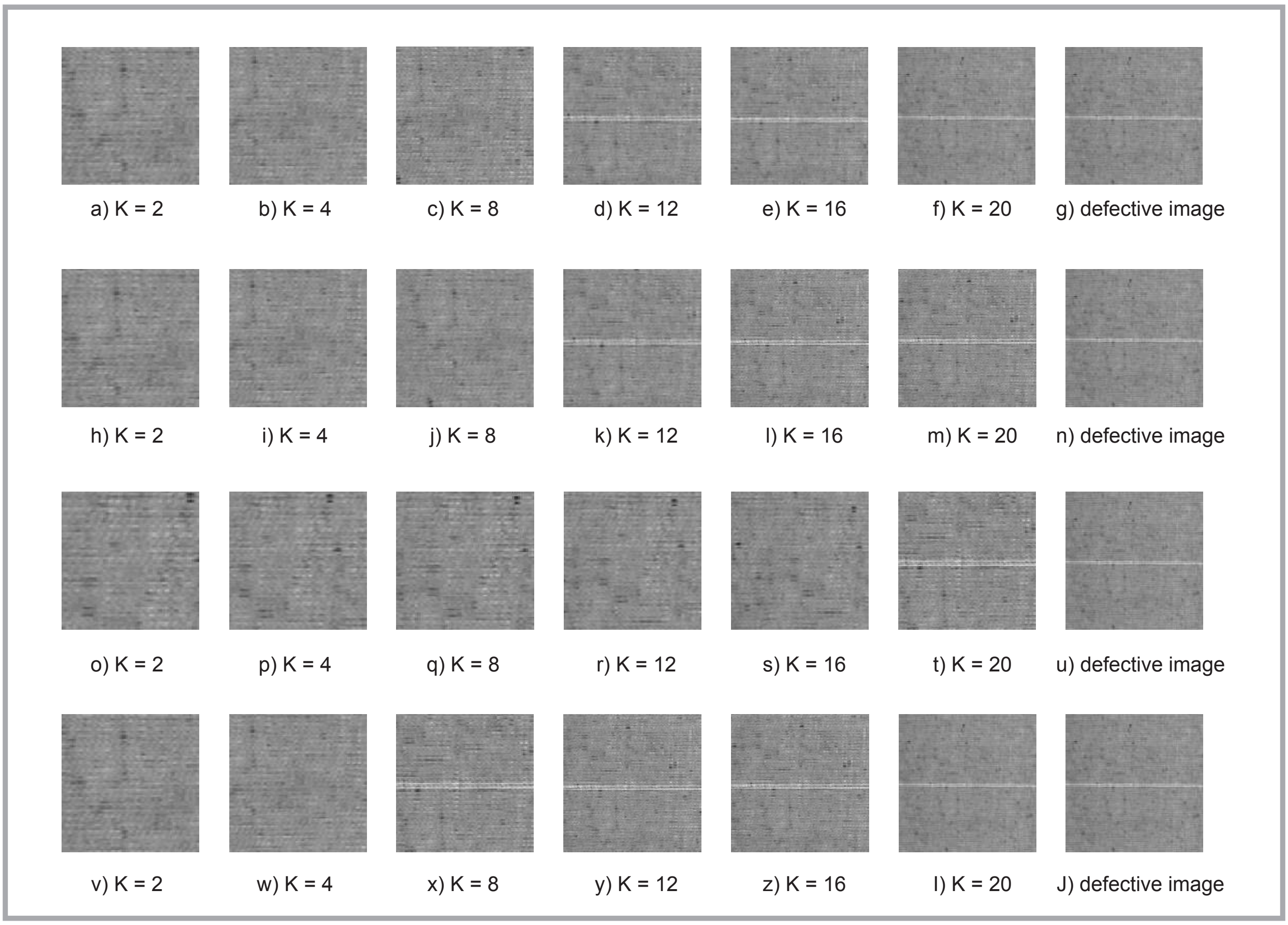

Figure 3. *Approximated results of defective image: rows from top to bottom, using 20*20, 25*25, 40*40 and multi-scale dictionaries, respectively.*

the diversity of the population. At the end of the optimisation, under the premise of finding the optimal solution, speeding up the algorithm converges it to the global optimum. In this paper, a detection model based on ADE algorithm optimised RELM is proposed. RELM [22-23] has a fast learning speed because of the input weights and hidden bias being generated randomly; however, the accuracy of RELM is low. The ADE algorithm is introduced to iteratively calculate the input weight and hidden bias. To easily obtain in the process of calculating the output weights, RELM is introduced. In fact, the regularisation parameter is an adopted term to represent structural risk in the process of solving the output weight. There are many parameters that need to be set in the original differential evolution algorithm, for most of which dynamic parameter selection is used; however, this leads to low efficiency and a high workload. In this paper, the adaptive mutation operator is used to prevent premature convergence in the early iteration and prevent hard convergence at the end of iteration.

In this paper, we proposed an ADE algorithm optimised RELM used for the training detection model and achieved high detection efficiency. Given a dataset: $N=\left\{(x_i,t_i)\,|\,x_i\in \mathrm{R}^{\mathrm{n}}, t_i\in \mathrm{R}^{\mathrm{m}}, \mathrm{i}=1,2......N\right\}$, RELM can be defined as an optimisation problem:

$$\min_{w,b,\beta}\sum_{i=1}^{L}\left\|C\beta_i g(w_i\cdot x_j+b_i)-t_j\right\|_2^2,$$

$$j=1,2,...,N \qquad (4)$$

Where, w_i represents input weights, b_i hidden bias, β_i output weights, C the regularisation parameter, and L denotes the number of hidden layer neurons of RELM. The optimisation problem is to find the most suitable w_i, b_i and β_i to minimise the error. Therefore the ADE algorithm is introduced to find the optimal input weights and hidden bias, and then the output weights are calculated. In this paper, the basic DE algorithm with an adaptive mutation operator is adopted to solve the problem of dynamic parameter selection in the process of iteration. A specific explanation of the algorithm flow is given below:

(i) Initialised number of hidden network neurons L, population size NP and maximum number of iteration $G_{\max}$.

(ii) Initialised population $G_{NP\times D}$, and D is the dimension of population G. The initialised population consists of the input weights w and hidden bias b. The i-th individual of the 0-th generation in the population is:

$$\min_{w,b,\beta}\sum_{i=1}^{L}\left\|C\beta_i g(w_i\cdot x_j+b_i)-t_j\right\|_2^2,$$

$$j=1,2,...,N \qquad (5)$$

Where, $x_{j,i}(0)$ means the j-th feature of the i-th individual, and x_{jmin} & x_{jmax} represent the lower and upper bounds of the j component, respectively.

(iii) Mutation operation. The ADE algorithm achieves individual variation through the mutation strategy. In this paper, we introduced the self-adaptive mutation operator λ; the adaptive mutation operator is used to prevent premature convergence in the early iteration as well as hard convergence at the end of itera-

Algorithm 1. *The ADE-RELM method proposed.*

Input: Population number M, Dimension D, Maximum number of iterations T, Number of neurons in hidden layer L

1. Initial population
2. Initial variation factor F_0 Difference strategy and crossover probability CR
3. After initialisation, the current population of the best individual β is calculated to find the overall optimal individual β
4. **if** $x_{best} = \beta$
5. $\beta = (\frac{I}{C} + HH^{T})^{-1} H^{T} T$
6. **end**
7. Mutation operation /* Generate variant intermediates $x_i(g_m)$*/
8. **While** t ≤ T
9. $\lambda = e^{1 - \frac{G_{\max}}{G_{\max} + 1 - G_m}}$
10. $F = F_0 * 2^{\lambda}$
11. **end**
12. Cross operation /* The crossover operation generates the next generation of individuals */
13. Selection operation /* Select the best output weight */
14. **for** i = 1: NP
15. $x_{best} = x_i(g + 1)$ /*Global optimal output weightβ*/
16. **end**

tion. The self-adaptive mutation operator is shown below:

$$\lambda = e^{1 - \frac{G_{\max}}{G_{\max} + 1 - G_m}} \tag{6}$$

Where, $G_{\max}$ represents the maximum number of iteration, and G_m denotes the current number of iteration. Thus the mutation factor is calculated as: $F = F_0 \cdot 2^{\lambda}$, where F_0 is the initialised mutation factor. The mutation strategy DE/rand-to-best-1 is selected, which can be written in the following form:

$$x_i(g_m) = x_{i4}(g) + F \cdot [x_{best}(g) - x_{i3}(g)] + \\ + F \cdot [x_{i1}(g) - x_{i2}(g)] \tag{7}$$

Where, $x_{best}(g)$ represents the best member in the current population, $x_{i1}(g)$, $x_{i2}(g)$, $x_{i3}(g)$, $x_{i4}(g)$, the members selected randomly in the population, respectively, and $x_i(g_m)$, means the variation intermediate of the g-th population through mutation.

(iv) Crossover operation. The crossover of individuals between the current g-th individual $x_i(g)$ and variation intermediate $x_i(g_m)$.

$$u_{j,i}(g_m) = \begin{cases} x_{j,i}(g_m) & rand(0,1) \le CR \text{ or } j = rand(1,2......D) \\ x_{j,i}(g) & other \end{cases} \tag{8}$$

(v) Selective operation. The ADE algorithm uses the greedy selection strategy to select the best offspring generation.

$$x_i(g+1) = \begin{cases} u_i(g_m) & f[u_i(g_m)] \le f[x_i(g)] \\ x_i(g) & other \end{cases} \tag{9}$$

(vi) Output weight calculation operation. The process of optimisation is done when the maximum number of iterations is reached. The maximum iterations refer to the number of iterations in which the classification correct rate tends to converge. The ending criterion of the algorithm is that the error of the classification correct rate in the current and next is less than 0.001, that is, with the increase of iterations, the classification correct rate tends to converge. We obtain the optimised input weights and hidden bias and calculate the output weights by using $\beta = (\frac{I}{C} + HH^{T})^{-1} H^{T} T$, and then the detection model is established.

An overview of the ADE-RELM is summarised in ***Algorithm (1)***.

The dictionary in this paper is learned from defect-free images. Therefore the

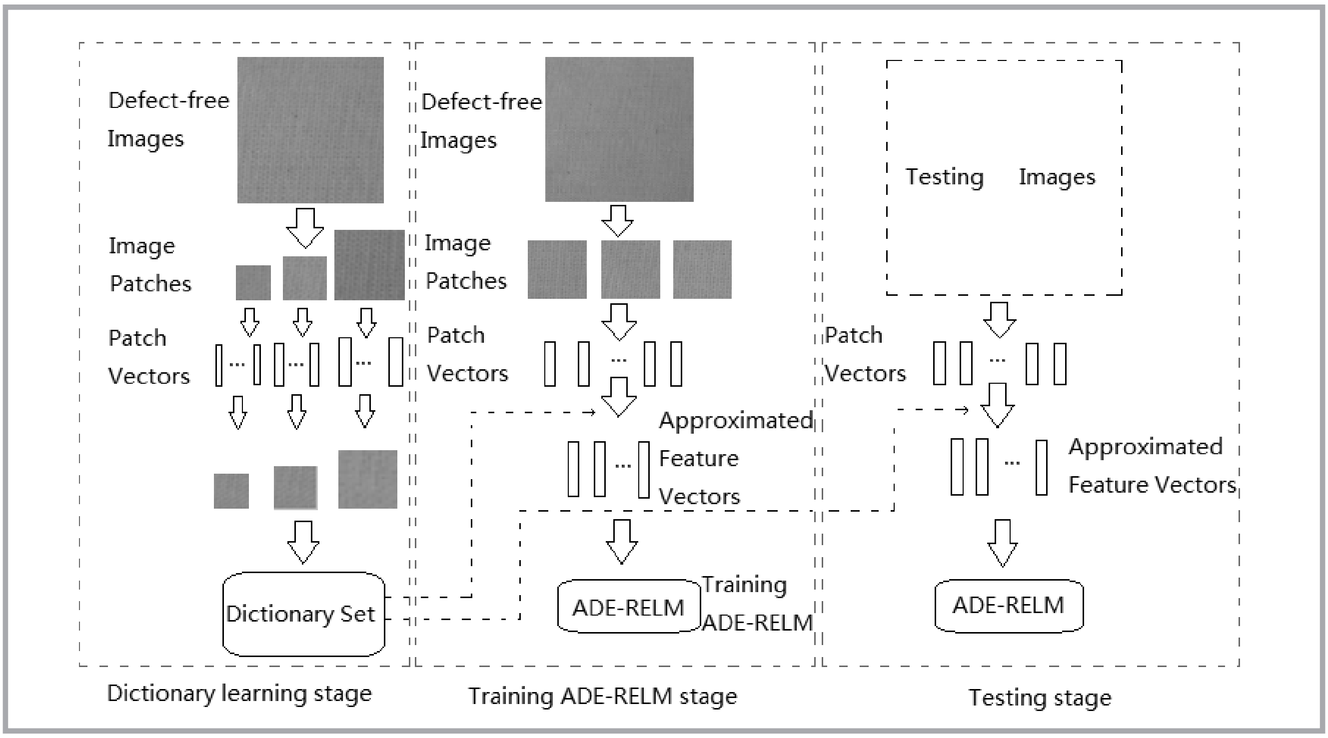

Figure 4. *Overview of defect detection and classifier model.*

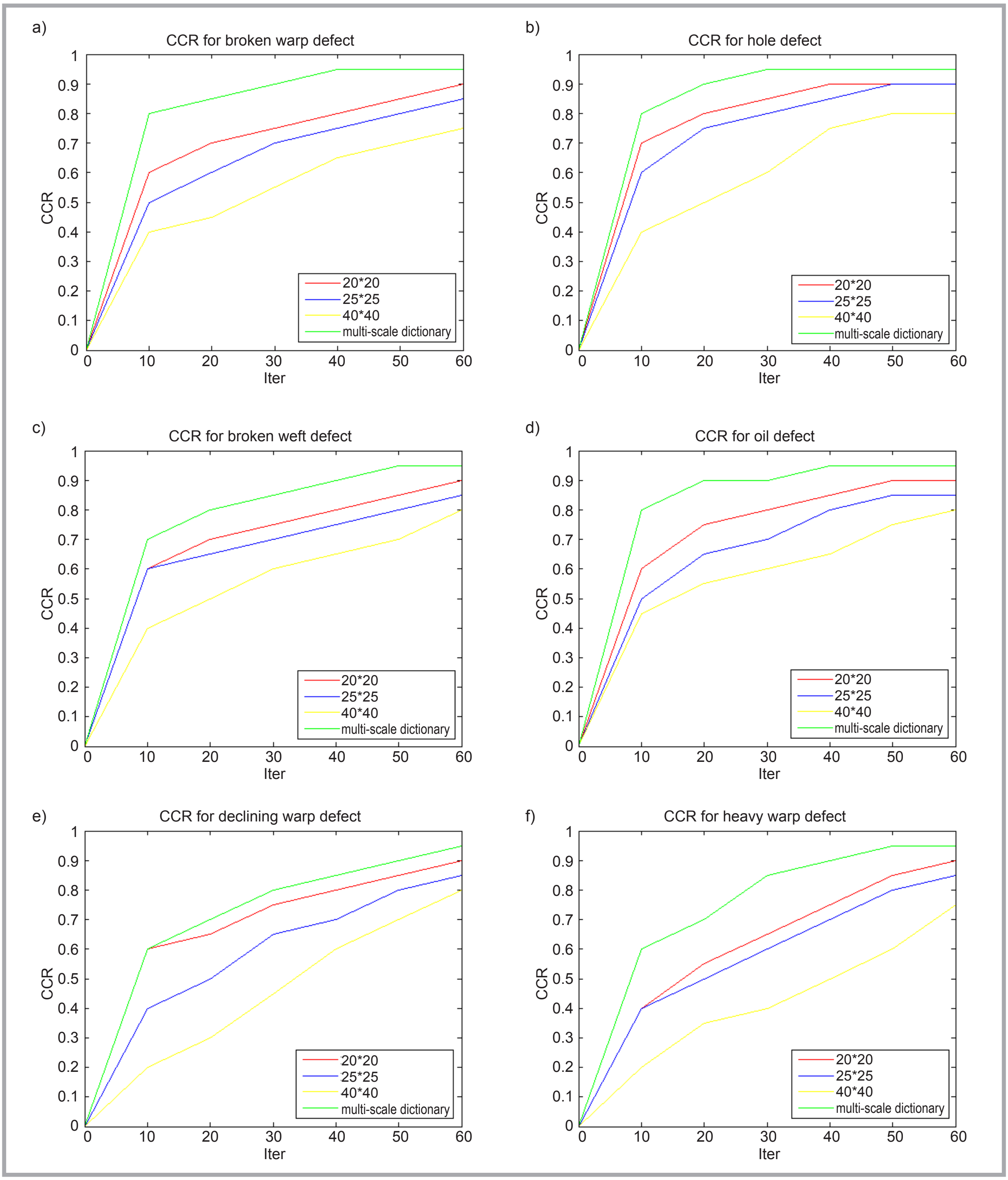

__Figure 5.__ CCR for each type of defective image with different iterations of ADE-RELM: a) broken warp, b) hole, c) broken weft, d) oil, e) declining warp, f) heavy warp.

dictionary elements only contain normal texture features and have good approximation performance for defect-free images. However, the defective image is the normal texture image with local abnormal texture, and hence the dictionary learnt can only approximate normal texture, but covers the defective area implicitly. The difference between the defective image and that approximated using the dictionary is the defective region. Therefore we train a single-class classifier using the dictionary which can approximate normal texture features well. Thus at the testing stage, the defective image can be detected.

Fabric defect detection and classifier model

Developing a fabric defect detection and classifier model has three stages: the dictionary learning stage, ADE-RELM classifier training stage, and testing stage. In the dictionary learning stage, defect-free images are selected to divide into image patches $p \times p$, which are non-overlapping. Each small patch is expanded into column vectors, which are then combined into a feature matrix. The KSVD method is introduced to the learning dictionary, where multiple scale dictionaries are learned from different sizes of image patches and consist of the dictionary set. In the training single-class classifier stage, defect-free images are still selected to divide into image patches $p \times p$, which are non-overlapping. The multi-scale dictionaries learned are used to approximate the image patches, extract similarity features and train the ADE-RELM classifier. For testing images, features and the defect detected are extracted via the ADE-RELM classifier in the testing stage. The whole fabric defect detection model is illustrated in ***Figure 4***.

In dictionary learning stage, we are committed to detecting defects on the surface of the same piece of fabric, and dictionary elements are only learned for the normal texture features using standard defect-free images. The defective area is characterised as a local abnormal texture, and the defective area is totally covered by the approximate defective image using the learned dictionary. Hence the difference between the approximate image and original image is the defective region. In the ADE-RELM training stage, we still use the defect-free images, and the learned dictionary extracting features are used to train the ADE-RELM classifier.

Experimental results and discussions

In this paper, each individual fabric image has a size of 200*200 with 256-grey levels. We chose six different types of grey-level fabric defective images, such as broken warp, hole, broken weft, oil, declining warp and heavy warp. Each type of fabric image consists of 15 defect-free images and three images containing anomalies. Three defect-free images of each type were used for learning the dictionary and six defect-free images of each type were taken for learning the ADE-RELM classifier. The remaining defect-free images together with those containing anomalies were used for testing. In training the ADE-RELM classifier, the initial population size and crossover probability of the ADE algorithm is 8D and 0.9, respectively. The mutation strategy selected was DE/rand-to-best/1, and the mutation factor was self-adaptively learned. The hidden neurons of RELM were 40. For evaluating detection efficiency, we defined the classification correct rate (CCR) to describe the performance of detection. Where CCR can be defined as N_c/N_{tn}, N_c represents the defective images classified correctly, and N_{tn} the total number of images. We curved the CCR of each type of defective image with different iterations of ADE-RELM using different single-scale and multi-scale dictionaries. This is shown in ***Figure 5***.

It can be seen from ***Figure 5***, that the CCR was raised following the increase in iterations. The CCR we get using the small-scale dictionary is higher than for the middle-scale and large-scale dictionaries. The multi-scale dictionary achieved the highest CCR. It is also verified that texture feature details of the fabric image can be described more clearly using the multi-scale dictionary, and a higher CCR will be obtained. A better performance of hole defects and oil defects was achieved with fewer iterations, because of their defective regions are relatively small and simple. The CCR of declining warp defects and heavy warp defects is smaller, due to their defective regions being relatively large and complicated. The figurative examples of detection results of six different types of grey-level fabric defective images are given in ***Figure 6***. They were obtained using the multi-scale dictionary learned from ***Equation (2)*** and compared with some existing fabric defect detection methods, such as the Gabor filter method [11], morphological operation method [10] and local binary pattern method [13]. Where, the first column is the original defective images, and the second to final columns represent defect detection results using the Gabor filter, morphological operation, local binary pattern and our proposed method, respectively.

The Gabor filter is a typical fabric defect detection method based on the frequency domain, where the image in the spatial domain is converted into a frequency domain. From ***Figure 6***, the defective region is roughly detected using the Gabor filter method. But the defective image is in the frequency domain, and the detection result is not clear. The morphological operation method used for defect detection compares the actual pixel and threshold. Generally speaking, the defective region is the high light region, and thus it will be regarded as the defective region if the pixel is larger than the threshold; otherwise it is a normal texture region. The method using the morphological operation was strongly dependent on the threshold set and has poor performance of generalisation. Defect detection based on the local binary pattern method can locate the defective region. But the defect-free areas will be detected as defective due to the threshold of binarisation being inappropriate. The dictionary learning method involves learning a set of sparse dictionaries and approximating a defective image using a multi-scale dictionary, which describes the texture feature of the original image more clearly. The ADE algorithm optimized RELM developed for the defect detection model can solve the problem of inefficiency and improve the robustness of the algorithm. It is seen from the above-mentioned experimental results that our proposed method can detect the defective area accurately and has the best efficiency. Furthermore, the defect detection method proposed in this paper also has good performance for pure colour fabrics. In ***Figures 7*** and ***8***, the detection results of pure red fabric defects and pure pink fabric defects are presented, respectively. We chose four types of defects, such as broken warp and weft, and declining warp and oil. Where the first column is original pure colour fabric defective images, the second – grey-level images, the third – approximated images of grey-level images, and the final column is the detection results from using the multi-scale dictionary learning method.

In this paper, we selected two categories of pure colour images: pure red fabrics and pure pink fabrics. Four types of common defects containing broken warp and weft, and declining warp and oil are detected on the surface of pure colour fabrics. The specific techniques are described below. Firstly the pure colour fabric image is converted into a grey-level image. Little feature information will be lost due to the background of the relatively simple pure colour images. Secondly grey-level images are used to learn dictionary elements and approximate original images via a multiple scale dictionary. The experimental results show that the approximated images are highly consistent with the normal region of the original images. Finally the defective region is the difference between the original images and approximated images, and then the defective region is visualised. From the above-mentioned experiment, the results show that the defective

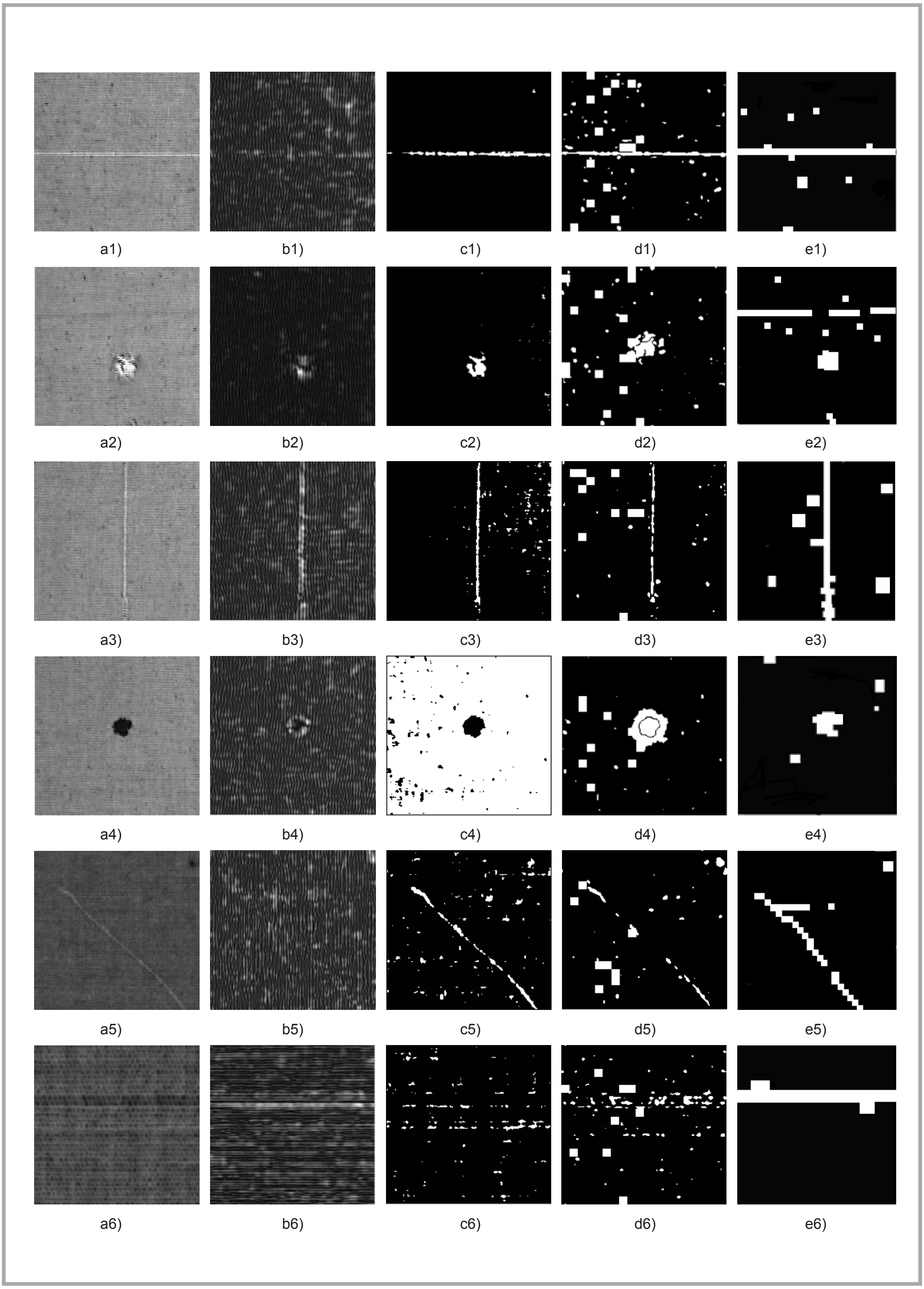

***Figure 6.** Some fabric defect detection examples obtained by the four detection algorithm: a) original defective image, b) Gabor filter detection results, c) morphological operation detection results, d) local binary pattern detection results, e) our proposed method.*

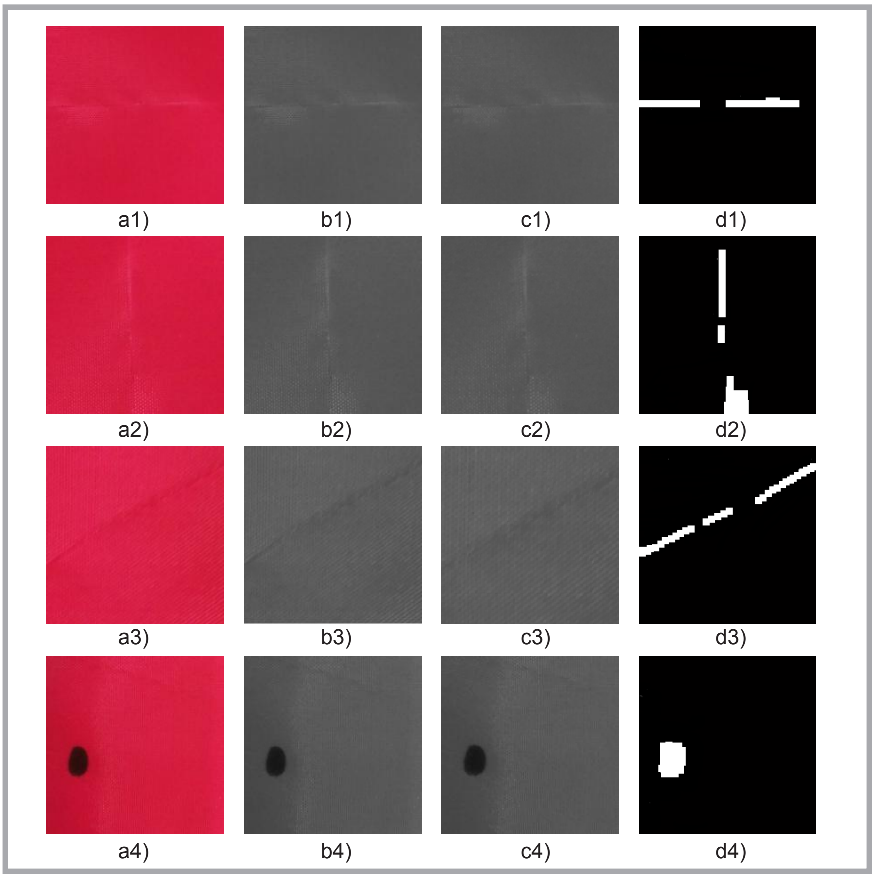

Figure 7. *Detect results of pure red fabric defects: a) original pure color images, b) grey-level images, c) approximated images, d) detect results.*

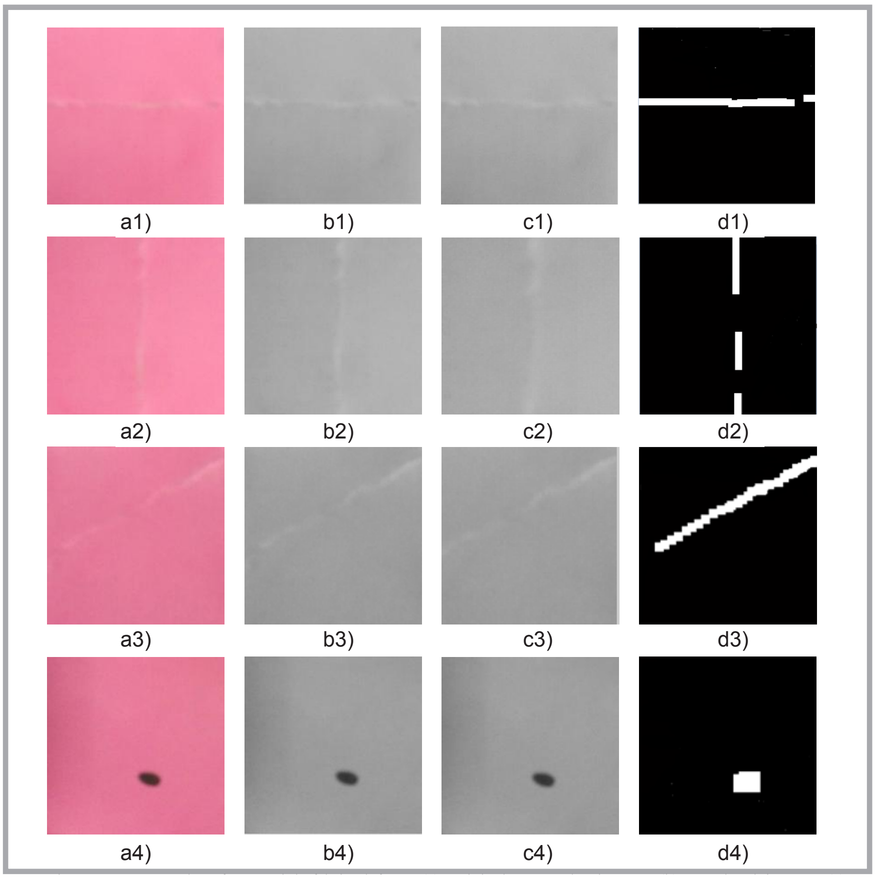

Figure 8. *Detect results of pure pink fabric defects: a) original pure colour images, b) grey-level images, c) approximated images, d) detection results.*

region is detected exactly based on the multiple scale dictionary. Moreover the defect-free region is not detected as the defective region because of the normal texture region of the original image and approximated image being more similar.

At the training stage, standardised defect-free images are used, for which the proportion of the defect area is mainly considered as usually small. It is found from the experiments that there is little difference between the dictionary learning of the defective image sample as a training sample and the corresponding normal image sample as a training sample. Therefore the image having no defects is selected as the training sample. Standard defect-free images are divided into image blocks of $p \times p$ size without overlapping, and then the learned dictionary is used to approximate the image blocks to obtain feature similarity. Since dictionary learning can be learned offline, the real-time performance of the algorithm is improved. The ADE-RELM classifier is trained by combining the multiple scale dictionary with the approximate image, the Euclidean distance extracted and the correlation coefficient. Most common types of defects can be defined previously according to the feature vector. For uncommon types of defects, they are classified into a new type of defect image by the feature vectors, such as the Euclidean distance and correlation coefficient.

Conclusions

This paper proposes a fabric defect detection and classifier method based on multi-scale dictionary learning combined with the ADE algorithm to optimised RELM. The main conclusions are as follows:

- The multi-scale dictionary is learned from different sizes of image patches to extract the texture feature more accurately, and approximated original image is learned via a multi-scale dictionary to minimise the difference between the original image and approximated image.
- The original differential evolution algorithm has many parameters, most of which are optimised by dynamic parameter selection, which leads to low efficiency and a large workload. The adaptive mutation operator is used in this paper, which can adaptively adjust itself to prevent prema-

ture convergence in the early iteration stage. Moreover it can prevent slow convergence at the end of iteration.

- The original ELM randomly generates input weights and hidden layer bias, and hence, although the training speed is fast, the classification accuracy is low. The adaptive DE is introduced to obtain the weighted and hidden layer bias of the regularisation ELM, which solves the problem of low classification accuracy in the original ELM.
- For the broken warp and weft, oil, oblique warp and so on of white greige and pure colour cloth fabric, the algorithm proposed realised the automatic detection of defects. Compared with the traditional application of a Gabor filter, the morphological operation and local binary mode, the proposed method obtained the highest classification accuracy 95% in detection stage. Compared with the existing defect detection algorithm, the method proposed can locate the defect more accurately and detect the defect area.

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