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RESEARCH OF PRINTING QUALITY DETECTION BASED ON IMAGE RESTORATION

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When kernel methods are applied to detect the defection, there is a need to select the training samples, because kernel methods are based on the statistical learning theory. To extract the defects, the pre-image is calculated. In this paper, a sampling algorithm based on the alignment is designed to improve the calculation efficiency, where kernel alignment can measure the similarity between different kernel functions and matrices. A local linear algorithm is proposed to calculate the pre-image. When obtain the 0–1 difference image, an algorithm is designed to determine whether there are defects. An algorithm is designed to calculate the center coordinates and the areas of defects in the 0–1 image. Using this method, the accuracy of detection can be improved, because the method can remove the effect from recovery errors. When using the algorithms on a data set of printing products, the experiment results show that the detection results are more accurately than using the difference matrix.

Keywords: Alignment; kernel principal component analysis; pre-image; defect inspection; sampling algorithm.

1. Introduction

Notes as the most important commodity exchange media require very high printing quality. At present, there are two ways to detect the printing quality, including step by step inspect and finished products detection. Machine vision is one of the most effective detection technology to replace the eye, and has been successfully applied to the products inspection. The complex printing process often make the notes with difference, such as mechanical noise, the paper deformation, displacement for separate printing of offset and gravure print, etc. The noise brought great difficulty to the image processing in vision inspection.

Although the notes from the same printing template, affected by the noise, there are great changes among them. The images from the camera have bigger difference at pixel level. There are rarely identical images even from the same camera. Kernel machine learning method is a kind of machine intelligence algorithm, which is based on the statistical learning theory and artificial intelligence. Compared with other methods in machine learning, the methods can more effectively reveal the appropriate causal relationship among data of production through a nonlinear mapping. This make kernel methods a kind of high-profile machine intelligence algorithm. In the production processes, products are affected by various factors, so the characters of different examples follow a nonlinear distribution, which becomes a non-negligible barrier to the products' defect detection. Kernel methods are especially suitable for dealing with such kind of problems because of its nonlinear nature.

Kernel matrix plays an important role in kernel methods [Schölkopf *et al.*, 1997]. The kernel matrix contains all of the topology information included in the training sample set, which inspired us to select the significant samples out of a large data set by the kernel matrix. A good training sample set can greatly improve the learning efficiency. Therefore, a variety of sample selection algorithms have been developed. In 1968, Hart proposed the condensed nearest neighbor rule (CNN rule) to select the training subset [Hart, 1968], which plays an important role in selecting the boundary samples. In 1979, Gowda and Krishna improved the CNN rule using the mutual nearest neighborhood [Gowda and Krishna, 1979]. And in 2005, Angiulli gave the fast condensed nearest neighbor rule (FCNN rule) for computing a training subset [Angiulli, 2005]. In 2002, a nonparametric data reduction method was designed by selecting a small representative subset from a very large data set [Mitra *et al.*, 2002]. In 2007, the subspace sample selection algorithm was introduced, which was confirmed more effective for the SVMs on face recognition [Jiang *et al.*, 2007]. And in 2007, Zhang utilized the selection method for speeding up the feature extraction [Xu *et al.*, 2007].

Kernel methods as nonlinear techniques can be used for image processing, which are effective in image de-noising and visualization of high dimensional data [Yu *et al.*, 2002; Shi, 2012]. In printing industry, the reconstruction of image is required to detect the defects. The defects can be obtained using the difference between the pre-image and the original image. So the defects detection efficiency is dependent on the effect of the reconstruction. Calculating the pre-image problem based on the kernel PCA is valuable. Many researchers have done lots of important contributions to the pre-image problem.

In the process of defect detection, an important step is the recognition of real defects from the 0–1 value image, and the calculation of the position and size of defects. In this paper, we take advantage of the excellent performance of kernel alignment to select the optimal training sample set. And use the designed algorithm to calculate the pre-image. The real defect's position and size is calculated by algorithm 2. The experimental results show that the algorithm 2 can remove the errors from the pre-image algorithm.

2. Sampling Algorithm

In the statistical learning theory, the similarity measurement plays an important role [Vongehr *et al.*, 2011]. Usually, the distance is used to measure the similarity between the samples. In a large sample set, usually there are many redundant samples. One purpose of sampling is to remove these redundant samples, in order to reduce the storage space and the computational time complexity and simultaneously to improve the calculation accuracy. The selected sample set must be capable to best represent the distribution of the whole sample set.

A color image can be expressed as a three-dimensional matrix $I \in R^{p\times q\times 3}$. Rewrite the matrix I as $x \in R^n$, where $x(pq(l-1)+p(j-1)+i) = I(i,j,l)$, $i = 1,2,\ldots,p$, $j = 1,2,\ldots,q$, $n = 3pq$. In kernel methods, N images $X = \{x_1, x_2, \ldots, x_N\}$ constitute the training sample set.

Kernels k_1 and k_2 are positive semi-definite and symmetrical (PDS). The kernel alignment can be written as [Cristianini *et al.*, 2002]

$$\hat{A}_s(K_1, K_2) = \frac{\langle K_1, K_2\rangle_F}{\sqrt{\langle K_1, K_1\rangle_F \langle K_2, K_2\rangle_F}}, \quad (1)$$

where $K_1, K_2 \in R^{N\times N}$ denote the kernel matrices, $K_1(i,j) = k_1(x_i, x_j)$ and $K_2(i,j) = k_2(x_i, x_j)$. And the inner product between matrices is defined by

$$\langle K_1, K_2\rangle_F = \sum_{i,j=1}^{N} k_1(x_i, x_j) k_2(x_j, x_i) = \mathrm{trace}(K_1' K_2).$$

It is obvious that alignment $\hat{A}_S(K_1, K_2) \in [-1, 1]$, particularly $\hat{A}_S(K_1, K_2) \in [0, 1]$ when $K_1, K_2 \geq 0$.

In this paper, we take the alignment (1) as the measurement to select the training samples.

In this section, we design the sampling algorithm 1 based on the alignment in Table 1.

3. Kernel Methods and Pre-Image Problem

In 1997, Schölkopf *et al.* used the KPCA for feature extraction [Schölkopf *et al.*, 1997], and then applied the method to image de-noising in 1999 [Mika *et al.*, 1999]. Giving the sample set S and kernel k, the inner corresponding to the nonlinear mapping $\phi(x)$ is defined as

$$k(x, x^*) = \langle \phi(x), \phi(x^*)\rangle. \quad (2)$$

Nonlinear principal components

$$V_k = \sum_{i=1}^{N} \alpha_i^k \phi(x_i) \quad (3)$$

can be calculated using the kernel trick, where vector $\alpha^k = [\alpha_1^k, \alpha_2^k, \ldots, \alpha_N^k]'$ is the kth eigenvector of kernel matrix K. Using the eigenvectors, the linear projection

$$P_m\phi(x) = \sum_{i=1}^{m} \beta_k V_k \quad (4)$$

can be calculated in feature space, where the kth coefficient $\beta_k = (\phi(x), V_k) = \sum_{i=1}^{N} \alpha_i^k k(x, x_k)$.

Table 1. A sampling algorithm based on alignment.

Algorithm 1: Sampling algorithm based on alignment	
Input:	$X = \{\mathbf{x_1}, \mathbf{x_2}, \ldots, \mathbf{x_M}\} \subset \mathrm{R}^{\mathrm{M}}$, kernel k, $\delta(\delta \in (0,1))$, selection number$N$
1	$\mathbf{D_2} \in \mathrm{R}^{M\times M}, [\mathbf{D_2}]_{(i,j)} = (\mathbf{x_i} - \mathbf{x_j})'(\mathbf{x_i} - \mathbf{x_j})$, $i, j = 1, 2 \ldots, M$ let Label = zeros$(M, 1)$ find $x_{t(1)}, x_{t(2)} = \arg\max(D_2)$, let $S = [x_{t(1)}\ x_{t(2)}]$, Label$(t(2)) = 1$, Label$(t(2)) = 1$
2	$D_{S2}(1,1) = D_2(t(1), t(1))$, $D_{S2}(1,2) = D_2(t(1), t(2))$, $D_{S2}(2,1) = D_2(t(2), t(1))$, $D_{S2}(2,2) = D_2(t(2), t(2))$, $S_n = 2$
3	if length (Label == 0) $\neq 0$ && $S_n < N$, go to step5 else go to output
4	$S_n = S_n + 1$, $\mathbf{K_0} = k(D_{S2})$, $nn = 0$, $N_0 =$ length(find(Label == 0)) let $X_0 = \{x_{k1}, x_{k2}, \ldots, x_{kN_0}\}$
5	for $p = 1 : S_n$ for $q = 1 : N_0$ $D_{tS} \leftarrow D_2(S(x_{t(p)} \leftarrow x_{kq}))$ $\mathbf{K_{pq}} = k(D_{tS})$ $\mathbf{A}(p,q) = \frac{\langle \mathbf{K_0}, \mathbf{K_{pq}}\rangle_F}{\sqrt{\langle \mathbf{K_0}, \mathbf{K_0}\rangle_F \langle \mathbf{K_{pq}}, \mathbf{K_{pq}}\rangle_F}}$ end end
6	$[\mathbf{r1}, \mathbf{c1}] =$ find$(\mathbf{A} > 1 - \delta)$ Label$(\mathbf{c1}) = -1$, $\mathbf{A}(:, \mathbf{c1}) = 1$
7	$\mathbf{A_{sum}} =$ sum$(\mathbf{A})$, $[r2, c2] =$ find$(\mathbf{A_{sum}} ==$ min$(\mathbf{A_{sum}}))$ Label$(k_{c2}) = 1$, $S = [S\ x_{kc2}]$, $S_n = S_n + 1$
Output:	S, Label

For an unseen test sample x, the pre-image can be obtained by solving the following optimization problem:

$$\underset{z\in R^n}{\mathrm{Minimize}} \|\phi(z) - P_m\phi(x)\|. \quad (5)$$

To tackle the blurring of pre-image, we adopt the local linear image restoration algorithm [Tan *et al.*, 2012]. The optimization problem (5) is rewritten as

$$\begin{aligned}&\text{Minimize}\,\rho(t_1, t_2, \ldots, t_k)\\ &\quad= \left\| \phi\left(\sum_{i=1}^{k} t_i x_{k(i)}\right) - P_m\phi(x)\right\|^2, \end{aligned}\tag{6}$$

where $x_{k(i)} (i = 1, 2, \ldots, k)$ are the k nearest neighbors which are determined by calculating the distances in feature space. The optimal solution $x^* = \sum_{i=1}^{k} t_i^* x_{k(i)}$ can be obtained by solving problem (6).

When the kernel k is a Gaussian function, the solution to optimization problem (6) can be achieved by the following iterative formula:

$$\begin{aligned}\begin{bmatrix} t_1 \\ t_2 \\ \vdots \\ t_k \end{bmatrix} &= \begin{bmatrix} (x^1)'x^1 & (x^1)'x^2 & \cdots & (x^1)'x^k \\ (x^2)'x^1 & (x^2)'x^2 & \cdots & (x^2)'x^k \\ \vdots & \vdots & \cdots & \vdots \\ (x^k)'x^1 & (x^k)'x^2 & \cdots & (x^k)'x^k \end{bmatrix}^{-1} \\ &\quad\times \begin{bmatrix} (x^1)'x_1 & (x^1)'x_2 & \cdots & (x^1)'x_N \\ (x^2)'x_1 & (x^2)'x_2 & \cdots & (x^2)'x_N \\ \vdots & \vdots & \cdots & \vdots \\ (x^k)'x_1 & (x^k)'x_2 & \cdots & (x^k)'x_N \end{bmatrix} \\ &\quad\times \begin{bmatrix} \beta_1/\sum_{\ell=1}^{N}\beta_\ell \\ \beta_2/\sum_{\ell=1}^{N}\beta_\ell \\ \vdots \\ \beta_N/\sum_{\ell=1}^{N}\beta_\ell \end{bmatrix}, \end{aligned}\tag{7}$$

where coefficients $\beta_\ell = w_\ell k(\sum_{i=1}^{k} t_i x^i, x_\ell)$, $(\ell = 1, 2, \ldots, N)$, $w_\ell = \sum_{j=1}^{d}\sum_{i=1}^{N} \alpha_i^j k(x, x_i)\alpha_\ell^j$, $(\ell = 1, 2, \ldots, N)$, eigenvectors $\alpha^i (i = 1, \ldots, N)$ are corresponding to the eigenvalues $\lambda_i (i = 1, 2, \ldots, N)$ of matrix K.

In the numerical experiments, both the two algorithms will be used to evaluate the effectiveness of our sampling algorithm.

For convenience, we note Eq. (7) as

$$T = ((X^k)'X^k)^{-1} \cdot ((X^k)'X^k) \cdot B, \tag{8}$$

where vector $B = [\beta_1/\sum_{\ell=1}^{N}\beta_\ell, \beta_2/\sum_{\ell=1}^{N}\beta_\ell, \ldots, \beta_N/\sum_{\ell=1}^{N}\beta_\ell]'$. The Jacobi matrix of nonlinear iterative algorithm can be calculated as

$$\begin{aligned} J_T &= ((X^k)'X^k)^{-1}(X^k)'X \\ &\quad\cdot \left[\frac{1}{\sigma^2\sum_{\ell=1}^{N}\beta_\ell}\Lambda(X - X^k te)'X^k \right.\\ &\quad\left. - \frac{1}{\sigma^2(\sum_{\ell=1}^{N}\beta_\ell)^2}\Lambda((X - X^k t)\beta e)'X^k\right], \end{aligned}\tag{9}$$

where $e = [1, 1, \ldots, 1]$ with $1 \times N$ entries, $\beta = [\beta_1, \beta_2, \ldots, \beta_N]'$, $t = [t_1, t_2, \ldots, t_k]'$ and

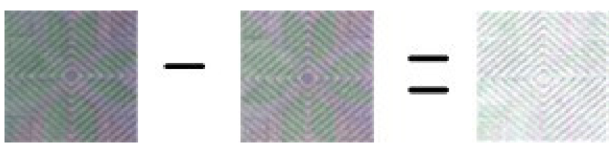
$$\Lambda = \begin{pmatrix} \beta_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \beta_N \end{pmatrix}. \tag{10}$$

According to local convergence theorem [LeVeque, 1994], if the spectral radius $\rho(J_T)$ of Jacobi matrix J_T is less than 1, the nonlinear iteration algorithm is local convergent. So we can take a large enough σ so that $\rho(J_T) < 1$.

4. Detection Algorithm Based on Clustering

Affected by the light, the machining accuracy and the printing precision, difference often exists between collected images. In Fig. 1, images (a) and (b) are from the training set, and (c) shows the difference image, where (c)=255–abs((a)–(b)). In the detection process, to remove these factors impact on the test results, design the following algorithm.

For the new sample x, the pre-image z is calculated by the methods in Sec. 3. And using the simple threshold segmentation algorithm with abs(x–z), we can get the 0–1 image I1. In the following algorithm, take the image I1 as input in Table 2.



(a) (b) (c)

Fig. 1. The difference between images in training set.

Table 2. An algorithm for the defect location.

Algorithm 2: Defect location algorithm

Input: I1, threshold

```
[H,L] = find(I1==1);
Cord(1,:) = H;
Cord(2,:) = L;
T2 = Cord'*Cord;
T1 = ones(length(H));
D2 = T1*diag(diag(T2))+diag(diag(T2))*T1-2.*T2;
T2 = [];
T1 = [];
Cord(3,:) = 1 : length(H);
for i = 1 : length(H)
    for j = i + 1 : length(H)
        if D2(i, j) <= 2
            Cord(3, j) = Cord(3,i);
        end
    end
end
ClusterNum = 0;
for i = 1 : length(H)
    if length(find(Cord(3,:)== i)) > threshold
        ClusterNum = ClusterNum + 1;
        ss = find(Cord(3,:)==i);
        Cluster(1,ClusterNum) = mean(H(ss));
        Cluster(2,ClusterNum) = mean(L(ss));
    end
end
```

Output: ClusterNum, Cluster,

5. Experimental Result

To verify the algorithm's effectiveness, we evaluated the algorithm on a data set. The images are from a particular printing note in the data set. The printing process of tickets used in the experiments includes offset and intaglio printing. The two channels make up the pixels and hence there are great differences between two samples, which bring much trouble into the defect detection.

When using the template matching to detect the samples, a large number of good samples are mistaken as the defective ones, which leads to a lot of waste. To avoid this problem, KPCA is adopted to solve the nonlinear changing caused by the offset and intaglio printing.

In the experiments, the samples are all the color images with three RGB channels. In Fig. 7, we show part of the samples using in the experiments. The image size of the data set is $64 \times 64 \times 3$. We first select 200 samples out from large sample set include 724 samples by the sampling algorithm based on the alignment.

Figure 2 shows the result of three-dimensional visualization to the three data sets by the MVU method. And Fig. 3 shows the distributions of the spectrum to the kernel matrix used in the MVU method. From Fig. 3, we can find that the distribution of samples can be visualized in a three-dimensional space. From Fig. 2, we can find that the sampling algorithm can uniformly choose the significant samples from the large sample set. And the selected training set can be approximated on behalf of large sample sets. In Fig. 4, we provide the simple diagram

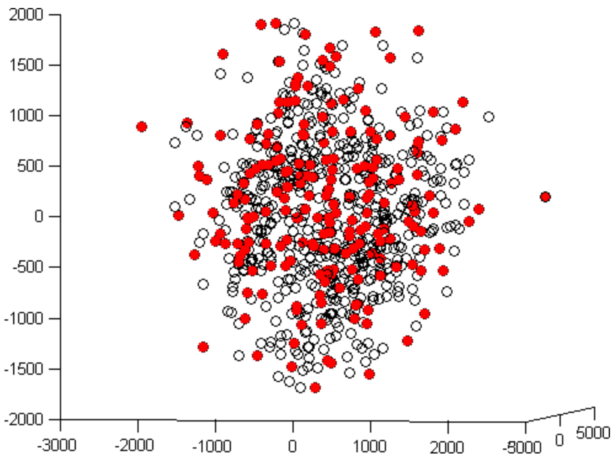


Fig. 2. Three-dimensional MVU embedding of data set II.

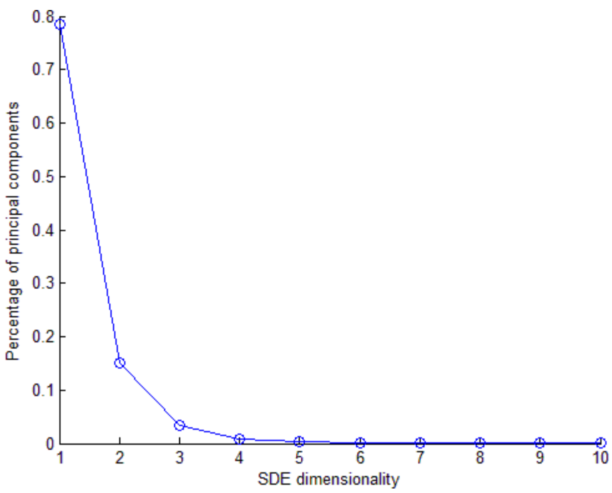


Fig. 3. Distribution of spectrums to the three data sets I, II and III in the MVU method.

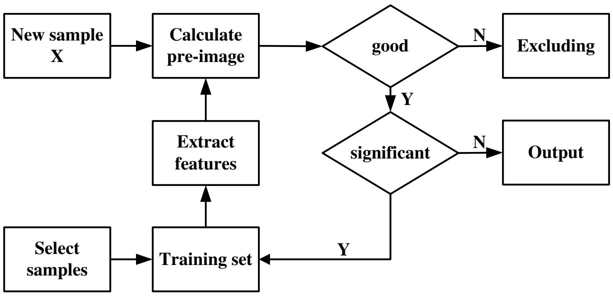


Fig. 4. The diagram of second online detection by the statistical learning methods.

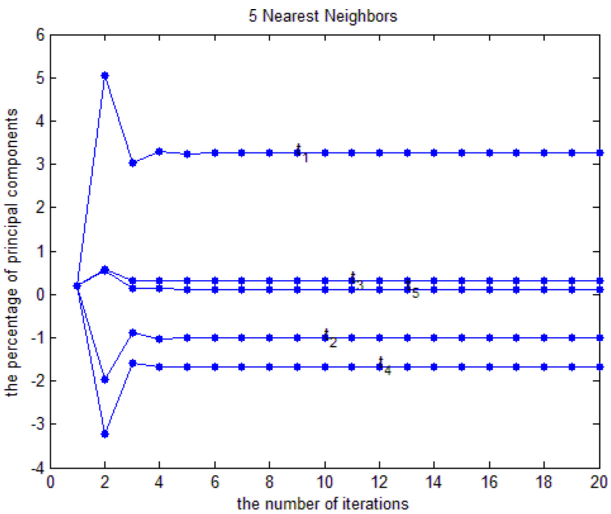


Fig. 5. Part results for defects detecting in data set III.

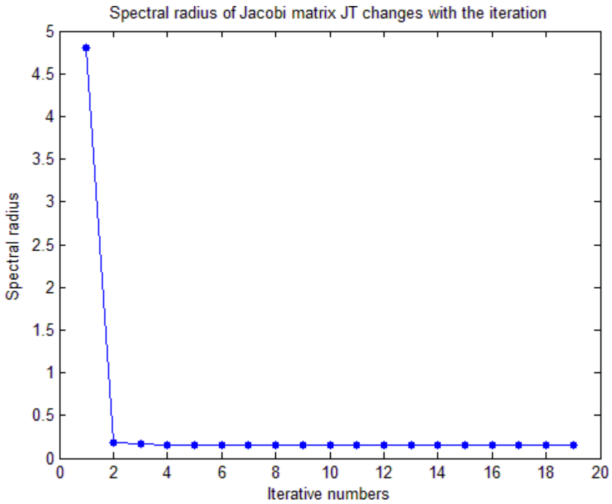


Fig. 6. The average errors with different numbers of training samples.

for the second online detection by the statistical learning methods using the selected training sample set in the printing process.

In Fig. 5, the changing of coefficients in iterative process is showed with five nearest neighbors. The results clearly indicate that the convergence speed is very fast using the new method taking the center point as the initial value.

Figure 6 shows that the spectral radius of Jacobi matrix J_T changes with the iterations. From this we can find that the spectral radius gradually become smaller with the iteration of t. And the spectral radius meets $\rho(J_T) < 1$ after a few iterations, which illustrates our pre-image algorithm is the local convergence.

And we design some experiments according to the inspection process. In order to verify the efficiency of inspection algorithm, we first add some noises to the known good samples, and then calculate the pre-images by the iterative formula (10) using the sampling algorithm based on alignment. Figure 7 shows the samples added noise in the first line (I), the pre-images calculated by the KPCA using the selected samples in the second line (II), the binary images are in the third line (III) and the defects images are in the fourth line (IV). The binary images are from the difference between the samples

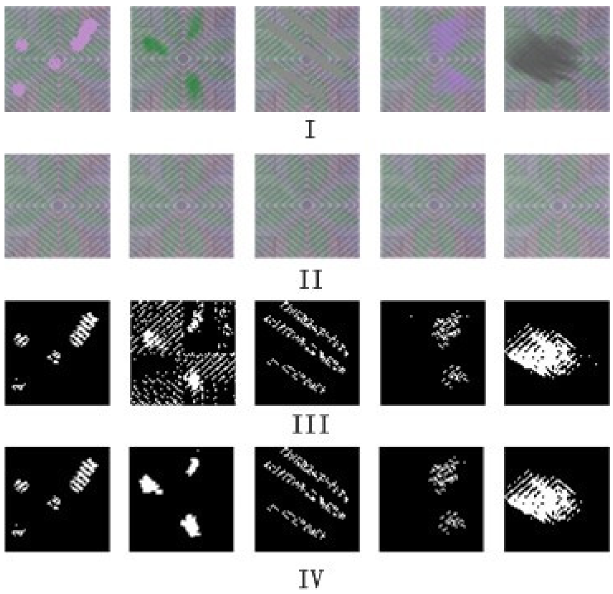


Fig. 7. The average errors with different numbers of training samples.

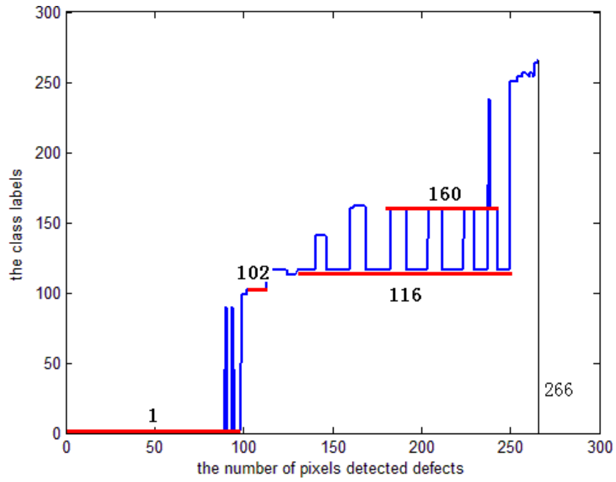


Fig. 8. Three-dimensional MVU embedding of data set II.

added noise and the pre-images calculated by the KPCA. From Fig. 7, we can find that the defects detected usually contain many interference components. Using algorithm 1, the interference components can be easily removed.

Figure 8 shows the clustering results to the defects in the first image of line (IV) in Fig. 7. Taking the threshold with 10, we can get the four real defects.

6. Conclusion

This paper aims to introduce the kernel theory into the "image of ultra high precision printing defect automatic inspection" field. To improve the capability of detecting defects with high precision and speed, on one hand, a sampling algorithm is designed to select the optimal training set; on the other hand, an image restoration algorithm is designed to calculate the pre-image, take the pre-image as the template, which meet the requirement of second verification for high printing quality. The experimental results show that, the proposed method can reduce the error rate to a certain extent, and improve the accuracy of detection.

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