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Bar Image Identification Based on Laplacian Eigenmap and Fuzzy SVM

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ABSTRACT

Bar code image recognition is a key technology in modern logistics management. An efficient identification system is built based on manifold learning and fuzzy SVM. By integrating the fractal image segmentation technology, it realizes high automatic classification and identification of bar code image. At first, the authors conduct the preprocessing of the collected code image, including three steps, tilt correction, image binarization based on globally dynamic threshold, and fractal segmentation technology. Then, a graph-based fuzzy support vector machine is proposed to realize the high accuracy classification and identification. Experimental results indicate that the accuracy of the proposed method is higher than other compared methods in both pure and noisy samples, reaching 96.6% and 94.5%. And no huge decrease exists when some noise is added to the pure dataset, and the percentage is only 2.1%, which is much lower than the drop of other methods. It shows that the proposed method can significantly promote the identification accuracy, the generalization, and robustness to noise.

KEYWORDS

Automatic Classification, Fractal, Fuzzy-SVM, Global Binarization, Image Identification, Laplacian Eigenmap

1. INTRODUCTION

In recent years, with the rapid development of logistics and the rapid growth of logistics demand, the logistics industry is facing transformation and change on a global scale, Both the introduction of new technology, equipment and the improvement of intelligence level, have a profound impact on logistics practice. New logistics solutions are evolving to meet various needs (Islam et al. 2016, Tang et al. 2017, Xie et al. 2005, Huang et al. 2013, Han et al. 2017). Recently, soft computing and decision technology has evolved to analyze field data and generate intelligent algorithms that enables automated logistics systems to control the workflow, material flow and information flow of the global supply chain network based on IC tags, achieving intelligent logistics through the seamless integration of intelligent, decision technology and IT technology. Logistics systems have completely changed the way we manage factories, logistics, outsourcing and supply chain networks. Among them, information intelligent management technology in logistics has gradually increased its

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importance in China, the competition within the logistics industry is becoming increasingly fierce, each enterprise is required to build logistics distribution system with more efficient and lower cost, so as to increase enterprise benefit.

In the process of logistics, large amounts of data will be automatically transferred to bar code, and then automatic identification and classification of the bar code images on the goods can be realized, real-time information of goods transport can be obtained, which is very important to both the distribution of the cargo transport and the efficiency of logistics management. Due to its power and operability, bar code image recognition technology is the most widely used automatic recognition technology so far. The barcode image classification problem belongs to the scene character recognition problem in natural scene images. The main process of character recognition is divided into two parts, the detection and segmentation of the numbered area in the image must first be conducted. Next, the individual bar code image can be put into the character recognition system to complete the whole character recognition process. On the other hand, bar code images often appear uneven, contaminated and damaged; At the same time, since the influence of natural factors on the scene of image collection, such as the intensity of light, shooting Angle and so on, will lead to low quality of the collected image, the image must be preprocessed.

In pattern recognition methods, support vector machine (SVM) is often utilized for classification and regression tasks due to its good nonlinear discrimination. SVM is a classical machine learning method by Vapnik (Vapnik et al. 1999, Vapnik et al. 1999) based on statistics in 1990s. The main idea of the algorithm is to construct an optimal decision hyperplane, to maximize the distance between the hyperplane and the near support vectors, so as to avoid the over-fitting and curse of dimensionality (Liu et al. 2020, Zhang et al. 2020). The original SVM is a supervised learning algorithm, which needs certain number of labeled samples in different classes to train a good classifier, but it fails when there are limit number of labeled samples. That is why the semi-supervised learning has gradually become the hot topic of SVM research (Di et al. 2019). Semi-supervised learning has combined the clustering information of few labeled samples and unlabeled samples, to achieve the target of classification accuracy promotion. In 2013, Liang et al. (Liang et al. 2014) proposed automatic cargo number identification system based on Least Square-SVM (LS-SVM), which fits all samples by least square, but its drawback is the high computational cost of 4^{th} power of sample numbers. Cao et al. (Cao 2015) introduced manifold regularizer to realize semi-supervised character classification under few labeled samples. But it will fall into local optimum and the manifold regularizer will also keep the local feature of noise. What is more, recent research often lacks generalization. The generalization indicates that the classifier would have high classification accuracy on different environments, which means that the performance on one dataset is good while bad on another dataset. Fuzzy-SVM (FSVM) (Lin et al. 2002, Leng et al. 2008, Yang et al. 2016, Chen et al. 2013) provides an efficient method to deal with the sensitivity of noise and outliers. Its goal is to allow different input to make different contributions for decision surface learning. When constructing the objective, different samples are given different memberships, specifically, small membership will be given to noise and outliers. Via this, training vector's contribution of decision surface can be tuned based on its relevance to the rest of the training set. Meanwhile, Manifold learning algorithms are one of the effective methods to keep the geometric structure of images in machine learning (Cai et al. 2011). Based on deep learning, a medical label barcode acquisition and identification system (Zhang et al. 2018) is proposed to realize linear distortion correction, and deal with uneven illumination and complex background. Bachi et al. (Bachi et al. 2020) generalized quantum hypothesis testing model to multi-partite setting of barcode pattern recognition. Zheng et al. (Zheng et al. 2022) proposed a logistics barcode ID character recognition method which utilized locality of AKAZE features to realize the detection and identification of logistics barcode ID in a long distance and a large range.

This paper proposes a barcode image recognition algorithm based on FSVM and manifold learning with good generalization ability and better robustness to noise.

2. BARCODE IMAGE PREPROCESSING ALGORITHM

There are various image preprocessing methods to transform the input images into the style the computer can recognize. Common preprocessing methods include image enhancement, image segmentation, edge detection, different forms of filtering, image geometry change et al. Thus, in this paper, the collected images are processed by skew correction and binarization.

2.1 Skew Correction

As bar code images are generally skewed to a certain extent, skew correction is necessary for easy recognition. In this paper, the improved Hough transform is used to detect the two parallel lines along the edge of the numbered area, obtain the skew angle of the lines, and then correct the bar code image.

2.2 Image Binarization

Image binarization aims to set the gray value of each pixel in the pixel point matrix of the image to 0 or 255, where 0 represents black and 255 represents white, that is, the whole image presents only black and white colors (Wang et al. 2004). Gray histogram is used in this paper, so as to determine the threshold value according to gray histogram. And we finally divide the image and background according to the threshold value. Gray histogram is a function of gray, representing the number of pixels with a certain gray value in the image. 2D image $f\left(x,y\right)$ is transformed to the function of a binary image, T denotes the threshold, which is critical in the binarization process. From the view of size, the binarization process can be divided into global and local methods. We utilize the global dynamic threshold iteration method, which aims to realize the binarization by determining the optimal segmentation threshold via image histogram or gray level distribution as follows:

$$g_t\left(x,y\right)=\begin{cases}1, & g\left(x,y\right)\geq T\\ 0, & g\left(x,y\right)<T\end{cases}, \tag{1}$$

in which the maximum and minimum of the gray values are g_1 and g_2, set the initial as

$$T^0=\frac{g_1+g_2}{2}, \tag{2}$$

Via the threshold T^k of the $k-th$ iteration, the image is segmented into the background and character, and average gray values of the two parts g_0 and g_B are obtained:

$$g_0=\frac{\sum_{g\left(i,j\right)<T^k} g\left(i,j\right)\times N\left(i,j\right)}{\sum_{g\left(i,j\right)<T^k} N\left(i,j\right)}, \tag{3}$$

$$g_B=\frac{\sum_{g\left(i,j\right)>T^k} g\left(i,j\right)\times N\left(i,j\right)}{\sum_{g\left(i,j\right)>T^k} N\left(i,j\right)}, \tag{4}$$

in which $g\left(i,j\right)$ and $N\left(i,j\right)$ are the $\left(i,j\right)-th$ gray value and weight coefficient, respectively. The weight coefficient is empirically 1.

a) Threshold after the $\left(k+1\right)-th$ iteration:

$$T^{k+1}=\frac{g_0+g_B}{2} \tag{5}$$

b) If $T^k=T^{k+1}$, the iteration ends; Otherwise, $k\leftarrow k+1$, back to step b).
c) After the above process, the bar code image is given as Fig 1:

2.3 Digital Character Segmentation

The use of character segmentation is to divide the binarized digital image into disjoint areas. Since the scenery may be complex or the combination of different objects in human vision, it is indispensable for segmentation. As shown in Fig 1, character segmentation first partitions the entire image into individual characters to generate several character images. The character segmentation technology mainly includes vertical projection, contour projection, template matching and cluster analysis and so on. Since the first three methods will lead to error when there exists deformation in bar code images and the clustering method suffers from high computational complexity, we utilize fractal geometry to deal with it.

The theory of fractal geometry was first proposed by Mandelbrot (Dou et al. 2008, Tang et al. 2020). The target of fractal geometry is the irregular geometric shape which is ubiquitous in nature. Compared to traditional geometry, its biggest difference is the existence of self-similarity and fractal dimension. Fractal dimension is able to effectively represent the geometric feature of fractal signal. To be specific, firstly, Different substances of different categories usually has different dimensions, and then if its surface is fractal, the gray level image surface is also fractal, or vice versa. This means it is available to achieve fractal dimension from the gray level. N. Sarkar et al. proposed a fast and accurate differential box-counting (DBC) fractal algorithm, which significantly strengthens the texture feature. This method regards the surface $\left(x,y,g\left(x,y\right)\right)$ of a 3D space, then each column of the image matrix is normalized into unit square area, and in total $r\times r$ sub-image patches. Each character patch can be seen as a series of $L\times L\times h$ boxes, whose height is h.

If the maximal and minimum of gray level value in the $\left(i,j\right)$ gird are located on the $k-th$ and $l-th$ box, respectively, $n_r\left(i,j\right)$ boxes are needed to cover the $\left(i,j\right)$ gird:

$$n_r\left(i,j\right)=l-k+1 \tag{6}$$

Figure 1. Processed Binary Image

The number of boxes needed to cover the entire image:

$$N_r = \sum_{i,j} n_r(i,j). \tag{7}$$

The least square method is utilized to solve the fractal dimension D with different r. Let $\psi_i = \log(1/r_i)$, $\phi_i = \log(N_r)$, then

$$D = \frac{\left(\sum_{i=1}^{M}\psi_i\right)\left(\sum_{i=1}^{M}\phi_i\right) - M\left(\sum_{i=1}^{M}\psi_i\phi_i\right)}{\left(\sum_{i=1}^{M}\phi_i\right)^2 - M\left(\sum_{i=1}^{M}\phi_i^2\right)}. \tag{8}$$

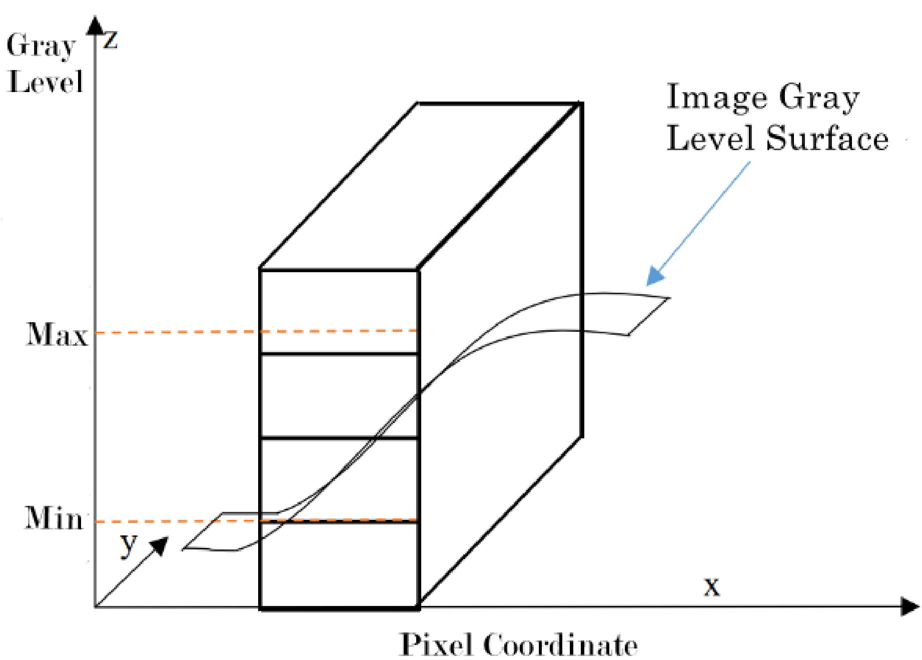
As shown in Fig 2, The sketch of box dimension is given. When appropriate threshold is set, the segmentation interval of different characters will be confirmed. After the segmentation process, the processed images will be input into the Lap-FSVM to complete the final classification and recognition.

3. LAP-FSVM CLASSIFICATION ALGORITHM

3.1 The Loss Function

Assume S denotes a group of training samples $\{(x_i, y_i, s_i)\}_{i=1}^{l}$ with class labels, each training sample $x_i \in \mathbb{R}^N$ has a corresponding class label $y_i \in \{-1,1\}$ and a fuzzy membership value $\sigma \le s_i \le 1$, in

Figure 2. Sketch of fractal dimensions



which $\sigma > 0$ is small enough. Since the fuzzy membership value s_i denotes the weight of sample x_i belonging to class y_i, parameter ξ_i denotes the error of SVM, $s_i \xi_i$ is the weighted error. Then the optimal hyperplane is transformed into the solution of the following problem

$$\min \frac{1}{2} \quad w \quad ^{2} + \mathrm{c} \sum\nolimits_{\mathrm{i}=1}^{l} s_i \xi_i \tag{9}$$

satisfies

$$y_i \left(w \cdot \varphi\left(x_i\right) + b \right) \geq 1 - \xi_i \tag{10}$$
$$\xi_i \geq 0,\, i = 1, \ldots, l\,. \tag{11}$$

Here c is a constant. When s_i is smaller, ξ_i is smaller, consequently, less impact of $\varphi\left(x_i\right)$ will be exerted on classification. To deal with it, the Lagrange function is constructed:

$$\mathcal{L} = \frac{1}{2} \quad w \quad ^{2} + c \sum\nolimits_{i=1}^{l} s_i \xi_i - \sum\nolimits_{i=1}^{l} \mu_i \xi_i + \sum\nolimits_{i=1}^{l} \alpha_i \left(1 - \xi_i - y_i \left(w^T \varphi\left(x_i\right) + b \right) \right) \tag{12}$$

in which $\alpha_i \geq 0$, $\mu_i \geq 0$, take the partial derivatives of $\mathcal{L}$ with respect to w, b, ξ_i to be 0,

$$\begin{aligned} & w - \sum_{i=1}^{l} \alpha_i y_i \varphi\left(x_i\right) = 0 \\ & \sum_{i=1}^{l} \alpha_i y_i = 0 \\ & s_i c - \alpha_i - \mu_i = 0 \end{aligned} \quad . \tag{13}$$

Eq.1 can be transformed into

$$\min W\left(\alpha\right) = \sum\nolimits_{\mathrm{i}=1}^{l} \alpha_i - \frac{1}{2} \sum\nolimits_{\mathrm{i}=1}^{l} \sum\nolimits_{\mathrm{j}=1}^{l} \alpha_i \alpha_j y_i y_j K\left(x_i, x_j\right) \tag{14}$$

satisfies

$$\begin{aligned} & \sum_{i=1}^{l} y_i \alpha_i = 0 \\ & K\left(x_i, x_j\right) = \varphi\left(x_i\right)^T \varphi\left(x_i\right) \\ & 0 \leq \alpha_i \leq s_i c, i = 1, \ldots, l \end{aligned} \quad . \tag{15}$$

In manifold learning, Laplacian Eigenmap is an important method to preserve the local geometric features of data due to its simple implementation and good theoretical basis. Laplacian eigenmap provides a nonlinear dimension reduction method through graph embedding with high efficiency. Its advantages over other manifold learning technologies is its robustness to outliers, which is naturally suitable for our question. It assumes if 2 samples are "close" to each other in initial data space, it is also "close" to the embedded space. Since it does not use labelled information, it is often used in unsupervised learning. The format is as follows,

$$\begin{aligned} L &= \frac{1}{2}\sum_{i,j=1}^{N}\left\|f\left(x_i\right)-f\left(x_j\right)\right\|^2 W_{ij} \\ &= \sum_{i=1}^{N} f_i^T f_i D_{ii} - \sum_{i,j=1}^{N} f_j^T f_i W_{ij} \\ &= tr\left(FDF^T\right) - tr\left(FWF^T\right) \\ &= tr\left(F\left(D-W\right)F^T\right). \end{aligned} \tag{16}$$

in which when x_i belongs to the k -neighbors of x_j , $W_{ij} = \exp(-\left(x_i - x_j)^2 / 4\right)$ denotes the weight matrix, or $x_i = 0$.

Combing Eq. 13 with Eq. 15, the final objection will be

$$\min_{\alpha} W\left(\alpha\right) + \lambda L , \tag{17}$$

which is the proposed Lap-FSVM classifier.

3.2 FCM based Fuzzy Membership Function Selection

An appropriate fuzzy membership is essential in deciding the importance of each data to the classification model. Lin et al. proposed a membership computation method based on FSVM. One drawback of the membership computation is that it only considers the same class center, which means data far from the class center and close to the decision boundary will be regarded as outliers and noise, this will bring misestimation to the contribution of each data on the hyperplane. To solve it, this paper adopts Fuzzy C-Means (FCM) based FSVM algorithm (Yang et al. 2016).

FCM is one of the most widely used fuzzy clustering algorithms. The idea is to maximize the similarity between objects divided into the same cluster and minimize the similarity between different clusters. The fuzzy C-means algorithm is an improvement of the ordinary C-means algorithm. The ordinary C-means algorithm is rigid for data partition, while FCM is a flexible fuzzy partition. FCM aims to

$$\min \sum\nolimits_{i=1}^{l} \sum\nolimits_{j=1}^{C} s_{ij}^m d_{ij}\left(x_i, c_j\right), \tag{18}$$

in which $s_{ij} \in \left[0,1\right]$ denotes the clustering fuzzy membership of sample x_i belonging to center c_i . $d_{ij}\left(x_i, c_i\right)$ denotes the Euclidean distance between x_i and c_i . Then we can have the functions of fuzzy membership and clustering center:

$$s_{ij} = 1 / \left(\sum\nolimits_{k=1}^{K} \left(\frac{d_{ij}\left(x_i, c_j\right)}{d_{ik}\left(x_i, c_k\right)}\right)^{\frac{2}{m-1}}\right), \tag{19}$$

$$c_j = \left(\sum\nolimits_{i=1}^{N} s_{ij}^m x_i) / (\sum\nolimits_{i=1}^{N} s_{ij}^m\right). \tag{20}$$

According to the principle of maximum membership in fuzzy set, we can determine which class each sample point belongs to. The cluster center represents the average feature of each class and can be regarded as the representative point of this class. Via the obtained membership, FSVM will be used on training data to achieve appropriate FSVM classifier.

3.3 Bar Code Automatic Recognition

Since the number of bar code includes 10 classes from 0 to 9, then 10 SVM classifiers are needed. When training the $i-th$ classifier, the belonged samples are labelled +1, others are labelled -1. In the training process, the extracted feature is input into each SVM to cyclically detects the output of each classifier. When all outputs are labelled -1, then the system refuses to recognize the number.

To sum, the flowchart of the entire algorithm is given as Fig 3, and the pseudo-code of the Lap-FSVM is given as table 1.

4. RESULT EVALUATION

4.1 Bar Code Image Recognition Experiment Setting

This paper selected 500 images from 2000 bar code images for training, and the rest samples for testing. Firstly, we preprocess the samples before recognition includes denoising, binarization and image segmentation. To validate the efficiency of the algorithm, we compare our proposed algorithm

Figure 3. Fractal and FSVM based image recognition flow chart

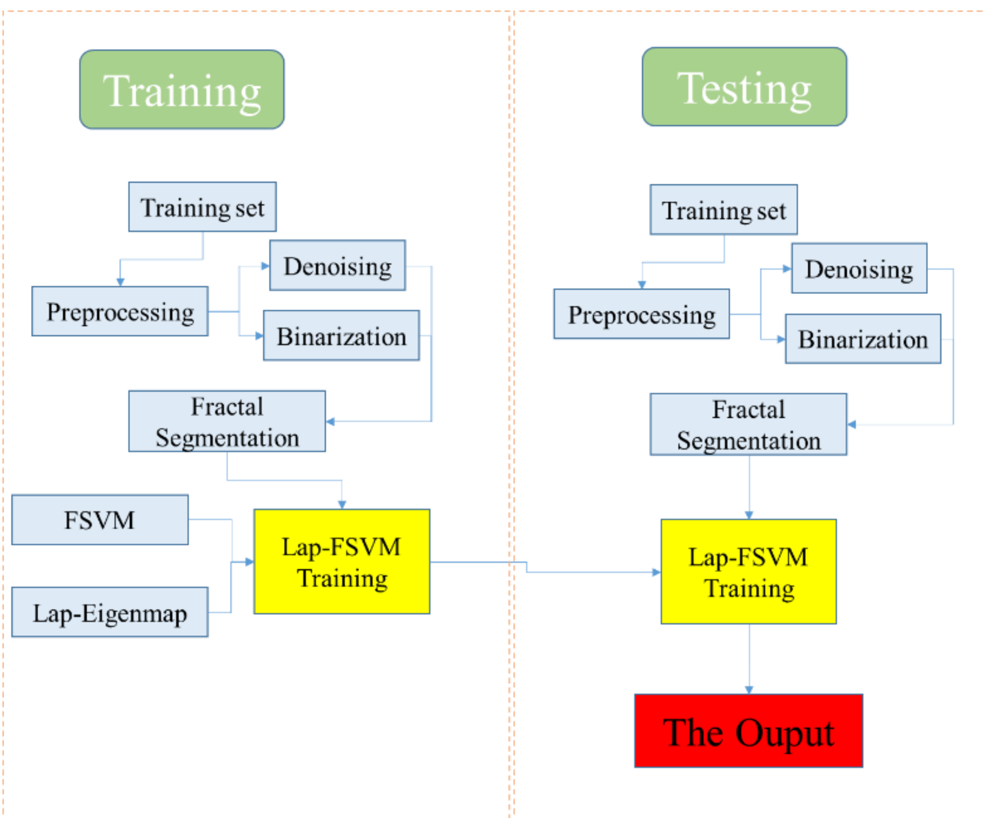


Table 1. The pseudo-code of the Lap-FSVM

Lap-FSVM Algorithm
Input:preprocessed samples $\{x_i \in \mathbb{R}^N\}_{i=1}^{l}$, the corresponding class labels $\{y_i \in \{-1,1\}\}_{i=1}^{N}$, a small $\sigma > 0$, fuzzy coefficient m ;
1. Calculate the fuzzy membership $\left(u_{ij}\right)$ of each class by eq.(19) and eq.(20) on randomly chosen 1/5 samples as training samples
2. Choose penalty factor c , and Gaussian kernel $K\left(x_i, x_j\right) = \exp\{-\parallel x_i - x_j \parallel^2 / \delta^2\}$,
3. Training sample with eq.(17) to get optimal solution α^* , which meets eq.(15)
4. Choose the positive factor in α_j^* and calculate $b^* = y_j - \sum_{i=1}^{l} a_i^* y_i K\left(x_i, x_j\right)$;
5. Construct decision function $f\left(x\right) = \mathrm{sgn}(\sum_{i=1}^{l} a_i^* y_i K\left(x_i, x_j\right) + b^*)$;
6. Utilize the decision function for classification on testing dataset.
Output: testing samples labels $\left\{y_i\right\}$

with SVM, LS-SVM, Lap-SVM and FSVM, in which SVM is the classical SVM and often suffers from misclassification and sensitivity to noise.

LS-SVM is the least square based SVM, which uses least square as loss function instead of traditional square programming in SVM. Lap-SVM is the Laplacian SVM, which adds a manifold regularization to realize the inner structure and prevent overfitting. FSVM is the original fuzzy SVM. FSVM can significantly the impact of outliers in classification issue via appropriate fuzzy membership function and improve the generalization performance. We use radial basis kernel function and 5-fold cross validation; the penalty coefficient is 50. The implementation environment is win 10, matlab-2017a. The number of neighbors is set to be 5.

This paper conducts two series of experiments, one is experimented on original bar code image, the other is on the bar code image with noise. The noise is to add Gaussian noise with SNR=15 on a pointwise manner.

4.2 Comparison on Pure Image

For pure dataset, we compare the Lap-FSVM with SVM, LS-SVM, Lap-SVM and FSVM by experiments to demonstrate the performance of the proposed algorithm.

4.3 Comparison on Noisy Image

From Table 2 and Fig 4(a), we can see that from the testing results, the proposed method gets 1449 correct identification number, i.e. the accuracy is 96.6%. In the compared algorithms, the original SVM only get 66.2% accuracy. Compared to the 92.3% of Lap-SVM and 86% of FSVM, the proposed algorithm has a significant improvement on the performance. From the results of Lap-SVM, FSVM and Lap-FSVM in Figure 4(a), we release the performance of Laplacian eigenmap and FCM, respectively.

From Table 3 and Fig 4(b), under noisy condition, the proposed method achieves 1417 correct identification number, i.e. the accuracy is 94.5%. Compared to the original 96.6%, there exists a slight drop of 2.1%. In the comparative algorithms, the accuracy of SVM algorithm dropped by 8.9%. The

Table 2. Compared experiments of pure bar code image

No.	Algorithm	Misrecognition Number				
		0	1	2	3	>3
1	SVM	993	210	79	66	122
2	LS-SVM	1185	178	70	30	37
3	Lap-SVM	1385	93	55	29	31
4	FSVM	1290	121	47	30	12
5	Lap-FSVM	1449	30	11	6	4

Figure 4. (a) Accuracy comparison on pure logistics image; (b) Accuracy comparison on pure bar code image

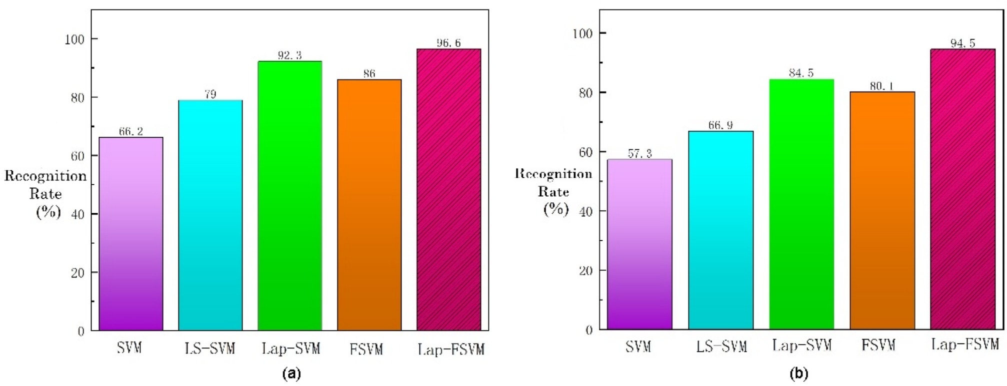


Table 3. Compared experiments of noisy bar code image

No.	Algorithm	Misrecognition Number				
		0	1	2	3	>3
1	SVM	860	380	109	55	96
2	LS-SVM	1003	298	121	50	28
3	Lap-SVM	1267	139	26	25	43
4	FSVM	1201	171	66	57	5
5	Lap-FSVM	1417	50	16	9	8

accuracies of LS-SVM, Lap-SVM and FSVM dropped by 12.1%, 7.8% and 5.9%. From the results, we validate not only the robustness of the proposed algorithm to noise, but also the generalization performance.

4.4 Overall Comparison

From Fig 4(a) and 4(b), we can observe the effect of noise on the overall performance in reducing the accuracy of recognition and the number of misrecognition. But from the accuracy result of Lap-FSVM on the noisy dataset, there is only 2.1% decrease, but turning to other compared method, the minimum decrease is 3.8%, which shows the efficiency and necessity of the combination of Laplacian eigenmap and FCM. From table 2 and table 3 of Lap-SVM and Lap-FSVM, we can see the in-depth effectiveness of FCM in reducing the misrecognition of the pure dataset.

5. CONCLUSION AND FUTURE WORK

This paper incorporates modern intelligent image processing technology with fractal image segmentation method, to introduce a bar code image recognition method based on Laplacian Eigenmap and fuzzy SVM, for high accurate bar code image classification and recognition. This method can preserve stable performance even in high noise conditions. Firstly, the paper preprocesses the samples including tilt correction, binarization and image segmentation feature extraction; then realizes classification and recognition by integrating manifold learning and fuzzy SVM. The experimental results show that, the recognition accuracy reaches 96.6% on pure dataset, and 94.5% on noisy dataset, which guarantees the robustness and generalization of the proposed method. With the blossom of deep learning, the traditional barcode image recognition will also face the shock of deep learning, especially in more complex background and more practical application. Moreover, the barcode image recognition technology in real practice often requires more on instantaneity, it is a new direction in the future.

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