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A Novel Method of Shoe Print Recognition Based On KLT And Support Vector Machine

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Abstract

Shoe print recognition is an important research field of pattern recognition. It's a typical multi-class pattern recognition problem. For a long time, it caused researchers concern from pattern recognition greatly, computer vision, and physiology, and so on. Various recognition algorithms have been proposed [1]. Shoe print recognition technology has a wide application, and various commercial Shoe print recognition systems can be applied. Feature extraction is an important part of pattern recognition, whose main purpose is dimensionality reduction. In this paper, we take Principle Component Analysis (PCA) method based on algebraic statistics to extract the essential characteristics of Shoe print images. We use Support Vector Machine (SVM) as classifier. We take one against one classification strategy for multi-class pattern recognition. Our study is based on 2D static Shoe print image. At the same time, a small Shoe print recognition system is designed. It can find Shoe print images of corresponding category from training Shoe print database when we input any Shoe print to be identified of a category.

Keywords: KLT, Vector Machine

Feature Extractor: PCA

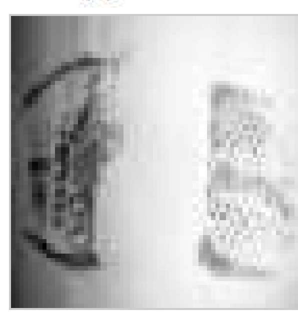
In this system, we take PCA method to extract shoe print feature. PCA based on K-L transform is an effective method to do data analysis in statistics, which was originally put forward by Turk and Pentland [3]. We use low dimension subspace to describe human shoe print and keep important shoe print recognition information though K-L transform. We use total scatter matrix of training sample set as a generation matrix of eigenvector. That is:

$$S_t = \frac{1}{N}\sum_{n=1}^{N}(\Gamma_n - \psi)(\Gamma_n - \psi)^T$$

Where N is training sample total number, ψ is training sample average vector, Γn is the nth training sample vector. We acquire a set of orthotropic feature vectors. That is "eigenfaces" well known by people. A group coordinate coefficient will be obtained though projecting any image onto feature subspace expanded by "eigenfaces", i.e., K-L decomposition coefficient. The group coefficient indicates this image's position in the feature subspace. They are viewed as the basis for shoe print recognition. This approach of feature extraction includes the following some operations:

1.Given c classes, each class has the same number training samples, total N training samples. According to column connection, each training shoe print sample $I(x, y)$'s pixel grey values constitute M ($M = x*y$) dimension vector Γn . We can view this training shoe print sample as a data point in M dimension original image space. A sample set of N vectors is $\{ \Gamma 1, \Gamma 2 ,..., \Gamma n \}$. The acquired sample set's average vector is viewed as average shoe print, it can be expressed as:

$$\Psi = \frac{1}{N}\sum_{n=1}^{N}\Gamma_n$$



The average shoe print is shown in Fig. 2:

2.The difference of between each training shoe print sample and average shoe print is given by:

$$\Phi_n = \Gamma_n - \Psi_n$$

Training sample set's covariance matrix C* :

$$C^* = \frac{1}{N}\sum_{n=1}^{N}(\Gamma_n - \Psi)(\Gamma_n - \Psi)^T = \frac{1}{N}\sum_{n=1}^{N}\Phi_n\Phi_n^T = AA^T$$

Where A = [Φ1, Φ2 ,...,ΦN], the dimension of matrix C*is M × N × N ×M , this is M ×M . taking appropriate linear combination of the shoe print images Φi . Considering the eigenvectors Vi of AAT as:

$$A^T A v_i = \mu_i v_i$$

And pre-multiplying both sides by A , we get:

$$AA^T A v_i = \mu_i A v_i$$

From which we see that **Av**i are the eigenvectors of $C^* = AA^T$. While eigenvectors Vi of $A^T A$ will be acquired easily. The eigen values of both matrixes are μi . We can arrange all nonzero μi from big to small: $[\mu_1, \mu_2, \ldots, \mu_r]$ ($1 \le r < N$), and make eigenvectors of μi orthogonal become $[e_1, e_2, \ldots e_i, \ldots, e_r]$, so we can obtain $U = [e_1, e_2, \ldots e_i, \ldots, e_r] \in R^{M*r}$ the feature space. if the number of data points in the image space is less than the dimension of the space (N < M), there will be only $N-1$ meaningful eigenvectors. The remaining eigenvectors will have associated eigen values of zero.

$$Z = U^T \Phi \in R^{r*1}$$

Where the dimension of Φ is $M \times 1$, z is the K-L decomposition coefficient, z can represent algebraic human shoe print features, sent to the classifier to learn and classify.

3.Dimension reduction. The above analysis shows that the dimension of shoe print image in original image space is M . The dimension after projected onto the feature space is only $r\ (r < N \ll M)$. In addition, not all $e_i\ (i = 1, 2, \ldots, r)$ are meaningful according to the actual application requirements. So we can select the front m eigenvectors of corresponding eigen values as feature space, at this moment, $m < r$ to reach the purpose of further dimensionality reduction. m Can be obtained according to the following formula:

Where α is the ratio. The principal components results are shown in Fig.3:

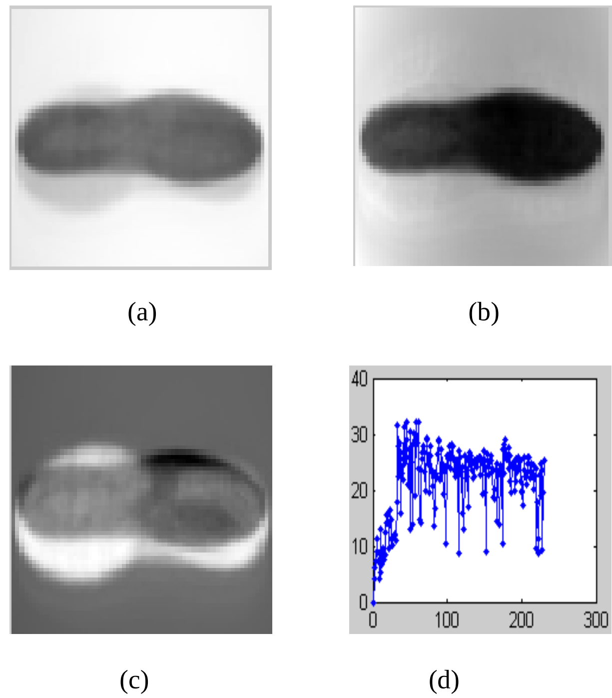


Figure 3. The principal components result of 200 training samples.
a) Mean shoe print b) first Eigen image c) first Eigen image and d) Euclidean distance

Support Vector Machine And Discriminate Of Multi-Class Value

Support Vector Machine, which is based on statistical learning theory, is a pattern recognition algorithm [4]. SVM has many advantages in solving small sample, nonlinear and high dimensional pattern recognition problems, it is effective method to solve structural risk minimization and get one best compromise between learning accuracy and learning ability under the finite samples circumstance to achieve the best generalization performance. It contains almost all the problems of machine learning: Pattern Recognition, Regression Estimation and Probability Density Estimation.

Basis Theory of SVM

For binary classification, Support Vector Machine is dedicated to seeking an Optimal Separating Hyper-plane from training samples. The so-called Optimal Separating Hyperplane is one that it can error-freely separate two classes and maximize the margin between two classes [5-6]. We consider the example in Fig. 4, where there are many possible linear classifiers that can separate the data, but there is only one that maximizes the margin shown in Fig.5. This classifier is termed the optimal separating hyper-plane (OSH).

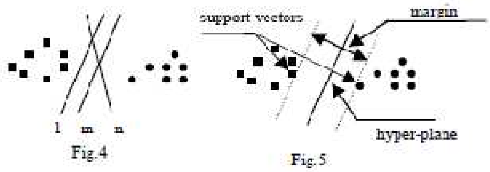


Figure 4. Arbitrary hyper-planes: l, m, n;
Figure 5 Optimal hyper-plane

(1) For Linearly Separable

Given the set of samples (xi, yi) , i =1, 2,..., n , where $x_i \in R^n, y \in \{-1,+1\}$ with a hyper-plane $w \bullet x + b = 0$ set of vectors can be optimally separated by the hyper-plane if it is separated without error and the margin is maximal. W is weight coefficient vector which decides the direction of hyper plane. b is a threshold value that decides the position of hyper plane. The defined discrimination function can be expressed as:

$$g(x) = w \bullet x + b$$

The distance of a point *x* from the hyper-plane is given by:

$$m\arg in = \frac{2|g(x)|}{\|w\|} = \frac{2}{\|w\|} \quad (1)$$

Hence the hyper-plane that optimally separates the data is the one that minimizes the following expression:

The solution to the optimization problem of (2) under the constraints of (3) is given by the saddle point of Lagrange function:

$$\min_{w,b} \frac{1}{2}\|w\|^2 \quad (2)$$

$$\text{so that } y_i(w \bullet x_i + b) - 1 \geq 0 \quad (3)$$

$$\min_{w,b} L(w,b,\alpha) = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{n} \alpha_i \left(y_i (w \bullet x_i + b) - 1 \right) \quad (4)$$

Where 0 αi ≥ is the Lagrange multiplier. The Lagrange function has a minimize value for *w*, *b*. Classical Lagrange duality enables the primal problem (4) to be transformed into its dual problem, which is easier to solve. The dual problem is:

$$\max_{\alpha} Q(\alpha) = \max_{\alpha} \left\{ \min_{w,b} L(w,b,\alpha) \right\} \quad (5)$$

That is:

$$Q(\alpha) = \sum_{i=1} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j x_i \bullet x_j \quad (6)$$

$$s.t. \quad \sum_{i=0}^{n} \alpha_i y_i = 0 \quad (7)$$

$$\alpha_i \geq 0, \forall_i \quad (8)$$

Solving Equation (6) with constraints (7) and (8) determines the Lagrange multipliers α∗. The OSH is given by:

$$w^* = \sum_{i=0}^{n} \alpha_i^* y_i x_i \quad (9)$$

$$b^* = -\frac{1}{2} w^* (x_1 + x_2) \quad (10)$$

Where x_1 and x_2 are support vectors. Now we can obtain the optimal discrimination function:

$$f(x) = \operatorname{sgn}\left(w^* \bullet x + b^*\right) = \operatorname{sgn}\left(\sum_{i=1}^{n} \alpha_i^* y_i \left(x_i \bullet x\right) + b^*\right)$$

(11)

For a new data point *x*, then the classifier is given by:

$$f(x) = \operatorname{sign}\left(w^* \bullet x + b^*\right)$$

(12)

(2) For Linearly Inseparable

Introducing a slack variable *i* ξ , so constraint (3) is modified as:

$$y_i\left(w \bullet x_i + b\right) - 1 + \xi_i \geq 0, \xi_i \geq 0, \forall_i$$

(13)

Objective optimization function is:

$$\Phi(w, \xi) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \xi_i$$

(14)

Where *C*, the so-called penalty factor, is a specified positive number. The larger *C* values, the smaller the margin. Optimization problem is transformed into:

$$Q(\alpha) = \sum_{i=1} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j x_i \bullet x_j$$

(15)

$$s.t. \quad \sum_{i=0}^{n} \alpha_i y_i = 0$$

(16)

$$0 \leq \alpha_i \leq C, \forall_i$$

(17)

Then we can solve the optimal α*.

Nonlinear SVM

Training data is mapped to high dimensional feature space though kernel function [7]. In this space, the decision boundary is linear. The above linear technology can be used directly. These Kernel functions *K*(*x*, *x*') which meet the condition of mercer theorem can substitute for inner product (*x*, *x*') of original feature space. This original feature space can be transformed into a new feature space. Objective optimization function (19) becomes as:

$$Q(a) = \sum_{i=1} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i \bullet x_j)$$

Corresponding classification function:

$$f(x) = \operatorname{sgn}(w^* \bullet x + b^*) = \operatorname{sgn}(\sum_{i=1}^{n} \alpha_i^* y_i K(x_i \bullet x) + b^*)$$

This is support vector machine. In this paper, we take radial basis function as kernel function:

$$K(x_i, x_j) = e^{-\gamma\|x_i - x_j\|^2}, \gamma > 0$$

Support vector machine classification strategy

SVM is essentially a binary class classifier, how to use a binary class classifier to get a multi-class classifier is our concern, usually including one-against-all, one-against-one and multi-class SVM (multi-class objective functions) [8].

For *c* classes, one-against-one method views one of the classes as positive sample, the rest as a negative sample to classify, total *c*(*c* −1) 2 classifiers. Every sample to be classified would be sent to all the classifiers, and then each classifier will give a class label, and do statistics on the class label, the class label which has the largest number is class label of sample. In this paper we use one-against-one classification strategy. The algorithm refers to LIBSVM [9].

Proposed Method

The proposed method has two parts viz training and testing phases. During training phase the images from the database are taken. The images are enhanced and denoised in the pre-processing stage. In this proposed technique, PCA based on KL Transform has been used to extract feature vectors. As the images taken here are shoe print images, edge information will be predominant and form the feature of different shoe print images. The HH sub band is chosen for next level of classification using Support Vector Machine classifier. The SVM classifier will be trained with these patterns of entire data base. Once the training is completed, testing phase will come into operation.

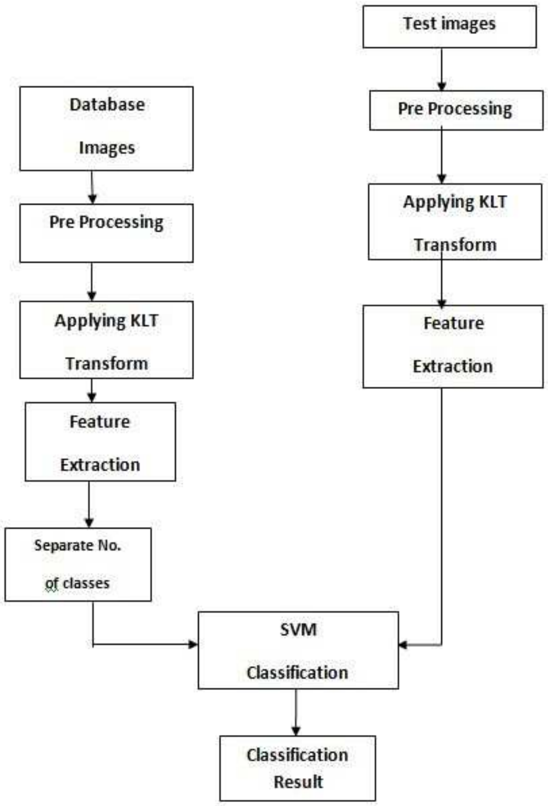


Figure 4 Flow diagram of the Proposed method

Any test image need to be classified and recognised can be given to the same system in testing or recognition mode. Same process will be done this test image such as pre-processing and Feature Extraction. The pattern generated from the testing phase will be compared with pattern already trained by SVM classifier. If the new patter generated with test image is matching with features already trained, the recognition will be done. This is illustrated in Figure 4.

Experimental Results And Analysis

In this paper, the database contains 230 shoe print images. Every image's size is 64 × 64 4096 grey level. Some of the shoe images tested in this method is given in Figure 5 below.

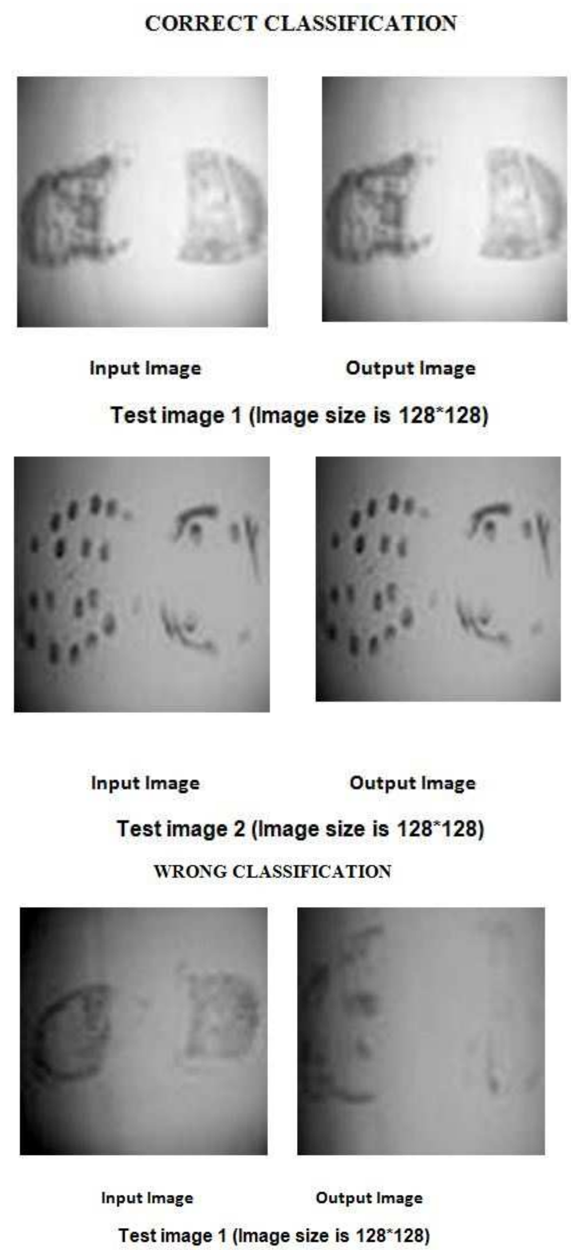
Figure 5 Samples of shoe image database

In this experiment, no pretreatment of the image is made. The SVM classifier is the same on parameter selection and classification strategy (Penalty factor *C* is 1, γ is 2, classification strategy is one-against-one). The experimental results are shown in Table 1.

Class number	Training samples	Test samples	Method	Accuracy (%)	Speed(s)
2	15	50	KLT+SVM	95	0.988932
2	25	100	KLT +SVM	86	1.306752
2	40	150	KLT +SVM	84	1.778882
2	50	200	KLT +SVM	81.5	2.660566
2	50	230	KLT +SVM	80	3.445947

Table 1: Outcome of the proposed method

The images from the correct and wrong classification from this method are given in Figure 6.



Training samples	Test samples	PCA from Covariance method +SVM		PCA from KLT + SVM	
		Accuracy (%)	Speed(s)	Accuracy (%)	Speed(s)
15	50	78.5	0.7521	79	0.7564
25	100	80	0.8546	80.5	0.9234
35	150	81	1.2985	82	1.3857
45	200	82	1.7492	84	1.8765
55	250	87.5	1.9923	89	2.0377

Table 2 Compares the above result with previous two methods other PCA methods.
Table 2 Comparison of results from other PCAs

Summary

A new PCA using KL Transform and Support Vector Machine method has been proposed for Shoe print recognition in this paper. Here we extracted feature vectors using KLT and classified the images using SVM for final recognition. The entire implementation and experimentation have been done on Cambridge ORL Shoe print database. Experimental results have demonstrated the efficacy of the proposed method.

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