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Two improved methods of KPCA algorithm

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Abstract: In order to improve the efficiency and accuracy of kernel principal component analysis, two novel improved methods of KPCA are come up with in this paper. One is the weighted KPCA (WKPCA) algorithm, the other is a face recognition method DKPCA based on discrete cosine transform (DCT) and kernel principal component analysis (KPCA). The former weights the projection matrix to improve the recognition rate, meanwhile, the latter performs DCT transformation on the database, selects low-frequency coefficients to reconstruct the face, extracts eigenvalues by KPCA, and adopts the nearest neighbor method for classification. The research results demonstrate that the two improved methods proposed in this paper can indeed improve the work efficiency and recognition accuracy of kernel principal component analysis.

1. Introduction

In recent years, as every one can see it, with the development of computer science, face recognition has become a hot research object. It proves self-evident that Kernel principal component analysis (KPCA), one of the commonly adopted methods to extract eigenvalues, is the nonlinear generalization of principal component analysis (PCA) in kernel space.

Nevertheless, KPCA can only get the distribution information of face samples, and the projection matrix may by no means be the best discrimination matrix, which affects the recognition rate. To solve this problem, this paper proposes weighted KPCA (WKPCA) to weight the projection matrix, which effectively reduces the influence of illumination, attitude change and other factors, so as to improve the recognition rate, but the operation is more than time-consuming and limited in application.

In addition, this paper improves the data compression method of KPCA. The utilization of discrete cosine transform can not only reduce the feature dimension, but also retain the insensitive information such as illumination and pose. In particular, DCT can be realized by fast Fourier transform, which saves the operation time to a great extent.

Based on this, this paper implements a face recognition method based on DCT and KPCA, namely DKPCA. The experiment on ORL database demonstrates that the algorithm improves KPCA in an effective manner.

2. Mathematical preparation

2.1 Introduction of KPCA

An exceedingly indispensable defect of principal component analysis is that it can never accurately represent its principal components when dealing with non-Gaussian data. In principal component analysis, the principal component can be uniquely determined by the second-order statistical characteristics of the data, which is sufficient for Gaussian distribution data, but it can fail to be utilized in non-Gaussian distribution. In order to accurately describe non Gaussian data, multitudes of methods have been proposed to introduce non-linearity into traditional principal component analysis. Among them, what the most famous and widely used is kernel principal component analysis (KPCA)[1] proposed by Scholkopf and other researchers. Kernel principal component analysis proves extraordinarily similar to principal component analysis in concept. The main difference is that kernel principal component analysis non-linearly maps the samples in the original input space to the feature space.

The main idea of KPCA is to map the initial data to a linearly separable high-dimensional feature space through a nonlinear mapping, and then carry out linear principal component analysis on the new feature space. To be specific, this paper analyzes the influence of polynomial kernel function and Gaussian kernel function, and the influence of the number of principal components on the accuracy, so as to maximize the accuracy of KPCA.

2.2 Literature Review

Kernel principal component analysis, in essence, proves a nonlinear principal component analysis method, one of which is based on support vector machine (SVM). There exist an increasing number of researchers have studied KPCA in a deep manner, and more and more experts and professors have put forward novel improvement methods. For instance, Yin Jianxing (2017) and others used KPCA algorithm to extract the diffraction wave characteristics of seismic data, which improves the efficiency of seismic data processing [2]. Luo dejiang (2012) used KPCA and k-fisher discriminant method to identify the characteristics of tight clastic rocks, which illustrates the superiority of KPCA in feature extraction [3]. Zhang Yongjie (2014) put forward a novel method to improve KPCA, namely Multiway KPCA (MKPCA) whose core idea is to block the samples, and then use KPCA to extract the features of each block, which optimizes the calculation process and reduces the complexity of calculation [4]. Zhao Jianhua et al. (2014) organically combined Gaussian kernel function with linear kernel function and polynomial kernel function to form a new kernel function, and applied the combined kernel function to face recognition method based on KPCA to improve the accuracy and speed of face recognition [5].

2.3 DCT for Discrete Cosine Transform

The degree of information concentration will be exceedingly different if the information set remains transformed differently. Compared with the traditional DFT (Discrete Fourier transform), DCT has stronger information concentration ability. Moreover, the combination of DCT and computational complexity keeps exceedingly excellent and has been widely adopted in recent years. For most natural images, DCT contains the most information with the least coefficients. All in all, this paper uses DCT to improve KPCA[6].

The characteristics of discrete cosine transform for face image are: the value of DCT coefficient $Y(k,l)$ decreases with the increase of frequency domain coefficient K and l; The larger $Y(k,l)$ is mainly distributed in the second quadrant and seems also the area where effective information is concentrated [7].

2.4 Introduction of WKPCA

The projection transformation matrix of traditional KPCA algorithm proves under no circumstances necessarily the best discrimination matrix, so it will affect the final recognition effect. In the process of projection transformation, the feature vector corresponding to the eigenvalue with large value is greatly affected by external factors, which has an affect on the improvement of recognition rate. Therefore, the method of weighting the projection matrix is adopted to adjust the eigenvector corresponding to each eigenvalue, so as to retain the useful information for recognition as much as possible while reducing the impact on the recognition information.

3. K- Nearest Neighbor

KNN method, namely k-nearest neighbor method, was first proposed by Cover and Hart in 1968. KNN algorithm proves, needless to say, one of the simplest machine learning algorithms. The idea of KNN algorithm keeps outstandingly simple and intuitive: specify a sample in the feature space. If most of its K most similar (i.e. the nearest) samples belong to a certain category, then the K most similar samples also belong to this category in this feature space. In the classification decision-making, KNN depends on the category of the nearest one or several samples to determine the category of the samples to be divided [8].

KNN algorithm has exceedingly significant advantages. It is an easy-understanding algorithm and has low requirements for the basis of mathematics. It has the advantages of fast training time, good prediction effect and low sensitivity to outliers. The disadvantage of KNN algorithm is the large amount of calculation, because for each sample to be classified, the distance from it to all known samples must be calculated to find its K nearest points. At present, the commonly used optimization method is to clip the known samples in advance and delete the samples that have little impact on classification [8].

KNN algorithm mainly has two steps:

(1) For a given training set, the value of K is determined according to a certain distance metric;

(2) In (1), The K most similar samples are classified into one class.

4. Algorithm principle

4.1 Discrete Cosine Transform

DCT represents the image as sinusoidal sum of different amplitudes and frequencies. Assuming that $F(x,y)$ is two-dimensional data, the two-dimensional DCT is defined as:

$$Y(k,l)=\frac{2}{\sqrt{MN}}c(k)c(l)\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}F(x,y)cos\frac{(2m+1)k\pi}{2M}cos\frac{(2n+1)l\pi}{2N} \tag{1}$$

Where $m,k=0,1,\ldots,M-1;n,l=0,1,\ldots,N-1$.

Meanwhile, DCT transform is reversible. IDCT transform, i.e. two-dimensional inverse discrete cosine transform, is defined as follows:

$$F(x,y)=\frac{2}{\sqrt{MN}}c(k)c(l)\sum_{K=0}^{M-1}\sum_{L=0}^{N-1}c(k)c(l)Y(k,l)cos\frac{(2m+1)k\pi}{2M}cos\frac{(2n+1)l\pi}{2N} \tag{2}$$

4.2 WKPCA

Let the projection matrix be $\boldsymbol{W}$, the weighting matrix be $\boldsymbol{T(\alpha)}$ and weighted post projection matrix be $\boldsymbol{W}^*$, then:

$$W^* = WT(\alpha) \tag{3}$$

$$T(\alpha) = diag\left((1+t_1{}^{\alpha})^{-\alpha},(1+t_2{}^{\alpha})^{-\alpha},\cdots,,(1+t_n{}^{\alpha})^{-\alpha}\right) \tag{4}$$

Where $ti=|\lambda_i|/\sum|\lambda_i|$ represents the proportion of each eigenvalue in all eigenvalues; The value parameter α which between 0 and 1 can be determined by experiment.

Because the shape and texture of face image contain some complementary identification information, the fusion of the two types of features will contribute to improve the recognition rate. Let the characteristic matrices of high-resolution and low-resolution images be $F1$ and $F2$ respectively, and the ratio of their dimensions θ, then the characteristic matrix after fusion is: $F=[F1,\delta\cdot F2]$

where the value of δ range from θ to 2θ[15].

5. Experimeents

The face data we use in this paper comes from ORL face database. The gray level of each image in the database is 256 and the resolution is 112×92.

5.1 KPCA kernel function selection

We compare the original KPCA with polynomial kernel function and Gaussian kernel function on the accuracy. When the parameter D of polynomial kernel function is selected as 1, the accuracy is the highest; The value of C has no effect on the accuracy. When the parameter $1/2\sigma^2$ of Gaussian kernel function is selected as 700, the accuracy reaches 96.875%.

5.2 Number of principal components

To study the influence of KPCA principal components on recognition performance, we select the first 6 samples of each type as training samples and the rest as test samples. Then we compare the changes of recognition accuracy with the increase of the number of principal components. The accuracy reaches the maximum when the number of principal components reaches 48, and then the increase has little effect on the accuracy.

Therefore, in the following comparative experiments, I select the Gaussian function as the kernel function, in which the parameter $1/2\sigma^2$ is 700 and the number of principal components is 48.

5.3 The comparison of DKPCA and WKPCA

To illustrate the effectiveness of this method, the author compares the recognition performance of KPCA method and DKPCA method when the number of training samples is 5. Table 1 demonstrates the performance parameters of the two approaches when reaching the optimal recognition rate.

Table 1 DKPCA and KPCA comparing

Method	DCT Components	Training Time	Accuracy%	Principal Components
DKPCA	10	2.65	99.38	38
KPCA	—	7.93	95.6	48

The reconstructed image after DCT transformation and inverse transformation as the representation of human face, on the one hand, reduces the dimension of data, reduces the time in the process of kernel function mapping and improves the recognition efficiency. On the other hand, in the DCT transformation coefficients, the position change, illumination, covering, expression and other nonlinear factors in the original face only affect the high-frequency coefficients. Therefore, the low-frequency component coefficients after DCT transform are selected to reconstruct the face, which reduces the interference of the above nonlinear factors and improves the recognition accuracy. Therefore, this method achieves better recognition performance than KPCA method.

To verify whether WKPCA algorithm can effectively improve WKPCA, this algorithm is compared with KPCA on ORL face database. In the experimental study, the first 4, 5 and 6 face images of each class are used for training, and the remaining face images are used for testing. The experimental results are demonstrated in the Table 2.

Table 2 WKPCA and KPCA comparing

Method	Sample	Principal Components	Accuracy	Training Time
	4	60	87.5%	13.90
KPCA	5	62	90.00%	15.01
	6	70	95.63%	17.42
	4	60	87.92%	8.91
WKPCA	5	62	89.50%	8.94
	6	70	96.25%	9.02

The effective recognition features increase with the increase of training samples as well as the recognition rate. It is the recognition rate of WKPCA algorithm that is generally higher than that of traditional KPCA algorithm, which greatly shortens the operation time while improving the recognition rate.

6. Summary

6.1 Innovation

(1) This paper analyzes the selection of kernel function and proves that when the parameter $1/2\sigma^2$is 700, the Gaussian kernel function can obtain higher accuracy and shorten the operation time than the polynomial kernel function.

(2) WKPCA algorithm uses projection matrix weighting method to make the extracted features more effective than traditional KPCA. Experiments on ORL face database illustrate that it overcomes the influence of nonlinear factors such as illumination on classification to a great extent. Experimental results show that this method is better than KPCA method in overall recognition performance.

(3) In this paper, kernel principal component analysis is improved with discrete cosine transform to obtain DKPCA, which not only greatly speeds up the running speed, but also effectively suppresses the adverse effects of illumination intensity, facial expression change, occlusion and other factors on face recognition effect, and improves the accuracy of KPCA recognition. Experimental results illustrate that this method is better than KPCA method in overall recognition performance.

6.2 Deficiency and Prospect

The standard KPCA algorithm has always been an exceedingly effective nonlinear feature processing method, which also makes the algorithm widely studied and utilized in multitudes of industries. However, it is worth noting that the two improved methods of KPCA proposed in this paper still need further analysis and research. Specifically, we ought to test the two methods proposed in this paper on more large data sets to verify whether the two methods have universal applicability. If it is found that the two methods proposed in this paper do not have universal applicability, then we need to make a further analysis in the respective application scope and the most suitable application scope of the two methods. Besides, it is how to improve and optimize the speed and accuracy of the two improved algorithms proposed in this paper that still need to be deeply analyzed and studied.

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