Eigenspace Interpolation for Appearance-Based Object Recognition

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Abstract

An eigenspace interpolation method smoothly interpolates between two different eigenspaces using high dimensional rotation. However, up to now its effectiveness in object recognition and the validity of the interpolation algorithm have not been discussed sufficiently. We therefore propose an appearance-based object recognition method combining the eigenspace interpolation method and a subspace method. We conducted face recognition experiments using images captured from multiple camera positions with various illumination conditions. Experimental results demonstrate the effectiveness of the proposed method and the validity of the interpolation algorithm.

1. Background and Motivation

In appearance-based object recognition, observation noises can seriously degrade recognition performance. The noises can be classified into the following two main types, unexpected noises and controllable noises.

The unexpected noises occur when they cannot be expected in the learning stages, e.g. during the change of illumination conditions in the test stages. One approach to this problem approximates an appearance distribution derived from the noises as a mathematical model constructed from a limited number of samples in the learning stages. A subspace method [1] has been widely used to achieve this approach. Due to its ease of use and effective results, various modifications of the method have been developed [2, 3].

The controllable noises, meanwhile, are controlled in the learning stages by certain parameters such as camera angles or object poses. Even if the ranges of parameters are known, the noises occur when the parameters in the test stages differ from those in the learning stages. A parametric eigenspace method [4] deals well with this problem by smoothly interpolating appearances between the learning parameters as points in the feature space. However, this method could not interpolate the appearance distributions, though it could interpolate the appearance points.

As one solution to achieving the interpolation of appearance distribution, Takahashi et al. have proposed a method for eigenspace interpolation [5]. The method could interpolate eigenspaces smoothly between two different eigenspaces. Lina et al. have proposed a method for object recognition based on the eigenspace interpolation [6]. They discussed the effectiveness of the method for recognition of images with artificial noises such as translation, rotation and blurring. However, the effectiveness for recognition of images with actual noises and the validity of the eigenspace interpolation method have up to now not been discussed sufficiently.

In light of the above background, we propose an appearance-based object recognition method combining a subspace method with the eigenspace interpolation method. We also conducted experiments using face images actually captured from multiple camera angles with various illumination conditions. The experimental results demonstrate the effectiveness of the proposed method for object recognition with actual noises and the validity of the eigenspace interpolation method.

2. Eigenspace Interpolation

A square matrix consisting of eigenvectors derived from a distribution could be considered a high dimensional rotation matrix since each pair of the eigenvectors is orthogonal. The eigenspace interpolation method interpolates between sets of eigenvectors derived from two different distributions by using high dimensional rotation. Interpolation preserving the orthogonality of eigenvectors is thus achieved.

There arises a problem of ambiguity in the interpolation process due to the alignment variety of eigenvectors and the sign indetermination of an eigenvector. To solve this problem, the following algorithm was presented in the literature [5].

2.1. Interpolation Algorithm

Square matrices consisting of eigenvectors derived from two different distributions of N dimensional vectors are represented as $\boldsymbol{E}'_0 = (\boldsymbol{e}'_{0,1}, \boldsymbol{e}'_{0,2}, \cdots, \boldsymbol{e}'_{0,N})$ and $\boldsymbol{E}'_1 = (\boldsymbol{e}'_{1,1}, \quad \boldsymbol{e}'_{1,2}, \cdots, \boldsymbol{e}'_{1,N})$. For a real number x, $\boldsymbol{E}_x = (\boldsymbol{e}_{x,1}, \boldsymbol{e}_{x,2}, \cdots, \boldsymbol{e}_{x,N})$ represents a matrix interpolated between $\boldsymbol{E}'_0$ and $\boldsymbol{E}'_1$. Here if $0 \leq x \leq 1$, then $\boldsymbol{E}_x$ represents interpolation; otherwise it represents extrapolation.

Step 1. Alignment between vectors: obtain $\boldsymbol{E}_0$, $\boldsymbol{E}_1$ by aligning eigenvectors $\boldsymbol{e}'_{0,n}$ and $\boldsymbol{e}'_{1,n}$ $(n = 1, 2, \cdots, N)$ in $\boldsymbol{E}'_0$ and $\boldsymbol{E}'_1$ in descending order of eigenvalue.

Step 2. Sign determination of vectors: replace $\boldsymbol{e}_{1,n}$ with $-\boldsymbol{e}_{1,n}$ if $\boldsymbol{e}_{0,n}^{\mathrm{T}} \boldsymbol{e}_{1,n} < 0$ for $n = 1, 2, \cdots, N$.

Finally, $\boldsymbol{e}_{0,N}$ is inversed if $\det(\boldsymbol{E}_0) = -1$ so that $\boldsymbol{E}_0$ becomes a rotation matrix. The same process is applied to $\boldsymbol{E}_1$.

The method calculates $\boldsymbol{E}_x$ with the equation

$$\boldsymbol{E}_x = \boldsymbol{R}_{0\to 1}^{x} \boldsymbol{E}_0. \tag{1}$$

Here $\boldsymbol{R}_{0\to 1}$ is a rotation matrix that represents transformation from $\boldsymbol{E}_0$ to $\boldsymbol{E}_1$ as given by the equation

$$\boldsymbol{R}_{0\to 1} = \boldsymbol{E}_1 \boldsymbol{E}_0^{\mathrm{T}}. \tag{2}$$

Using diagonalization of $\boldsymbol{R}_{0\to 1}$ with a unitary matrix $\boldsymbol{U}$, $\boldsymbol{R}_{0\to 1}^{x}$ that means interpolated rotation is calculated with the equation

$$\boldsymbol{R}_{0\to 1}^{x} = \boldsymbol{U} \boldsymbol{D}^{x} \boldsymbol{U}^{\dagger}. \tag{3}$$

Here $\boldsymbol{U}^{\dagger}$ is the complex conjugate transpose matrix of $\boldsymbol{U}$, and $\boldsymbol{D}$ is a complex diagonal matrix.

3. Subspace Method Combined with Eigenspace Interpolation

We propose an appearance-based object recognition method combining a subspace method with the eigenspace interpolation method. The proposed method is divided into two stages: a learning stage and a test stage.

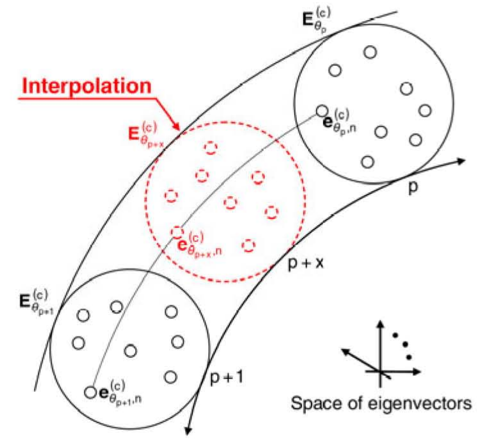

Figure 1. Conceptual overview of eigenspace interpolation

3.1. Learning Stage

An N dimensional feature vector for learning is represented as $\boldsymbol{y}'^{(c)}_{\theta_p,s}$ $(c = 1, 2, \cdots, C, \quad p = 1, 2, \cdots, P, \quad s = 1, 2, \cdots, S)$. Here C represents the number of categories, P the number of observation states, e.g. the number of cameras, θ_p the parameter of pth state, e.g. the position of pth camera, S the number of samples for constructing an eigenspace, e.g. the number of images captured in various illumination conditions. For each $c(= 1, 2, \cdots, C)$, the following steps are processed.

Step 1: construct $\boldsymbol{E}'^{(c)}_{\theta_p}$ consisting of eigenvectors derived from S samples for each $p(= 1, 2, \cdots, P)$.

Step 2: obtain $\boldsymbol{E}^{(c)}_{\theta_{p+x}}$ by interpolating between $\boldsymbol{E}'^{(c)}_{\theta_p}$ and $\boldsymbol{E}'^{(c)}_{\theta_{p+1}}$ with the method described in 2.1 for each $p(= 1, 2, \cdots, P - 1)$.

Figure 1 illustrates a conceptual overview of eigenspace interpolation in the proposed method.

3.2. Test Stage

The recognition result $\hat{c}$ of $\boldsymbol{z}$, the N dimensional feature vector for test, is obtained by the equation

$$\hat{c} = \arg\max_{c} \max_{p} \max_{x} \sum_{n=1}^{M} (\boldsymbol{z}^{\mathrm{T}} \boldsymbol{e}^{(c)}_{\theta_{p+x},n})^2. \tag{4}$$

Here $c \in \{1, 2, \cdots, C\}$, $\quad p \in \{1, 2, \cdots, P\}$, $\quad 0 \leq x \leq 1$, and $M(\leq N)$ represent the number of eigenvectors used for recognition of the subspace method.

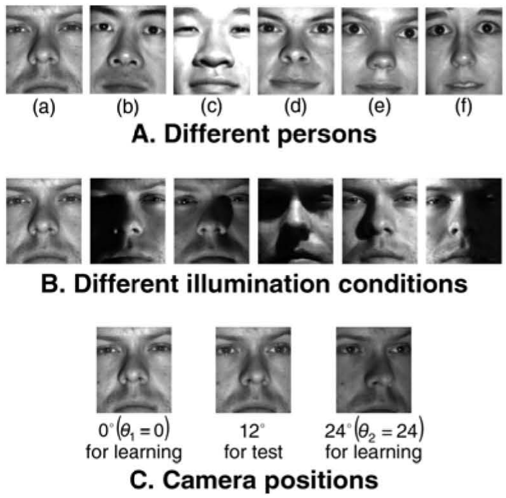

Figure 2. Samples of face images used for experiments

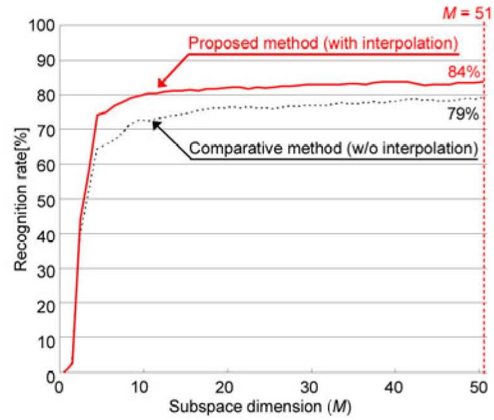

Figure 3. Comparison of recognition rates while varying subspace dimensions

4. Results and Discussion

We conducted face recognition experiments to demonstrate the effectiveness of the proposed method and the validity of the eigenspace interpolation method.

In these experiments, we used "Yale Face Database B" [7] and "Extended Yale Face Database B" [8]. The MIST library [9] was used for implementation of the proposed method. Face images of $37 (C = 37)$ different persons in their database were used. They were captured in $51 (S = 51)$ different illumination conditions and from three horizontally different camera positions. Figures 2 A and B show samples of the face images of different persons and of different illumination conditions respectively. Figure 2 C shows the camera positions used for the experiments. The cameras were placed at 0, 12 and 24 degrees from frontal to right. Two $(P = 2, \theta_1 = 0, \theta_2 = 24)$ side cameras of them were used for learning whereas the middle one was used for the test. We obtained $N (= 200)$ base vectors of an N dimensional feature space by applying PCA to the learning images. Table 1 describes parameters of the proposed method that were used for the experiments.

Table 1. Parameters used for experiments

Symbol	Parameter	Value
C	Num. of persons	37
S	Num. of illumination conditions	51
P	Num. of cameras for learning	2
θ_1, θ_2	Camera positions for learning	0, 24
N	Feature space dimension	200

4.1. Effectiveness of the proposed method

Table 2 shows that the proposed method with eigenspace interpolation gave a higher recognition rate than a comparative method without eigenspace interpolation. Here, the comparative method used only two actual eigenspaces derived from the cameras for learning. The proposed method on the other hand used nine interpolated eigenspaces and the two actual ones. We thus confirmed the effectiveness of the proposed method for improvement of recognition performance.

Figure 3 shows the comparison while varying M, the number of eigenvectors used for recognition. The result indicates that interpolated eigenvectors corresponding to small eigenvalues did not contribute well to the performance improvement.

Furthermore, Figure 4 visualizes samples of the first eigenvectors that were interpolated in this experiment. In this figure, (a)-(f) correspond to (a)-(f) of Figure 2 A. The first row and the last row represent actual eigenvectors and others were interpolated between them.

4.2. Validity of Interpolation Algorithm

We also conducted another experiment to evaluate the validity of the interpolation algorithm described in

Table 2. Comparison of recognition rates

Method	Interpolation	Recognition rate
Proposed	**Yes**	**84%**
Comparative	No	79%

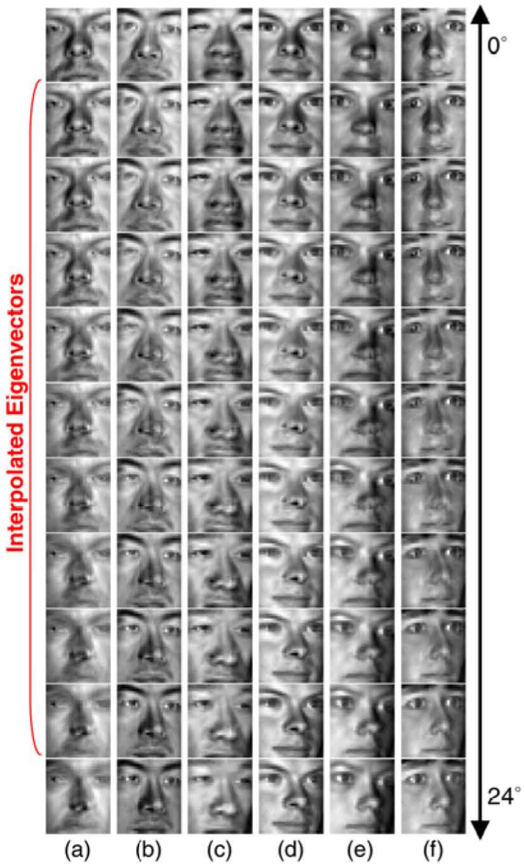

Figure 4. Samples of the first eigenvectors interpolated in experiments

2.1. Recognition rates of the proposed method, which uses the interpolation algorithm, and the following two different algorithms were compared in this experiment.

Random order method: aligns eigenvectors in random order instead of Step 1 in 2.1.

Inverse direction method: inverts signs of eigenvectors after Step 2 in 2.1 is processed.

As shown in Figure 5, the proposed method gave higher recognition rates than that by the random order method and the inverse direction method. From this result, we confirmed the validity of the interpolation algorithm.

Many other algorithms could, however, be considered to achieve the eigenspace interpolation. In the future, we will try to develop more effective algorithms, focusing especially on the improvement of recognition performance.

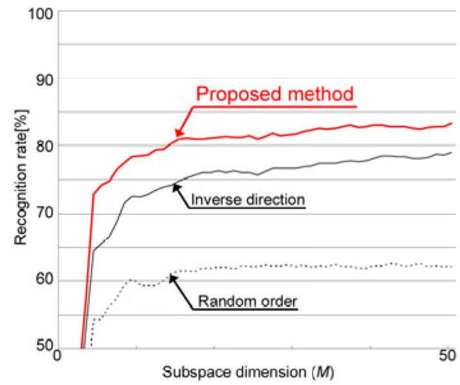

Figure 5. Comparison of recognition rates between interpolation algorithms

5. Summary

We proposed an appearance-based object recognition method combining a subspace method with the eigenspace interpolation method and also conducted face recognition experiments. The experimental results demonstrated the effectiveness of the proposed method and the validity of the interpolation algorithm.

References

[1] S. Watanabe and N. Pakvasa. Subspace method of pattern recognition. *Proc. Int. J. Conf. on Pattern Recognition*, pages 25–32, 1973.

[2] M. Turk and A. Pentland. Face recognition using eigenfaces. *Proc. IEEE Conf. on CVPR*, pages 568–591, 1991.

[3] B. Moghaddam. Principal manifolds and bayesian subspaces for visual recognition. *Proc. ICCV*, pages 1131–1136, 1999.

[4] H. Murase and S. K. Nayar. Illumination planning for object recognition using parametric eigenspaces. *IEEE Trans. PAMI*, 16(12):1218–1227, 1994.

[5] T. Takahashi, Lina, I. Ide, Y. Mekada, and H. Murase. Interpolation between eigenspaces using rotation in multiple dimensions. *Proc. ACCV*, 2:774–783, 2007.

[6] Lina, T. Takahashi, I. Ide, and H. Murase. Embedding view-dependent covariance matrix in object manifold for robust recognition. *Proc. IASTED Int. Conf. of SPPRA*, pages 24–29, 2008.

[7] A. S. Georghiades, P. N. Belhumeur, and D. J. Kriegman. From few to many: Illumination cone models for face recognition under variable lighting and pose. *IEEE Trans. PAMI*, 23(6):643–660, 2001.

[8] K. C. Lee, J. Ho, and D. Kriegman. Acquiring linear subspaces for face recognition under variable lighting. *IEEE Trans. PAMI*, 27(5):684–698, 2005.

[9] http://mist.suenaga.m.is.nagoya u.ac.jp. Media Integration Standard Toolkit.