A FACE IMAGE RECOGNITION SCHEME WITH STRONG TOLERANCES TO LIGHTING FLUCTUATIONS

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ABSTRACT

In this paper, we propose a face recognition scheme that has strong tolerances to changes in the lighting environment. The current spread of cellular phones with camera devices has made biometric certification of face images possible, without adding extra devices. However, face images taken via cellular phones are fluctuated by lighting environments, because cellular phones are used both indoors and outdoors without limit. Therefore, the most serious problem is that lighting fluctuations decrease its recognition accuracy. Our proposed scheme is very simple. This scheme uses the lighting canonical space and creates a virtual subspace that contains various elements of lighting, without actually taking many face images under different environments. Simulation results show the proposed scheme can achieve not only a lower equal-error-rate of verification, but also higher precision of identification than the conventional subspace scheme.

1. INTRODUCTION

Mobile banking, stock trade and on-line services were started recently, and their payments through cellular phone have been enabled. Therefore, people are becoming increasingly interested in biometric certification using human inherent information to maintain a more advanced security than the current PIN code. Especially, the spread of cellular phones with camera devices has made biometric certification of face images possible, without adding extra devices. However, if the face images taken by cellular phones are used in biometric certification, a most serious problem occurs. Lighting fluctuations decrease the certification precision, because cellular phones are used both indoors and outdoors.

In this paper, we propose a face recognition scheme that has strong tolerances to changes in the lighting environment. The proposed scheme uses the lighting canonical space, which contains various elements of lighting, and creates a virtual subspace, without actually taking face images under various environments. In section 2, face recognition by the conventional subspace scheme is described It forms the core techniques of the proposed scheme. In section 3, the concept of the lighting canonical space is also described. How to create the virtual subspace using the lighting canonical space is proposed. In section 4, simulations are performed and advantages of the proposed scheme are confirmed. section 5 is conclusion of this paper.

2. FACE RECOGNITION BY SUBSPACE SCHEME

Subspace scheme [1] forms the core techniques of the proposed face recognition. Face recognition by the conventional subspace scheme is described in this section.

2.1. Subspace scheme

We assume that all face images in this paper have already been normalized for position, size, pose and expression. When N face images $\boldsymbol{x}_i$ (i=1, 2, …, N) of a certain person are obtained, the correlation matrix $\boldsymbol{R}$ of these face images is defined as the following equation:

$$\boldsymbol{R} = \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{x}_i \boldsymbol{x}_i^T \tag{1}$$

$\boldsymbol{\Lambda}$ is the diagonal matrix in which N eigen values of $\boldsymbol{R}$ are arranged as diagonal components, and $\boldsymbol{e}_j$ (j=1, 2, …, N) is the eigen vector, which corresponds to each eigen value. $\boldsymbol{\Phi}$ is the transformation matrix in which eigen vectors $\boldsymbol{e}_j$ are arranged as column vectors. $\boldsymbol{R}$ can be transformed.

$$\boldsymbol{\Lambda} = \boldsymbol{\Phi}^T \boldsymbol{R} \boldsymbol{\Phi} \tag{2}$$

$$\boldsymbol{\Phi} = \left[\boldsymbol{e}_1, \boldsymbol{e}_2, \ldots, \boldsymbol{e}_N\right] \tag{3}$$

The concept of conventional subspace scheme is shown in Figure 1 . This scheme determines a judgment of certification, measuring distance or angle θ between input face image $\boldsymbol{x}$ and the subspace, which is spanned by M eigen vectors. M is less equal than N. M eigen vectors are selected sequentially with larger eigen values. Moreover, the distance and angle θ can be replaced by the similar S.

$$S = \cos^2\theta = \frac{\sum_{j=1}^{M}\left(\boldsymbol{e}_j^{\mathrm{T}} \cdot \boldsymbol{x}\right)^2}{|\,\boldsymbol{x}\,|^2}, \qquad \left(0 \le S \le 1\right) \tag{4}$$

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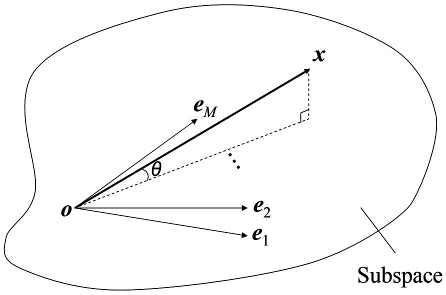

Fig.1 Subspace scheme

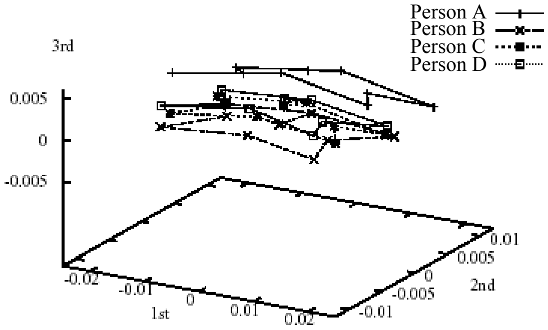

Fig.2 Continuous curve in the lighting canonical space

If the person of the input face image $\boldsymbol{x}$ is the same as the person of the subspace, S shows a large value near 1. That is to say, certification judgment can be determined by measuring whether S is close to 1 or not.

2.2. Decrease of certification precision by changes in lighting environment

The conventional subspace scheme has one serious problem. If input face image $\boldsymbol{x}$ is fluctuated by changes in the lighting environment, similar S between the input face image $\boldsymbol{x}$ and subspace decreases and shows a small value since the subspace doesn't contain an element of its lighting. In this case, although the person of the input face image is actually the same as the person of the subspace, certification may fail. Moreover, the similar to other persons increases, and the person may be identified incorrectly as another person. Therefore, we must take many face images under various lighting environments and create a subspace that contains various elements of lighting, to solve the problem with lighting fluctuation.

3. PROPOSED SCHEME

The conventional subspace scheme can work against lighting fluctuation only if the subspace is made from face images that have been taken under various lighting environments. However, it is actually difficult to do this, since registration operation of this system should be as simple and as easy as possible for users. Therefore, if face images were only taken under one or a few types of lighting environments, the subspace could not be perfectly adapted to the lighting fluctuations. In this section, we propose a new subspace scheme that can recognize fluctuating face images correctly even in such a situation. This scheme can also archive face recognition, which has strong tolerances to changes in the lighting environment.

3.1. Lighting canonical space

Face images $\boldsymbol{y}_{pl}$ of P persons (p=1, 2, …, P) are taken under L types of lighting environments (l=1, 2, …, L), respectively. Using this face image set, its eigen space can be introduced and various elements of lighting can also be modeled. This space is called the lighting canonical space and this face image set is called the canonical face image set. Mean $\bar{\boldsymbol{y}}$ and covariance matrix $\boldsymbol{C}$ of the canonical face image set are defined as the following equations:

$$\bar{\boldsymbol{y}} = \frac{1}{PL}\sum_{p=1}^{P}\sum_{l=1}^{L}\boldsymbol{y}_{pl} \tag{5}$$

$$\boldsymbol{C} = \frac{1}{PL}\sum_{p=1}^{P}\sum_{l=1}^{L}(\boldsymbol{y}_{pl}-\boldsymbol{m})(\boldsymbol{y}_{pl}-\boldsymbol{m})^{T} \tag{6}$$

Generally, $\bar{\boldsymbol{y}}$ is used as the center of lighting canonical space $\boldsymbol{m}$ to maximize covariance. However, the proposed scheme uses $\bar{\boldsymbol{y}}_{l=1}$ instead of $\bar{\boldsymbol{y}}$, since this scheme aims at adding various elements of lighting to the conventional subspace virtually. $\bar{\boldsymbol{y}}_{l=1}$ is the mean of face images, which were taken under the same lighting environment as registration operation, defined as the following equation:

$$\boldsymbol{m} = \bar{\boldsymbol{y}}_{l=1} = \frac{1}{P}\sum_{p=1}^{P}\boldsymbol{y}_{pl=1} \tag{7}$$

where it is now assumed that l=1 is the same lighting environment as the registration operation. PL–1 eigen vectors can be introduced from the principal component analysis of $\boldsymbol{C}$, and they become normalized on an orthogonal basis, which spans the lighting canonical space.

Next, face images were taken when lighting environments were changed continuously and they were mapped onto the lighting canonical space, as shown in Figure 2. Their tracking depicts a continuous curve. Each person depicts a continuous curve respectively. These curves differ slightly but their shapes are almost similar [3]. Therefore, if the face image was only taken under a certain lighting environment, using relations of this continuous curve, face images under other lighting environments can be deduced and created virtually, without actually taking many face images under various lighting environments. Figure 3 shows virtual face images under L=9 types of lighting environments. These face images were created from only one face image that was taken under the l=1 lighting environment, mapping so that

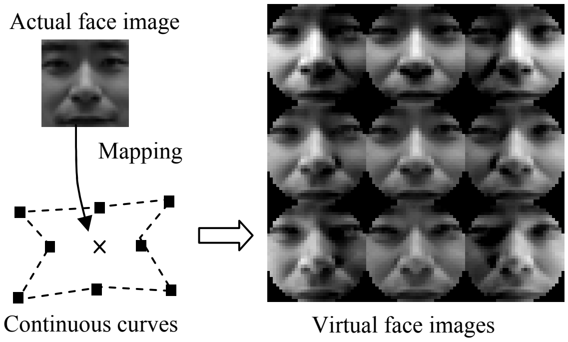

Fig.3 Deducing operation on lighting canonical space

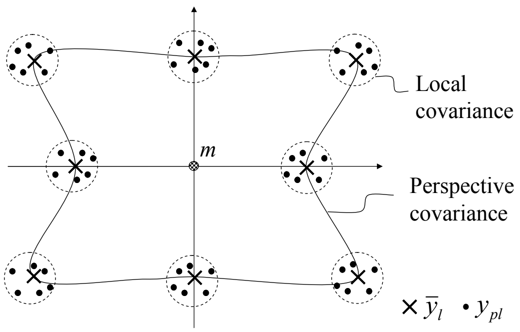

Fig.4 Separation of covariance matrix

their tracks would maintain a continuous curve on the lighting canonical space.

3.2. Simple creation algorithm of virtual subspace

L virtual face images could be deduced respectively from each face image using continuous curve on the lighting canonical space. If N face images $\boldsymbol{x}_i$ (i=1, 2, …, N) were taken in the registration operation, NL virtual face images can be obtained. These virtual face images can create a subspace, which contains various elements of lighting and its correlation matrix $\boldsymbol{R'}$. However, $\boldsymbol{R'}$ can be introduced from the summation of two matrixes $\boldsymbol{R}$ and $\boldsymbol{C}$ simply as shown in the following equation, without actually making these virtual face images.

$$\boldsymbol{R}' = \boldsymbol{R} + \boldsymbol{C} \tag{8}$$

Subspace of R' has strong tolerances to lighting fluctuations. From the above process, we can achieve a face recognition scheme that has strong tolerances to changes in lighting without actually taking face images under various lighting environments.

3.3. Separation of covariance matrix

The covariance matrix of lighting canonical space $\boldsymbol{C}$ can be separated into $\boldsymbol{C}_{per}$ and $\boldsymbol{C}_{loc}$ to archive stronger tolerances in lighting fluctuations as shown in the following equations:

$$\boldsymbol{C} = \boldsymbol{C}_{per} + \boldsymbol{C}_{loc} \tag{9}$$

$$\boldsymbol{C}_{per} = \frac{1}{L}\sum_{l=1}^{L}(\bar{\boldsymbol{y}}_l - \boldsymbol{m})(\bar{\boldsymbol{y}}_l - \boldsymbol{m})^T \tag{10}$$

$$\boldsymbol{C}_{loc} = \frac{1}{PL}\sum_{l=1}^{L}\sum_{p=1}^{P}(\boldsymbol{y}_{pl} - \bar{\boldsymbol{y}}_l)(\boldsymbol{y}_{pl} - \bar{\boldsymbol{y}}_l)^T \tag{11}$$

$$\bar{\boldsymbol{y}}_l = \frac{1}{P}\sum_{p=1}^{P}\boldsymbol{y}_{pl} \tag{12}$$

where $\bar{\mathbf{y}}_l$ is the mean of face images that are taken under lighting environment l. Figure 4 shows the concept of separating covariance matrix $\boldsymbol{C}$, which contains elements of L=9 lighting environments. $\boldsymbol{C}_{per}$ is the perspective covariance, which contains the main elements of the differences in lighting environments. $\boldsymbol{C}_{loc}$ is the local covariance, which contains the main elements of differences in people. Therefore, the proposed scheme uses $\boldsymbol{C}_{per}$ instead of $\boldsymbol{C}$ as shown in the following equation:

$$\boldsymbol{R}' = \boldsymbol{R} + \boldsymbol{C}_{per} \tag{13}$$

As a result, the proposed scheme can create a virtual subspace that has strong tolerance to changes in the lighting environment, even if face images were taken under only one or a few lighting environments.

4. SIMULATION

Computer simulations were performed to check the advantages of the proposed scheme. Face images of the Yale Face Database [4] were used in these simulations. This database is composed of 17 persons and the face images of each person were taken under 40 types of lighting environment. The resolution of all face images was normalized so that the width was 32 and the height was 32. All 17 persons were classified into two groups. The first group (A) was for making the covariance matrix of the lighting canonical space. The second group (B) was for measuring certification precision. This classification of test face images is shown in Table 1. First, for P=10 persons in group (A), $\boldsymbol{C}_{per}$ of the lighting canonical space was introduced from the face images, which were taken under L=9 types of lighting environments, containing l=1. Next, for 7 persons in group (B), which did not contain the persons in group (A), the correlation matrix of subspace $\boldsymbol{R}$ was introduced from N=2 face images, which were taken under the l=1 lighting environment.

4.1. Verification experiment

1:1 verification precision of face images fluctuated by changes in the lighting environment was measured in about 7 persons in group (B). Each $\boldsymbol{R'}$ was introduced simply from the addition of $\boldsymbol{R}$ and $\boldsymbol{C}_{per}$, and each subspace was created from this $\boldsymbol{R'}$ as shown in equation (13). Nine

Table 1 Classification of test face images

Lighting	Group (A) 10 persons	Group (B) 7 persons
$l = 1$ $l = 1$		2 images for making correlation R
$l = 1$ $l = 2$ … $l = 9$	9 types for making covariance matrix C of lighting canonical space (Total 90 images)	40 types for measuring certification precision (Total 280 images)
$l = 10$ … $l = 40$		

types of lighting environments were contained in not only group (A), but also in group (B). However, the other 31 types of lighting environments were not contained in the lighting canonical space of group (A). Similar was measured for all 40 types of lighting environments. The conventional subspace scheme used 2 eigen vectors and the proposed scheme used 10 ($=N+L-1$) eigen vectors.

First, FAR and FRR were calculated with the change in threshold. This result is shown in Figure 5. ERR of the conventional subspace scheme is about 0.45. In contrast, the proposed subspace scheme can archive about 0.25. It was confirmed that the proposed scheme could improve verification precision and reduce certification error. In addition, although the lighting canonical space contains only L=9 types of lighting environments, the proposed subspace could also verify the face images that were taken under other different lighting environments. This result shows that arbitrary lighting fluctuations can be calculated by linear summation of elemental lighting fluctuations, which are contained in the lighting canonical space.

4.2. Identification experiment

The proposed subspace scheme adds $\boldsymbol{C}_{per}$ equally to $\boldsymbol{R}$ of anyone and creates $\boldsymbol{R'}$. Therefore, there are some concerns that the proposed subspace may improve similar in anyone equally and in the end, its identification precision may be equal to the conventional subspace scheme. However, such a problem does not occur in fact, since subordinate components between $\boldsymbol{R}$ and $\boldsymbol{C}_{per}$ are canceled when eigen vectors of $\boldsymbol{R'}$ are introduced and individual features can be reflected in the subspace.

We measured 1:n identification precision to verify the justification of this theory. This result is shown in Table 2. R means the conventional subspace and R' means the proposed subspace. It was confirmed that the proposed scheme has higher identification precision than the conventional scheme in both two cases. The first case (a) contains L=9 types of lighting environments, which are all included in the lighting canonical space. The second case (b) contains 40 types of lighting environments, which are partly not included in the lighting canonical space. Moreover, the proposed scheme can improve the identification precision more as the number of used eigen vectors M increases, and can archive 100% in case (a) and 91% even in case (b).

Table 2 Identification precision

(a) 9 types of lighting environments (total 63 images)

M	1	2	3	4	5	6	…	10
R	0.87	0.87	---	---	---	---	…	---
R'	0.81	0.94	0.97	1.00	1.00	1.00	…	1.00

(b) 40 types of lighting environments (total 280 images)

M	1	2	3	4	5	6	…	10
R	0.71	0.73	---	---	---	---	…	---
R'	0.69	0.79	0.86	0.89	0.90	0.91	…	0.91

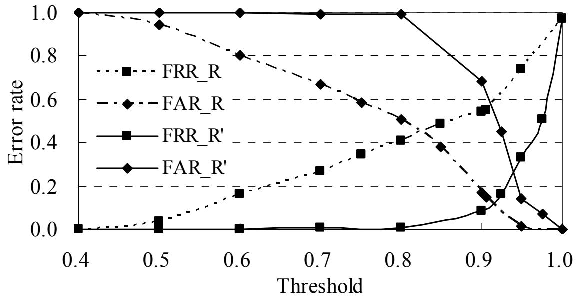

Fig.5 FAR and FRR of verification

5. CONCLUSION

We propose a face recognition scheme that has strong tolerances to changes in the lighting environment. The proposed scheme can simply create virtual subspace without actually taking many face images under various environments, even if face images were taken under only one or a few lighting environments. Simulation results show the proposed scheme can achieve not only a lower equal-error-rate of verification, from 0.45 to 0.25, but also higher precision of identification, from 73% up to 91% than the conventional subspace scheme.

Processing of this scheme is easy and simple. Therefore, the proposed scheme can realize face image biometric certification using cellular phones.

REFERENCES

[1] E. Oja, "Subspace methods of pattern recognition," *Research Studies Press*, Hertfordshire, 1983.

[2] M. A. Turk and A. P. Pentland, "Face recognition using eigenfaces," *Proc. of IEEE Conference on Computer Vision and Pattern Recognition*, pp.586–591, Jun. 1991.

[3] H. Murase, S. K. Nayar, "Illumination Planning for object recognition using parametric eigenspace," IEEE Trans. Pattern Anal. & Mach. Intell., vol.16, no.12, pp.1219-1227, 1994.

[4] Yale Face Database, http://cvc.yale.edu/projects/yalefaces/yalefaces.html