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# The improved relative entropy for face recognition

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**Abstract.**The relative entropy is least sensitive to noise. In this paper, we propose the improved relative entropy for face recognition (IRE). The IRE method of recognition rate is far higher than the LDA, LPP method, by experimental results on CMU PIE face database and YALE B face database.

**Keywords**.Face recognition; Relative entropy; Improved relative entropy

## 1 Introduction

Through decades of development, face recognition has gradually get one of the most attract research domain in image analysis and computer vision, because a large number of applications. A large number of face recognition methods have been investigated such as Principal component analysis (PCA) [1], Linear discriminate analysis (LDA) [2], Independent component analysis (ICA) [3], Elastic bunch graph matching (EBGM) [4], Support Vector Machine (SVM) [5], Isometric feature mapping (ISOMAP) [6], Locally linear embedding (LLE) [7] [8], Laplacian eigenmap (LE) [9] [10], Locality Preserving Projections (LPP) [11]. Principal component analysis (PCA) [1], linear discriminant analysis (LDA) [2] and locality preserving projections (LPP) [11] are typical linear algorithms for face recognition. Sirovich and Kirby first applied PCA, and then the well-known Eigenface method is proposed. PCA and LDA intend to project the vectors which represent face images onto lower dimensional subspace. PCA does not work for the class information, so it's an unsupervised method. LDA can take full consideration of the class labels of the input data. So the LDA is should be a supervised method. In fact, LDA is to find the projection axes that when face image data points of different classes are projected as much as possible the far from, while face image data points of the same class are nearly as much as possible. LPP can construct a face subspace by preserving local information which is a recently appeared method. LPP is also an unsupervised method, but LPP is to maintain the human face image space of the local structure, while PCA is to maintain the global structure.

In statistical physics the most important concept is the Boltzmann's entropy [12]. This concept is introduced by Shannon into information theory, called Shannon's entropy [13]. Some scientific field research and application of the concept of entropy is a wide range of [14] [15] [16] [17] [18] [19] [20] [21]. Guang Deng found the relative entropy appears to be the least sensitive to noise through experiments [23]. However, Relative entropy has a drawback that it is potentially sensitive to noise in dark areas. Therefore, it is performing a pixel-wise multiplication for an image to improve the relative entropy of this shortcoming. In this paper, we will use the improvement of the relative entropy for face recognition.

The rest part this paper is organized as follows: Section 2 introduced the proposed the improved relative entropy for face recognition (IRE). Section 3 reports the results of the experiment on CMU PIE face databases. Finally the conclusion of this paper is given in Section 4.

## 2 The relative entropy

### 2.1 The relative entropy

#### 2.1.1 Shannon' entropy

The Shannon' entropy can be defined as follows [13].

$$H = H(P) = -\sum_{n=1}^{N} p_n \log_2 p_n \quad (1)$$

$$p = \{p_n\} \quad (2)$$

$p_n$ is the probability of occurrence of the $i$ th outcome or state.

#### 2.1.2 Relative entropy

The relative entropy is defined as follows [22]

$$D(Q \parallel P) = \sum_{n=0}^{N-1} q_n \log \frac{q_n}{p_n} \quad (3)$$

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$$=\frac{1}{N}\sum_{n=0}^{N-1}(\log A-\log x_n) \quad (4)$$

$$=\log\frac{A}{G} \quad (5)$$

$$p_n=\frac{x_n}{S} \quad (6)$$

$$S=\sum_{n=0}^{N-1}x_n \quad (7)$$

$$q_n=\frac{1}{N} \quad (8)$$

$$A=\frac{S}{N} \quad (9)$$

$$G=\exp\left(\frac{1}{N}\sum_{n=0}^{N-1}\log x_n\right) \quad (10)$$

Where $Q$ is probability model, $P$ is also. $A$ is the arithmetic mean. $G$ is the geometric mean. So, Esq. (5) shows the relative entropy can be the ratio of the arithmetic mean to the geometric mean.

## 3 The improved relative entropy for face recognition (IRE)

The negative image is given as follows [23]

$$y=M-x \quad (11)$$

$x$ is a pixel of the original image and $y$ is a pixel of negative image.

We can compute a pixel-wise multiplication as follows [23]

$$Y=D_1\times D_2 \quad (12)$$

$D_1$ is the relative entropy of a pixel and $D_2$ is the relative entropy of a pixel .

The improved relative entropy for face recognition

Step.1. Input face images

Step.2. Compute the relative entropy of each pixel by Esq. (5), (9) and (10), using a neighboring (in this paper, the experiments using 3 × 3 neighborhood window).

Step.3. Computed by Esq. (11) and (12).

Step.4. Compute the Euclidean distance between of training face images and of testing face images.

$$d(Y_1-Y_2)=\|Y_1-Y_2\|_2 \quad (13)$$

## 4 Experiments

4.1 CMU PIE database

We checked the feasibility and effectiveness of IRE method on CMU PIE face database.

The CMU PIE face database includes 68 persons with 41,368 face images with varied pose, illumination and expression which were photographed by thirteen synchronized cameras and twenty-first flashes in different pose, illumination and expression. In this experiment, we used twenty-one face images of sixty-eight persons with illumination variations. Each image is resized to 92×112. We arbitrarily selected face image from CMU face database. Fig.1. displayed face sample images from the CMU PIE database.

**Fig.1** Illustration 21 images of one individual from CMU PIE face database.

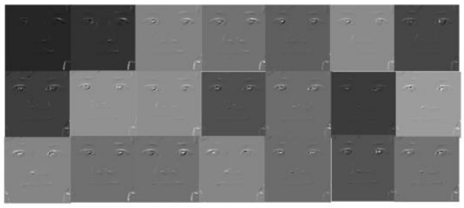

**Fig.2** Illustration 21 images of one individual from CMU PIE face database by the relative entropy.

**Table 1** displayed the three kinds of methods the highest recognition rate on the CMU PIE face database.

| Methods | 10 Train | 11 Train | 12 Train |
|---|---|---|---|
| LDA | 91.34 | 92.17 | 94.14 |
| LPP | 72.38 | 75.64 | 77.05 |
| IRE | 93.32 | 94.22 | 95.66 |

4.2 The YALE B database

On YALE B face database. We test positive images of 10 individuals who were shooting under 64 different lights. The above data set is divided into five subsets according to the direction of light: the best lighting conditions are Sub1, followed by Sub2, Sub5 worst.

We chose three images of each person as training samples Sub1, with the rest of the four samples for testing. Figure 3 displayed a sample image YALE B Sub1 face database.

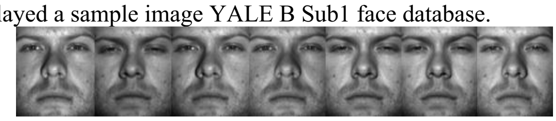

**Fig.3** Illustration 7 images of one individual from YALE B subset 1 face database.

**Table 2** displayed the three kinds of methods the highest recognition rate on the YALE B sub1 face database.

| Methods | 3 Train |
|---|---|
| LDA | 80.00 |
| LPP | 95.00 |
| IRE | 97.50 |

We chose each person's six Sub2 image as the training sample, with the rest of the six samples for testing. Figure 4 displayed a sample image YALE B Sub2 face database.

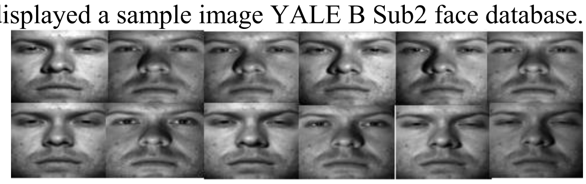

**Fig.4**Illustration 12 images of one individual from YALE B subset 2 face database.

**Table 3** displayed the three kinds of methods the highest recognition rate on the YALE B sub2 face database.

| Methods | 6 Train |
|---|---|
| LDA | 81.67 |
| LPP | 91.67 |
| IRE | 96.67 |

We chose each person's six Sub3 image as the training sample, with the rest of the six samples for testing. Figure 5 displayed a sample image YALE B Sub3 face database.

**Fig.5** Illustration 12 images of one individual from YALE B subset 3face database.

**Table 4** displayed the three kinds of methods the highest recognition rate on the YALE B sub3 face database.

| Methods | 6 Train |
|---|---|
| LDA | 58.33 |
| LPP | 25.00 |
| IRE | 68.33 |

We chose each person's seven Sub4 image as the training sample, with the rest of seven the samples for testing. Figure 6 displayed a sample image YALE B Sub4 face database.

**Fig.6** Illustration 14 images of one individual from YALE B subset 4 face database.

**Table 5** displayed the three kinds of methods the highest recognition rate on the YALE B sub4 face database.

| Methods | 7 Train |
|---|---|
| LDA | 38.57 |
| LPP | 22.86 |
| IRE | 75.71 |

## 5 Conclusions

In this paper, we proposed IRE method for face recognition. This method can make efficient recognition rate than LDA, LPP in CMU PIE face database and YALE B face database.

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