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FERET DATA SET 에서의 PCA 와 ICA 의 비교

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Comparison of PCA and ICA based Feature Extraction using FERET Database for Face Recognition

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Abstract

The purpose of this paper is to investigate two major feature extraction techniques based on generic modular face recognition system. Detailed algorithms are described for principal component analysis (PCA) and independent component analysis (ICA). PCA and ICA are statistical techniques for feature extraction and their incorporation into a face recognition system requires numerous design decisions. We explicitly state the design decisions by introducing a modular-based face recognition system since some of these decision are not documented in the literature. We explored different implementations of each module, and evaluate the statistical feature extraction algorithms based on the FERET performance evaluation protocol (the de facto standard method for evaluating face recognition algorithms). In this paper, we perform two experiments. In the first experiment, we report performance results on the FERET database based on PCA. In the second experiment, we examine performance variations based on ICA feature extraction algorithm. The experimental results are reported using four different categories of image sets including front, lighting, and duplicate images.

I. Introduction

The development of evaluation procedures for algorithms is starting to become an accepted practice in computer vision. One of the reasons is that evaluation procedures offer a way to assess competing performance claims. For one be able to make a fair assessment of these claims, it is necessary that the underlying assumptions of the evaluation procedure be clearly stated, and that the testing and scoring protocols are described. From this, a statistical model for comparing algorithms can be formulated.

For any given computer vision problem, there are numerous algorithms designed to solve it. The design of each algorithm is based on a set of decisions and assumptions. Because of these decisions and assumptions, it may not be appropriate to apply a particular test to an algorithm. The underlying test assumptions for scoring protocol are one of the criteria for determining if an evaluation procedure is appropriate for a particular algorithm.

In face recognition, the de facto standards for evaluating algorithms are the FERET evaluation procedures [1],[2]. The most recent of these procedures was the September 1996 FERET test, which provided a robust and comprehensive evaluation of face recognition algorithms. The success of our research was based on a few design assumptions from which a statistical model could be formulated. In this paper, we state these assumptions, present the resulting statistical model, and use it to assess the performance of modular based face recognition system (see Figure 1).

The primary goal of our experiment is to obtain an accurate assessment of the performance of face recognition algorithms based on PCA [3],[4] and ICA [5]. To get this assessment, the evaluation methodology needed to be robust and comprehensive [6]. To achieve this, scores had to be computed for a large range of galleries and probe sets. This led to the following design principles: (1) algorithms could not be trained during testing, (2) each facial image was treated as an unique face, and (3) the similarity score between a probe and a gallery image is a function of only those two images. The ***gallery*** is the set of known individuals. An image of an unknown face presented to the algorithm is called a ***probe***, and the collection of probes is called the ***probe set***.

Projection-based algorithms, the dominant approach to face recognition [7], include PCA and ICA. The structure of these algorithms is amenable to a comprehensive evaluation procedure. In this paper, an algorithm is projection-based if it projects the pixel intensity value onto a new basis, which need not be orthogonal. A projection-based algorithm consists of three steps. The first step is done off-line and determines the new basis for a facial image. The basis is either set by the algorithm designer or learned from a training set. The remaining steps are on-line and identify a face. The second step projects a facial image onto the new basis. The third step identifies a face using a nearest neighbor classifier in the projection space.

II. Design Principles

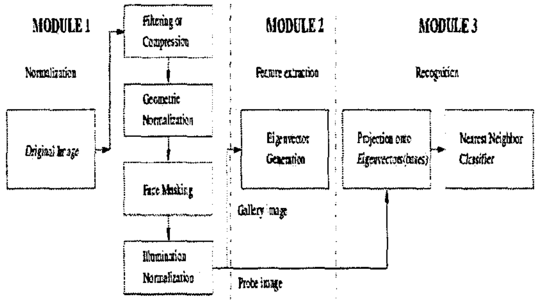

Figure 1. *Generic Modular Face Recognition System*

Both PCA and ICA algorithms were run on images from the FERET database of facial images using the FERET evaluation protocol[1]. The target set consisted of 3816 images and the query set consisted of 3323 images. In all the images, the eyes were manually located. Using the location of the eyes, the faces were translated, rotated, and scaled into a standard position. Once in the standard position, the background, hair, neck, and clothes were masked. From the target and query sets, we evaluated the algorithms of two categories of images. The first is the ***fb*** image. When the FERET database was acquired, two frontal images of each person were taken within five minutes under the same lighting conditions. One of these images is called the ***fa*** image and is in the gallery. The remaining image is the ***fb*** image, which is placed in the probe set. The **fb** test is a baseline test that evaluates the ability of an algorithm to recognize faces taken very close in time. The second category is the ***duplicate I*** images. An image is a duplicate of a person in the gallery, if it was taken on a different day or under different circumstances than the gallery image. The ***fc*** test is designed for various lighting conditions. The FERET database contains ***duplicate II*** images where the time between the first and most recent images is over a year and a half. (see Figure 2)

Figure 2. FERET Database categories of images

To demonstrate the statistical model, we ran the FERET protocol on variations of PCA and ICA algorithms. After the images were transformed into a standard position, they went through a preprocessing step. We experimented with three types of preprocessing: (1) normalizing the images to have mean zero and unit variance, (2) histogram equalization, and (3) histogram equalization followed by normalization.

The recognition algorithms first projected the preprocessed image onto a new basis, then recognizes by the nearest neighbor classifier. PCA projects the image on an orthogonal basis that minimizes the variance in the training set. In our implementation, the training set consisted of 500 images. We used the new basis with the first 128 eigenvectors. Normalized correlation performs recognition in the primal space (the images are not projected onto a new basis). For the nearest neighbor classifier, the normalized ***L1*** distances have been used for both the PCA and ICA algorithm.

III. Principal Component Analysis (PCA) and Independent Component Analysis (ICA)

Principal component analysis (PCA) is a statistical dimensionality reduction method, which produces the optimal linear least squared decomposition of a training set. Kirby and Sirovich [8] applied PCA to representing faces and Turk and Pentland [4] extended PCA to recognizing faces. (For further details on PCA, refer to [3].) In a PCA-based face recognition algoıithm, the input is a training set t_1, ..., t_W of N images such that the ensemble mean is zero ($\sum_i t_i = 0$). Each image is interpreted as a point in $R^{n \times m}$, where the image is n by m pixels. PCA finds a representation in a $(W-1)$ dimensional space that preserves variance. PCA generates a set of $N-1$ eigenvectors e_1, ..., e_{N-1} and eigenvalues $\lambda i, \ldots, \lambda(n-1)$. (In the face recognition literature, the eigenvectors can be referred to as ***eigenfaces***.).

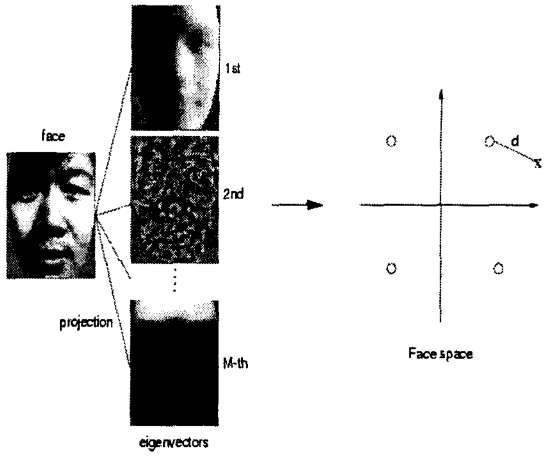

Figure 3. Feature vector generation using projection-based technique (Face Space)

We normalize the eigenvectors so that they are orthonormal. The eigenvectors are ordered so that $\lambda i > \lambda(i+1)$. The λi's are equal to the variance of the projection of the training set onto the *i-th* eigenvector. Thus, the low order eigenvectors encode the larger variations in the training set (low order refers to the index of the eigenvectors and eigenvalues). The face is represented by its projection onto a subset of M eigenvectors, whichis defined as ***face space*** (see Figure 3). Thus the normalized face is represented as a point in a M dimensional face space.

Independent component analysis (ICA) is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals. ICA defines a generative model for the observed multivariate data, which is typically given as a large database of samples. In the model, the data variables are assumed to be linear or nonlinear mixtures of some unknown latent variables, and the mixing system is also unknown. The latent variables are assumed nongaussian and mutually independent, and they are called the independent components of the observed data. These independent components, also called sources or factors, can be found by ICA [5].

ICA can be seen as an extension to principal component analysis and factor analysis. ICA is a much more powerful technique, however, capable of finding the underlying factors or sources when these classic methods fail completely. The data analyzed by ICA could originate from many different kinds of application fields, including digital images and document databases, as well as economic indicators and psychometric measurements. In many cases, the measurements are given as a set of parallel signals or time series; the term blind source separation is used to characterize this problem. Typical examples are mixtures of simultaneous speech signals that have been picked up by several microphones, brain waves recorded by multiple sensors, interfering radio signals arriving at a mobile phone, or parallel time series obtained from some industrial process.

Ⅳ. Experimental Results

In this paper, we conducted experiments that systematically varied the feature extraction step based on PCA and ICA in the second module based on face recognition system shown in Figure 1. Our goal is to understand the effects on identification (cumulative match score) and verification (equal error rate) performance from these variations. It is clear that selecting the feature extraction method is the critical decision in designing a projection-based face recognition system. However, design decision of similarity measure is critical factor based on the feature extraction technique that the system will process.

	fb	fc	Duplicate I	Duplicate II
PCA	92.3%	80.5%	82.4%	74.8%
ICA	95.1%	84.7%	85.6%	78.1%

Table 1. Cumulative Match Score (CMS) for FERET Database based on PCA and ICA features (Top 10 Match Result)

	fb	fc	Duplicate I	Duplicate II
PCA	7.1%	16.2%	14.7%	21.9%
ICA	5.4%	12.3%	11.8%	18.8%

Table 2. Equal Error Rate (EER) for FERET Database based on PCA and ICA features

Ⅴ. Conclusion

In this paper, we have used statistical methods to compare the performance of feature extraction algorithms based on PCA and ICA. This comparison allowed us to make intelligent and informed decisions. We were able to perform the tests based on a statistical model, and the formulation was possible because we stated the assumptions underlying the testing methodology. This is the critical step in applying testing methodologies to computer vision for face recognition system. Future work includes optimization of coefficients selection process based on these statistical features using inter-personal and intra-personal information.

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