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A linear regression based face recognition method by extending probe images

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ABSTRACT

In a general face recognition scenario, classifications attend to assign a label to a single probe image. So far a branch of classification methods, which assume that a probe image tends to lie on the same class-specific subspace as the gallery images from the same class, have drawn wide attention for their good performance. Actually, those linear regression based classifications are sufficient to achieve promising recognition accuracy. However if there are wide ranges of variations on probe images such as pixel noises, lighting variant, they could deviate the probe images from their correct locations in feature space. To solve this problem, we propose a new linear regression based method by generating an extended set for a probe image. In the first step of our method, we not only produce the low dimension features for a probe but also generate virtual samples by adding randomness into downsampling. The second step is to classify the probe by using canonical correlation analysis. As the generated virtual probe samples have high possibility to cover the correct location in feature space, our proposed method shows promising performance in the experiments.

1. Introduction

Face recognition belongs to biometrics identification technology which is one of the hottest research areas in pattern recognition and computer vision since it is of a potential wide application [1,2]. FR is a typical image recognition problem that the query patterns are in form of images. Generally, to recognize an image, it is converted into a vector at first which can be very high dimensional. Besides developing efficient classifier, many studies try to find low dimensional features to represent an image. In other words, it is important to transform a high dimensional image space into some low dimensional feature space where the distribution character of samples is retained as completely as possible [3]. The widely used feature extraction methods include principal component analysis (PCA) [3,4], linear discrimination analysis (LDA) [5], manifold learning methods [6] and etc. PCA can retain most variance information while data are linear transformed into a low dimensional feature space. LDA aims to reduce dimensionality of data while preserving as much of the class discriminatory information as possible [5]. Manifold learning seeks to discover the nonlinear manifold of high dimensional data which assumes that the manifold is of low enough dimension so that in low dimensional feature space the original manifold structure of data is not disrupted. However, according to [7], the authors argued that for the linear regression-based classifiers, such as sparse-representation based classification (SRC), features extracted linearly, including the above mentioned ones, have little difference among them. In other words, even we use very simple feature extraction method as downsampling, it is highly possible that the recognition results are equal to the cases that very complicated linear features are used [8,9]. Therefore some studies suggested that for face recognition issue more attention should be paid to design high robust classifier since simple linear features are competent [10–12]. Usually, a probe sample is with some variations, which makes the feature vector associated with this probe sample deviates from the correct location in the feature space. Since we cannot predict variations in advance, the recognition becomes more challenge for classifiers. To solve this problem, many face recognition methods are proposed to achieve robust classification [7,13].

In this paper we propose a new method to address face recognition problem using the idea of linear regression. We simply use downsampled images as the features for probe samples and training samples because in [10] the authors demonstrated that downsampled images can work very well as features compared

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with other linear features. For a linear regression based classification, a probe sample is represented as a linear combination of training samples by solving a linear regression problem. The training samples from the same class as the probe sample can represent this probe sample better than others since samples belonging to a same class tend to lie on a class-specific subspace. But the unpredicted variations on the probe sample would deviate it from its genuine location in the feature space, which reduces the recognition accuracy of linear regression based classifier. We generate different features for a probe sample by adding randomness into downsampling process. So that it becomes more likely that some of the multiply feature vectors are very close to or even cover the genuine point of the probe sample, which alleviates interference brought by variations on the probe images. Similar to nearest subspace classifier, we try to find a class whose training samples can represent a probe sample best. However, as a single probe sample is extended as a feature set, we need to find two linear combinations for both the feature set of a probe sample and the training sample set of a class. We attend to find the maximum correlation (MC) between those two sets, which can be done by using canonical correlation analysis (CCA). Finally, we decide the label of the probe image in favor of the class with the greatest value of the MC. The paper is organized as follows. Section 2 introduces the approaches that we use to downsample the images and generate a feature set of a probe images. We describe our linear regression based classification in Section 3. The experimental results are shown in Section 4. Section 5 concludes the paper.

2. Features generation and expansion of probe images

2.1. Block-wise downsampling

For a general face recognition system, face images are the available inputs. If a face image is transformed into a vector, this vector has many elements so that the vector is very high dimensional. For example, if a face image with medium resolution could have 100×100 pixel, the directly transformed vector is with the dimension of 10,000, which could lead to the "Curse of Dimensionality" for classifiers. Therefore to extract good features, which should be of strong representativeness and low dimensional, from the image data is very important for a face recognition classification system. As we mentioned in the first section, for linear regression based classifiers downsampled images can be served as features well. Here we introduce an approach to fast downsample high resolution face images. The core idea is to partition an image into small blocks at first and then mix the pixels of a block to generate a new pixel. The downsample feature vector consists of these new pixels.

Without loss of generality, let us assume the size of face images is $ak \times bl$ pixels, where a, b, k, l are positive integers, and the corresponding downsampled image, i.e. the used features, is with the size of $k \times l$ pixels. In other words, we transform the original images into a $k \times l$ dimension feature space, which means the features have $1/ab$ as many elements as the original image. In Fig. 1 we show an example of downsampling an image and the details are described

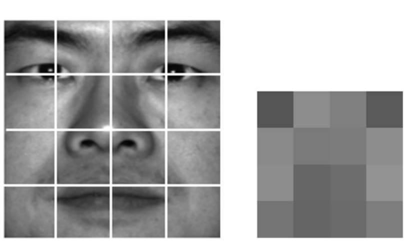

Fig. 1. A face image partitioned into 16 blocks is downsampled to a 4×4 feature image.

as follows: First, we partition the original image into $k \times l$ blocks each of which is an $a \times b$ matrix; second, each block is transformed into a vector by stacking columns of the matrix, $\mathbf{m}_\upsilon \in R^{ab\times 1}$ where $\upsilon = 1, \ldots, kl$ which is the index of blocks; third, the mean value of elements in vector m_υ is used as the υth feature which is referred to as the pixel $p_{i,j}$ in the downsampled image. This approach can be formalized as:

$$p_{i,j} = \mathbf{t} \times \mathbf{m}_\upsilon \tag{1}$$

where $i = 1, \ldots, k$, $j = 1, \ldots, l$, $\mathbf{t} = \left[1/ab, \ldots, 1/ab\right] \in R^{1\times ab}$ which is called mixing vector.

We can also express this approach as a linear dimensionality reduction: Let us express the origin image in a vector form $\mathbf{x} = \left[\mathbf{m}_1^T, \mathbf{m}_2^T, \ldots, \mathbf{m}_{kl}^T\right]^T \in R^{abkl\times 1}$. The feature vector associated with the downsampled image is obtained by

$$\mathbf{a} = T \times \mathbf{x} \tag{2}$$

where $\mathbf{a} = [a_1, a_2, \ldots, a_{kl}]^T \in R^{kl\times 1}$, $T \in R^{kl\times abkl}$ is the transformation matrix that is a block diagonal matrix:

$$T = \begin{pmatrix} t_1 & & 0 \\ & \ddots & \\ 0 & & t_n \end{pmatrix}, \quad t_1 = t_2 = \cdots = t_n = t. \tag{3}$$

We can see that T plays the same role as other transformation matrices which reduce the dimension of original data linearly.

2.2. Generating a feature set of a single probe image

For face recognition, feature extraction is to project the observed facial image from image space into a low dimensional feature space while the distribution and structure of samples should be preserved in the feature space. As we know, it is not avoidable that probe samples are with noises brought by the collection procedure. The typical noises include pose, illumination, pixel corruption, equipment noise, etc. Hence feature vector of a probe sample would deviate from the correct location, which has influence on the recognition accuracy of linear regression based classifiers.

Here we propose an approach to produce multiple different features for a single probe image by adding randomness into downsampling process. The aim of the approach is to rectify the deviation of feature vector of a probe image caused by noises. Specifically, the generated set of features is more likely to approach the correct location of the feature vector corresponding to the probe image without noise. The above idea is demonstrated in Fig. 2.

In the previous section, the mean value of pixels in a block of an original image is used as a pixel in the downsampled feature image. Here, by manipulating the mixing vector $\mathbf{t}$, randomness is added into the downsampling process. In order to highlight the difference with $\mathbf{t}$, we denote $\mathbf{z}$ as the random mixing vector. Each element of $\mathbf{z}$ ($\mathbf{z} = [z_1, \ldots, z_{ab}]$) is sampled from a uniform distribution between 0 and 1, i.e. $\mathbf{z}_j \in [0, 1]$, and $\sum_{j=1}^{ab} z_j = 1$. Then Eq. (1) should be rewritten as

$$p_{i,j} = \mathbf{z} \times \mathbf{m}_\upsilon. \tag{4}$$

In the meantime, we rewrite Eq. (2) as

$$\mathbf{a} = \mathbf{Z} \times \mathbf{x} \tag{5}$$

and

$$\mathbf{Z} = \begin{pmatrix} \mathbf{z}_1 & & 0 \\ & \ddots & \\ 0 & & \mathbf{z}_n \end{pmatrix} \in R^{kl\times abkl} \tag{6}$$