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Robust and Low Rank Representation for Fast Face Identification with Occlusions

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Abstract

In this paper, we address the problem of robust face recognition with undersampled training data. Given only one or few training images available per subject, we present a novel recognition approach, which not only handles test images with large intraclass variations such as illumination and expression. The proposed method is also to handle the corrupted ones due to occlusion or disguise, which is not present during training. This is achieved by the learning of a robust auxiliary dictionary from the subjects not of interest. Together with the undersampled training data, both intra and interclass variations can thus be successfully handled, while the unseen occlusions can be automatically disregarded for improved recognition. Our experiments on four face image datasets confirm the effectiveness and robustness of our approach, which is shown to outperform state-of-the-art sparse representation-based methods.

KEYWORDS: *[Dictionary learning, sparse representation, face recognition]*

I. INTRODUCTION

FACE recognition has been an active research topic, since it is challenging to recognize face images with illumination and expression variations as well as corruptions due to occlusion or disguise. A typical solution is to collect a sufficient amount of training data in advance, so that the above intraclass variations can be properly handled. However, in practice, there is no guarantee that such data collection is applicable, nor the collected data would exhibit satisfactory generalization.

Moreover, for real-world applications, e.g. e-passport, driving license, or ID card identification, only one or very few face images of the subject of interest might be captured during the data acquisition stage. As a result, one would encounter the challenging task of undersampled face recognition. Existing solutions to undersampled face recognition can be typically divided into two categories: patch-based methods and generic learning from external data. For patch-based methods, one can either extract discriminative information from patches collected by different images, or utilize/integrate the corresponding classification results for achieving recognition.

II. OBJECTIVE

Experimental results on four different face image datasets confirmed the effectiveness and robustness of our method, which was shown to outperform state-of-the-art sparse representation and dictionary learning based approaches with or without using external face data.

III. PROBLEM DEFINITION

In particular, assumes that the objective function can be approximated by a first order Taylor expansion with a quadratic residual term. As a result, what RSC minimizes is an approximated version of the original objective function. On the other hand, our approach directly solves the optimization problem by the technique of variable substitution and the chain rule for calculating the derivatives. We note that the derivations of RSC and ours lead to similar algorithms that both iteratively solve a weighted sparse coding problem and update the weight matrix accordingly. However, our derivation guarantees the optimal solution, while the derivation of RSC might result in an approximated one. We note that RSC is extended from SRC, which requires a sufficient amount of training data and thus is not able to handle under sampled recognition problems

IV. PROJECT MODULE

- Low Rank Representation
- K-Singular Value Decomposition
- Dictionary Learning for Sparse Coding
- Robust Auxiliary Dictionary Learning
- K-Nearest Neighbours

a. LOW RANK REPRESENTATION

We address the problem of robust face recognition, in which both training and test image data might be corrupted due to occlusion and disguise. From standard face recognition algorithms such as Eigen faces to recently proposed sparse representation-based classification (SRC) methods, most prior works did not consider possible contamination of data during training, and thus the associated performance might be degraded. Based on the recent success of low-rank matrix recovery, we propose a novel low-rank matrix approximation algorithm with structural incoherence for robust face recognition. Our method not only decomposes raw training data into a set of representative basis with corresponding sparse errors for better modeling the face images, we further advocate the structural incoherence between the basis learned from different classes. These basis are encouraged to be as independent as possible due to the regularization on structural incoherence. We show that this provides additional discriminating ability to the original low-rank models for improved performance.

Motivated by the LRR model on recovering the row space information of observation data, the new model of double LRR is formulated as follows,
Besides illumination, pose, and expression variations, it is possible that one can be taking a scarf, gauze mask, or sunglasses when his/her face image is taken by the camera. When using such images for training, the learned face recognition algorithm might over fit the extreme noise of occlusion instead of modeling the face of the subject, and thus the performance will be degraded. The low-rank matrix recovery (LRR) can be applied to alleviate the aforementioned problem by decomposing the collected data matrix into two different parts, one is a representative basis matrix of low rank and the other is the associated sparse error. The low-rank matrix decomposition, so that the extracted low-rank matrix would preserve the structure of the data and thus the corresponding error matrix will be sparse. The face images are typically with high dimensionality, standard dimension reduction techniques such as PCA can be performed on the derived low-rank matrix A.

b. K -SINGULAR VALUE DECOMPOSITION

SVD-based face recognition method which applies singular value decomposition for face image reconstruction and recognition. It could be viewed as a two-sided 2DPCA method. The matrix inverse of huge image size is also reduced. The face features are stored in the matrix composed of left and right singular vectors of the face image under studies. Let the gray level face images of m rows and n columns from the jth person out of K persons be denoted as

$F(j)\ 1$, $F(j)\ 2$, $\cdots$, $F(j)\ Nj \in Rm\times n$ with $1 \leq j \leq K$ and $N1 + N2 + \cdots + NK = N$, such that $F(j)\ i\ (s, t) \in \{0, 1, \cdots , 255\}$, $1 \leq i \leq Nj$, $0 \leq s \leq m - 1$, $0 \leq t \leq n - 1$.

We search for unit vectors $y \in Rm$ and $x \in Rn$ such that $\alpha = yt\ Ax$ for the average image A from the training set to maximize

$$J(y, x) = \alpha = yt\ Ax \quad (1)$$

The solution from numerical linear algebra supports that the vectors y and x are the left and right singular vectors corresponding to the largest singular value. In practical applications, we first compute the mean image.

$$\Psi = 1\ N\ \ K\ j=1\ \ Nj\ i=1\ F(j)\ i \quad (2)$$

For each image $A \in Rm\times n$, we obtain the left singular vectors $\{yi : 1 \leq i \leq r \leq m\}$ and the right singular vectors $\{xj : 1 \leq j \leq c \leq n\}$ with the singular values $\sigma1 \geq \sigma2 \geq \cdots \geq \sigma k \geq 0$, $k = \min\{m, n\}$.

The face features are stored in the matrix $F \in Rr\times c$ acquired by

$$F = [y1, y2, \cdots , yr]\ t\ A\ [x1, x2, \cdots , xc] \quad (3)$$

For reconstruction,

$$A = \ k\ \ i=1\ \sigma iyixt\ i\ , k \leq \min\{r, c\} \quad (4)$$

Let the gray level face images of m rows and n columns from the jth person out of K persons be denoted as $F(j)\ 1$, $F(j)\ 2$, $\cdots$, $F(j)\ Nj \in Rm\times n$ with $1 \leq j \leq K$ and $N1 + N2 + \cdots + NK = N$, such that $F(j)\ i\ (s, t) \in \{0, 1, \cdots , 255\}$, $1 \leq i \leq Nj$, $0 \leq s \leq m - 1$, $0 \leq t \leq n - 1$.

c. DICTIONARY LEARNING FOR SPARSE CODING

To improve the performance of dictionary learning algorithm with noises, we propose a discriminative low-rank dictionary learning scheme. We learn a sub-dictionary Di for the ith class, then we can get a structured dictionary $D = [D1, D2, \cdots Dc]$, where c is the number of classes. Then classification can be applied based on D. Given a set of training data vectors $Y = [Y1, Y2, \cdots Yc] \in Rd,N$, where Yi is the samples from class i, d is the feature dimension, and N is the number of total training samples. Assume that X is the coding coefficient matrix of Y over D, then we can write $Y = DX + E$, where E is the sparse noises separated by DLRD SR. We can write X as $X = [X1, X2, \cdots , Xc]$, where Xi is the sub-matrix containing the coding coefficients associated with the training samples Yi over D. In the proposed dictionary learning model, we require that the sub-dictionary Di should be pure and compact so that the noises E in training samples Y can be separated, and the structured dictionary D should have powerful discriminative and reconstructive capability of samples Y .

i. Dictionary based on matrix rank minimization

Given the samples Yi from class i, the samples are linearly correlated in many situations. More precisely, the matrix $Yi = [Yi,1, Yi,2, \cdots Yi,Ki\ ]$ should be approximately low-rank, where Ki is the number of the samples. This assumption holds generally, for example, according to the work of Basri and Jacobs , images of convex and Lambertian objects which taken under different illumination lie near an approximately nine-dimensional linear subspace that known as the harmonic plane. Based on sparse representation, we seek a low-rank subdictionary Di in which the bases can be linearly combined to represent the samples from class i. In practice, the low rank structure can be easily violated with occluded or corrupted samples. So, a matrix E should be added to approximate the sparse error. Take sub-dictionary Di as an example, the following model is proposed for dictionary learning:

$$\text{Min } Di, X, Ei\ Xi0 + \alpha\text{rank}\ (Di) + \beta\ Ei0$$

$$Yi = D\ Xi + Ei$$

where Xi is the coding coefficients of Yi over D, Ei is the error matrix corresponding to Yi, α and β are positive weighting parameters that trade off the rank of the subdictionary and the additive error.

ii. Dictionary based on Discriminative Learning

The coding coefficients of Yi over D can be written as $Xi = [Xi,1; Xi,2; \cdots ; Xi,C\ ]$, where Xi,j is the coding coefficient of Yi corresponding to Dj. The discriminative power of Di comes from following: First, the sub dictionary Di should be able to well represent Yi, and there is $Yi = DiXi,i + Ei$.

Second, for the samples from class $j(j = i)$, Xj, i should have nearly zero coefficients such that r(Di) =

C j=1,j=i DiXj,i2 F is small, which means that the correlation between Di and Yj (j = i) should be updated to be small . Then problem can be developed to the following problem:

min Di ,Ei, Xi Xi0 + αrank(Di) + β Ei0 + λr(Di) s.t. Yi = D Xi + Ei, Yi = DiXi,i + Ei

Solving problem is difficulty with the rank function and 0-norm, recent researches in low-rank completion and sparse representation suggest that we can replace the rank function by the convex surrogate, that's Di∗ for rank (Di), and replace Xi1 for Xi0, Ei1 for Ei0 under certain condition. Thus, problem yields the following optimization problem:

min Di ,Ei, Xi Xi1 + α Di∗ + β Ei1 + λr(Di) s.t. Yi = D Xi + Ei, Yi = Di Xi + Ei

where .∗ denotes nuclear norm of a matrix(i.e., the sum of singular values of the matrix), .1 denotes the sum of absolute values of matrix entries.

d. K-NEAREST NEIGHBORS

A novel fast k-nearest neighbor (k-NN) search method is proposed for the face identification task. It is well suited for this task because it works well with high dimensionality, it can be used with various similarity scores such as inner product, Euclidean distance, and correlation coefficient, it can achieve not only fast exact k-NN search but much faster approximate search, and it does not require any training or special data structure, resulting in low maintenance cost for the target database. Similarity scores between query and target samples are aggregated sequentially along with their dimensions, and target samples with no possibility of being included in k-NNs are rejected. The possibility is evaluated on the basis of the upper and lower bounds of the score for residual dimensions. Experimental results for a face database demonstrated that the proposed method achieves equal or better accuracy than other methods and is ten times faster than an exhaustive search with no degradation in the rank-k identification rate.

The goal of face identification is to determine the identity of the person corresponding to a query facial image by comparing the image to previously registered target facial images. This face identification technology is widely used in many systems, such as surveillance systems. In many state-of-the-art face identification methods, a facial image is represented as a feature vector, and the similarity between a query face and a target face is evaluated on the basis of the similarity score between the feature vectors. A k-nearest neighbor (k-NN) search is then used to extract the k target images corresponding to the top- k similarity scores. The extracted target images are used to determine the identity of the person corresponding to the query image. How to find such target images, that is, how to conduct the k-NN search, is more important in large-scale face identification because the calculation cost increases with the number of target images. In many practical cases, even a small degradation in accuracy is undesirable, so accurate as well as fast k- NN search is greatly required.

V. CONCLUSION

We presented a novel learning-based algorithm for undersampled face recognition. We advocated the learning of an auxiliary dictionary from external data for modeling intra-class image variants of interest, and utilized a residual function in a joint optimization formulation for identifying and disregarding corrupted image regions due to occlusion. As a result, the proposed algorithm allows one to recognize occluded face images, or those with illumination and expressions variations, even only one or few gallery images per subject are available during training.

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