LOW RANK GROUP SPARSE REPRESENTATION BASED CLASSIFIER FOR POSE VARIATION

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ABSTRACT

Face recognition under uncontrolled environment persists to be an unresolved problem having challenges such as varying pose, illumination, occlusion etc. In this research, we propose an algorithm for identification of faces with pose and illumination variations. An adaptive dictionary learning framework built upon group sparse representation classifier is presented in order to learn dictionary parameters and pose invariant sparse codes for given images. Low rank regularization is utilized for dictionary learning, to address the noise present in training samples that can hinder the discriminative power of the learnt dictionary. Experimental results illustrate state-of-the-art performance on the CMU Multi-PIE dataset.

Index Terms— Dictionary, Group Sparse Representation based Classifier, Low Rank, Pose and Illumination variation

1. INTRODUCTION

Face recognition has been the focus of many biometrics researchers since the past few decades [1]. Face has been observed to be one of the least invasive biometric modalities, thereby, making it one of the most well explored signatures for person identification as well. It provides discriminative textural and structural information, which is often used for identity recognition. Many algorithms have been proposed to automate this task under several covariates such as varying resolution, occlusion, and disguise [2, 3, 4]. Though recent algorithms claim high accuracies [5, 6], the performance of the same in real-world conditions is still an unresolved issue.

One of the major challenges associated with automated face recognition in completely unconstrained scenarios is the presence of pose and illumination variations. Algorithms that utilize only frontal, well-illuminated face images for learning a classification model are often ineffective in the presence of such variations. This is primarily because the distribution of data on which the classifier is trained might differ from the distribution of the test samples. Fig. 1 shows sample images of an individual with varying pose and illumination. Such variations can often affect the performance of automated face recognition systems. One possible solution to address this is to obtain large amount of training samples for all possible variations, which in itself is a challenging task. This generates a need for a less data-intensive algorithm that can handle such variations in the data distribution.

Fig. 1. Sample images of a subject from CMU Multi-PIE dataset [7] with pose and illumination variations. First row shows illumination variations and second row shows the pose variations.

In this research, a Low Rank Group Sparse Representation based Classifier (LR-GSRC) is proposed for face recognition with pose and illumination variations. The algorithm is built upon the existing Group Sparse Classifier [8] and utilizes incremental learning [9] with trace norm regularizer [10] for addressing the given problem. In Dictionary Learning approaches, images are represented as a linear combination of atoms of a dictionary. Generally, for a given dictionary, the total number of atoms are large as opposed to the atoms used for the reconstruction of a given image, which results in sparse coefficients for the image. Recently, Group Sparse Classifier has been proposed which assumes that a test sample can be represented as a linear combination of training samples belonging to the same group as that of the given test sample. Since the samples are linearly correlated, the dictionary for a particular group should fall in a low dimensional manifold [11, 12]. To enforce this, a trace norm regularizer on the group-wise dictionaries is introduced in the dictionary learning protocol. As mentioned earlier, since the distribution of the test samples (target domain) might differ from the distribution of the training samples (source domain), the above framework is learnt in an incremental manner.

The paper is organized as follows: Section 2 briefly describes the existing work on this problem, which is followed by the proposed algorithm in Section 3. Section 4 gives details about the experimental setup and results of the proposed algorithm, as well as comparison with existing approaches. Conclusion and future work are presented in Section 5.

2. RELATED WORK

In literature, approaches applied to face recognition with pose and illumination variations include methods like 3-D face reconstruction, image mosaicing, deep learning and domain adaptation. Passils *et al.* [13] have proposed learning a 3-D model for face recognition using facial symmetry across different poses. Zhu *et al.* [14] aim to learn face Identity-Preserving features (FIP) using deep learning, however, as is the case with deep learning, this approach requires large amount of training data. Singh *et al.* [15] describe a face mosaicing scheme to generate a composite face from frontal and semi-profile faces. Qiu *et al.* [9] proposed a dictionary learning framework, Domain Adaptive Dictionary Learning (DADL), to transfer information from source domain to target domain for re-identification of faces. This algorithm addresses the problem of variation in data distribution between source and target domain but it is unable to handle any variation within the target domain itself. The next section presents the proposed algorithm, which aims to overcome these shortcomings.

3. LOW RANK GROUP SPARSE REPRESENTATION BASED CLASSIFIER (LR-GSRC)

This section describes the proposed algorithm, prior to which some background knowledge about sparse coding, dictionary learning and group sparse representation based classifier is discussed.

3.1. Sparse Representation and Dictionary Learning

Sparse modeling of data has attracted a lot of attention in the past few years. In dictionary learning algorithms, images are represented as a linear combination of few atoms of a dictionary. Given a signal y and dictionary D, sparse representation of y can be learned through the following optimization problem:

$$\hat{x} = \arg\min_{x} \|x\|_o \text{ subject to } y = \mathrm{D}x \qquad (1)$$

where, $\|x\|_o$ refers to l_o norm that gives the number of nonzero entries in vector x.

Recently, many new approaches have been discussed to learn an efficient dictionary [16, 17] from the given data which has mainly been influenced by recent advances in sparse algorithms and representation theory. One of the established methods of learning a dictionary from training samples is the K-SVD algorithm [18]. Given a sample y, K-SVD aims to learn a dictionary D and its sparse code x such that the reconstruction error is minimized:

$$\arg\min_{D,X} \|Y - DX\|_F^2 \quad \textit{s.t.} \vee_i,\ \|x_i\|_o \leq T \qquad (2)$$

where, $X = [x_1, ..., x_N]$ are sparse codes of N input signals Y, such that $x_i \in R^m$, where m represents the dimension of the input signal. $D = [d_1, ..., d_k]$ is the dictionary learnt with where k represents the number of atoms in the dictionary and $d_i \in R^m$. T restricts the signal to have less than T items in its decomposition.

3.2. Group Sparse Representation based Classification

Sparse Representation based Classification (SRC) [19] is an established approach which assumes that a given test sample can be represented as a linear combination of training samples belonging to the same class as the given test sample:

$$v_{test} = \alpha_{k,1}v_{k,1} + \alpha_{k,2}v_{k,2} + ... + \alpha_{k,n}v_{k,n} + \epsilon \qquad (3)$$

where, v_{test} belongs to class k, $v_{i,k}$ represents i^{th} training sample from k^{th} class, and ϵ is the approximation error.

Since the correct class of v_{test} is not known at the time of classification, therefore, SRC represents v_{test} as a linear combination of the training samples from all classes. For classification, SRC aims to learn the coefficients α in eq.(3) for v_{test} such that α values for the correct class are non-zero while the remaining values are zero. This results in a sparse vector for α which is solved by the following minimization problem:

$$\min_{\alpha} \|v_{test} - V\alpha\|_2^2 + \lambda \|\alpha\|_1 \qquad (4)$$

Majumdar *et al.* [20] and Elhamifar *et al.* [21] have claimed that l_1-norm does not explicitly impose the sparsity constraint, instead, it can be better enforced using supervised $l_{2,1}$-norm. Thus, the minimization problem changes to:

$$\min_{\alpha} \|v_{test} - V\alpha\|_2^2 + \lambda \|\alpha\|_{2,1} \qquad (5)$$

Using SRC as basis, Group Sparse Representation based Classification [8] aims to handle multiple data sources and features for each data point:

$$v_{test}^i = \alpha_{k,1}^i v_{k,1}^i + \alpha_{k,2}^i v_{k,2}^i + ... + \alpha_{k,n}^i v_{k,n}^i + \epsilon \qquad (6)$$

where, v_{test}^i refers to i^{th} modality of the test sample v_{test}.

The following subsection builds upon these pre-requisites and presents the proposed algorithm.

3.3. Proposed Algorithm

In this subsection, the proposed algorithm, Low Rank Group Sparse Representation based Classification (LR-GSRC) is presented for face recognition. Some notations that are needed to facilitate further discussions are given below.

Let Y_s = [$Y_{1,s}$, $Y_{2,s}$,....,$Y_{c,s}$] contain all samples from source domain, with a total of N_s instances from c different classes. Hence, $Y_{i,s} \in R^{n*ms_i}$, where n is the dimension of the samples and ms_i refers to the i^{th} class size in the source domain. Similarly, Y_t = [$Y_{1,t}$, $Y_{2,t}$,....,$Y_{c,t}$] contains samples from the target domain such that $Y_{i,t} \in R^{n*mt_i}$. From Y_s, a dictionary D_j is learnt for each class j, such that D = [D_1,D_2,..,D_c] and $D_j \in R^{n*p}$. Here p represents the number of atoms in the dictionary.

For Group Sparse Classifier with i groups in the source domain, Y_t^i represents the instances from target data belonging to the i^{th} group and D_j^i represents dictionary from the i^{th} group and j^{th} class. Our aim here is to incrementally learn group sparse coefficients and dictionary such that at k^{th} iteration dictionary $D_{*,k}$ is closer to the target domain as compared to the $(k-1)^{th}$ iteration dictionary. Here $D_{*,k}$ refers to the dictionary $D = [D_1, D_2, .., D_c]$ learnt at k^{th} iteration for all classes c in the data.

3.3.1. Training

Given Y_t and Y_s (instances from target and source domains respectively), the algorithm is as follows:

Step 1: Learn the source dictionary $D_{*,o}$ using samples from Y_s. Using this dictionary as initial point, our aim is to incrementally learn group sparse coefficients α and target dictionary that gives the best representation for the target domain.

Step 2: Given source dictionary $D_{*,o}$, α for GSRC is learnt using the following formulation:

$$\min_{\alpha} \left\|Y_t^i - D_{*,k}^i \alpha^i\right\|_2^2 + \lambda \left\|\alpha^i\right\|_{2,1} + \sum_j \left\|D_{j,k}^i\right\|_* \tag{7}$$

here, $\|a\|_*$ refers to trace norm that is used as low rank regularization on dictionary. $D_{j,k}^i$ represents dictionary for i^{th} group and j^{th} class at k^{th} iteration.

Step 3: $D_{*,k}$ is updated for the next intermediate domain $k+1$ to incrementally adapt to the target data [9]. $D_{*,k+1}$ is learnt on the basis of its coherence with the dictionary in k^{th} domain and residual of instances in Y_t. The residual, $Z_{*,k}$, is obtained using the following equations:

$$X_{*,k} = \arg\min_X \|Y_t - D_{*,k}X\|_F^2 \,, s.t. \vee_i, \|p_i\|_o \leq T \tag{8}$$

$$Z_{*,k} = \|Y_t - D_{*,k}X_{*,k}\|_F^2 \tag{9}$$

here, $X_{*,k} = [p_1, ..., p_{N_t}]$ refers to the sparse coefficients of data instances in Y_t, obtained using the dictionary from k^{th} iteration. p_i refers to sparse coefficients of data instances belonging to class i. The updation in $D_{*,k}$ atoms, Δ $D_{*,k}$, to obtain $D_{*,k+1}$ is formulated using the following minimization:

$$\min_{\Delta D_{*,k}} \|Z_{*,k} - \Delta D_{*,k}X_{*,k}\|_F^2 + \lambda \|\Delta D_{*,k}\|_F^2 \tag{10}$$

The first term is responsible for adjustments in atoms of dictionary $D_{*,k}$ in order to decrease the residual reconstruction error $Z_{*,k}$. The second term is used to control sudden changes in dictionary atoms between current domain and next domain. Hence, $D_{*,k+1}$ can be formulated using:

$$\Delta D_{*,k} = Z_{*,k}X_{*,k}^T(\lambda I + X_{*,k}X_{*,k}^T)^{-1} \tag{11}$$

$$D_{*,k+1} = D_{*,k} + \Delta D_{*,k} \tag{12}$$

The above two steps are repeated to learn intermediate representations till the best representative dictionary of the target data is obtained. This is enforced by a stopping criteria: $\|\Delta D_{*,k}\|_F < \delta$. This complete approach has been summarized in Algorithm 1.

Data: Source dictionary $D_{*,o}$ learnt after step 1, target data Y_t, sparsity level T,
Result: $D_{*,k}$ and α for intermediate domains
initialization;
do
1. Learn group sparse coefficients α for dictionary $D_{*,k}$ using equation (7)
2. Obtain $Z_{*,k}$ from Y_t and $D_{*,k}$ using equations (8) and (9)
3. Update atoms in $D_{*,k}$ to get next intermediate domain $D_{*,k+1}$ using (10), (11) and (12) ;

while $\|\Delta D_{*,k}\|_F < \delta$;

Algorithm 1: Low Rank GSRC

3.3.2. Testing

For a given test sample, following steps are followed:

Step 1: For each class c, reconstruct a sample $v_{recon}(c)$ by the linear combination of training samples from that class:

$$v_{recon}(k) = V_k \alpha_k \tag{13}$$

Step 2: Calculate error between the given test sample and reconstructed sample.

Step 3: Assign the test sample to the class having minimum reconstruction error.

4. EXPERIMENTS AND RESULTS

Experiments are performed on a subset of CMU Multi-PIE dataset [7] consisting of 20 images per subject with varying pose and illumination conditions. This subset was further

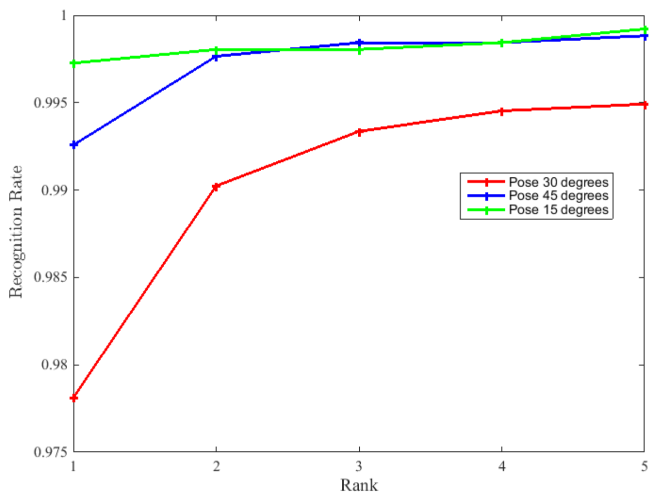

Fig. 2. CMC curve of the proposed algorithm with each target domain (pose) individually.

divided into source and target domains. The source domain was only used for training while the target domain was divided into mutually exclusive training and testing sets. The source domain contained instances having pose variations of 0°, 45° and -45°. For each user, the source dictionary is learnt on this data. The target domain contained instances having pose variations of 30°, 15° and -30°. Using the proposed algorithm, the learnt dictionaries are adapted to get the best representation of the target domain, individually. The trained and adapted classifier is tested on data consisting of face images having pose variations of 15°, 30° and 45°.

Comparison has been drawn with existing algorithms, such as Generalized Multiview LDA (GMLDA) [22], Fisher Discriminant Dictionary Learning (FDDL) [23], Shared Domain-adaptive Dictionary Learning (SDDL) [24], and individual descriptors such as Histogram of Oriented Gradients (HOG) [25] and Local Binary Pattern (LBP) [26]. Comparison has also been drawn with a commercial-off-the-shelf (COTS) system, Verilook [27]. The key results obtained are reported below:

- From Table 4, it can be seen that individual descriptors such as Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP) work well for slight variation in pose, such as 15°, (90.5% and 90.3% at rank-1), however, their performance goes down as the variation increases. HOG achieves a rank-1 identification accuracy of 76.3% for 30° pose variation, while an accuracy of 84.7% for 45° pose variation is obtained. On the other hand, LBP achieves a rank-1 accuracy of 85.5% and 85.7% for 30° and 45° respectively.
- COTS (Verilook) achieves a rank-1 identification accuracy of 93.3%, 95.5% and 90.1% for 15°, 30° and 45° pose variations respectively.
- From Table 4, it is observed that the proposed algorithm outperforms existing state-of-the-art algorithms for poses at 15° and 45° by obtaining an accuracy of 99.7% and 99.3% respectively. Also, it performs well for pose variations of 30° by reporting an accuracy of 97.8%. The cumulative match characteristic (CMC) curves obtained for the given setup are given in Fig. 2.

Table 1. Rank-1 accuracy (%) comparison of proposed algorithm with other existing domain adaptation algorithms for pose variations. Accuracies of existing algorithms have directly been taken from Shekhar *et al.* [24].

Method	15^o	30^o	45^o
HOG [25]	90.5	76.3	84.7
LBP [26]	90.3	85.5	85.7
COTS [27]	93.3	95.5	90.1
GMLDA [22]	99.7	**99.2**	98.6
FDDL [23]	96.8	90.6	94.4
SDDL [24]	98.4	98.2	98.9
LR-GSRC	**99.7**	97.8	**99.3**

These results motivate the use of trace-norm with group sparse classifier for incremental dictionary learning. The performance of the proposed algorithm for face recognition with varying pose and illumination conditions encourages the usage of LR-GSRC for domain adaptation as well.

5. CONCLUSION

In this research, a novel framework for addressing the problem of face recognition with pose and illumination variations has been proposed. The algorithm, Low Rank Group Sparse Representation based Classifier (LR-GSRC), learns group-sparse coefficients on low-rank dictionaries. Results on the CMU Multi-PIE dataset support the effectiveness of the algorithm and encourage it's usage for other similar problems as well.

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