Collaborative Representation for Face Recognition based on Bilateral Filtering

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Abstract

A great deal of research has shown that sparse representation based classification (SRC) is a powerful tool for face recognition. Sparse coding is an unsupervised learning algorithm that learns a succinct high-level representation of the inputs, given only unlabeled data; representing each input as a sparse linear combination of a set of basic functions, whereas the importance of sparsity is greatly affirmed in SRC and in abundant relevant research. Most researchers neglected the collaborative representation (CR) in SRC. In this paper, a modified and efficient approach for face recognition is proposed, based on combining two of the most successful local face representations, collaborative representation based classification and regularized least square (CRC_RLS) with bilateral filtering (BF). The combination of the two yield considerably better performance than either when implemented alone. Furthermore, experiments and their results show that the proposed method in this work outperforms several alternative methods.

Keywords: *Sparse representation, Collaborative Representation, Bilateral Filtering.*

1. Introduction

Face recognition is an active topic of research in computer vision and pattern recognition driven by its wide range of practical applications in access control, identification systems, surveillance, pervasive computing, social networks, etc. This is due to the fact that present methods perform well under relatively controlled environments but tend to suffer when variables (such as pose, illumination, etc.) exist. The sparse representation-based classification (SRC) is widely used among face recognition schemes and various extensions to the basic sparse algorithms have been published in recent years.

The main aim of SRC is to represent a given test sample as a sparse linear combination of all training samples, then classify the test sample by evaluating which class leads to the least error. Wright et al. introduced a framework for robust face recognition via sparse representation [1]. Zhou et al. [2], the Al. Application applies the Markov random field to existing face recognition SRC to improve performance under severe neighboring blockage. Yang and Zhang [3] used image Gabor-features for SRC in order to reduce the cost in coding occluded faces while meanwhile improving accuracy. Yang et al. reviewed five representative l_2-minimization methods in the context of SRC-based face recognition [4].

Moreover after (SRC) had become a prominent technique in face recognition, a new approach emerged from it, adopted by Lei Zhang et al. [5]; they proposed a classification scheme, namely CR based classification with regularized least square (CRC_RLS), which has significantly less complexity than SRC. Sparse representation (or coding) codes a signal $\boldsymbol{y}$ over a dictionary β such that $y \approx \beta x$ and x is a sparse vector, while collaborative representation (CR) uses the training samples from all classes to represent the query sample $\boldsymbol{y}$ [6]. In this paper we propose a new approach to face recognition based on CRC_RLS and bilateral filtering (BF). Collaborative representation (CRC)-based Classification is a new algorithm for digital image classification. CRC_RLS is noteworthy for its resilience to corruption and occlusion in face recognition. Bilateral filtering (BF) , an edge-preserving diffusion filter, was introduced in image processing and computer vision literature as an efficient tool to combat noise [6].

The edge-preserving property comes from the use of a range kernel (along with the spatial kernel) to control the diffusion in the vicinity of edges. In this paper, the bilateral filter (BF) is used where both the spatial and range kernels are Gaussian in order to highlight more features of images followed by use of CRC_RLS to classify images into face recognition. This algorithm can attain a recognition rate for FR better than using other algorithms, such as NN, LRC, SVM, SRC and CRC_RLS. The paper is organized as follows. The new proposed algorithm of the CRC_RLS+BF is introduced in section 2. Section 3 describes extensive experiments of CRC_RLS+BF algorithm on FR, and some conclusions are presented in section 4.

2. Collaborative Representation Method Based on Bilateral Filtering

In this section, we review the general framework of the collaborative representation method based on classification and bilateral filtering.

2.1 Collaborative Representation Based Classification (CRC).

The idea of the CR-based classification (CRC) scheme is based primarily on the role of collaboration between classes in representing the query sample.
In order to collaboratively represent the query sample X with low computational burden, it is proposed to use the regularized least square method. [6], i.e.

$$(\hat{\rho}) = argmin_{\rho}\{\|y - X \cdot \rho\|_2^2 + \lambda\|\rho\|_2^2 \qquad (1)$$

where λ is the regularization parameter. The role of the regularization term is twofold. First, it makes the least square solution stable, and second, it introduces a certain amount of sparsity to the solution $\hat{\rho}$, yet this sparsity is much weaker than that by l_1-norm. The solution of CR with regularized least square in Eq.(1) can be easily and analytically derived as

$$\hat{\rho} = (X^T X + \lambda \cdot I)^{-1} X^T y \qquad (2)$$

Let $P = (X^T X + \lambda \cdot I)^{-1} X^T y$. Clearly, P is independent of y so that it can be pre-calculated as a projection matrix. Once a query sample y is obtained, one can just simply project y onto p via Py. This makes CR very fast. The class specific representation residual $\|y - X_i \cdot \hat{\rho}_i\|_2$, where $\hat{\rho}_i$ is the coefficient vector associated with class i, the l_2 -norm "sparsity" $\|\hat{\rho}_i\|_2$ can also provide some discrimination information for classification. Therefore we propose to use both of them in classification. Based on our experiments, this improves the classification accuracy slightly over that by using only the representation residual. The proposed CRC with regularized least square (CRC_RLS) algorithm is shown as below [5].

Algorithm 1. The CRC_RLS Algorithm

1. Normalize the columns of X to have unit l_2-norm.
2. Code y over X by $\hat{\rho} = Py$ Where $P = (X^T X + \lambda \cdot I)^{-1} X^T y$.
3. Compute the regularized residuals $r_i = \|y - X_i \cdot \hat{\rho}_i\|_2 / \|\hat{\rho}_i\|_2$.
4. Output the identity of y as $Identity\ (y) = argmi_i\{r_i\}$.

2.2 Bilateral Filtering.

A bilateral filter (BF) is an edge-preserving smoothing filter. Whereas many filters are convolutions in the image domain, a bilateral filter also operates in the image's range—pixel values. Rather than simply replacing a pixel's value with a weighted average of its neighbors, as for instance the Gaussian filter does, the bilateral filter replaces a pixel's value by a weighted average of its neighbors in both space and range (pixel value). This preserves sharp edges by systematically excluding pixels across discontinuities from consideration. Next, the Gaussian bilateral filter is described, which is described as follows:

$$\tilde{f}(x) = \frac{1}{\eta}\int_{\Omega} k_{\sigma s}\ (x - y) k_{\sigma r}\ (f(x - y) - f(x)\ ) f(x - y)\mathrm{dy} \qquad (3)$$

Where

$$\eta = \int_{\Omega} k_{\sigma s}\ (x - y) k_{\sigma r}\ (f(x - y) - f(x)\ )\mathrm{dy}\ .$$

Here, $k_{\sigma s}$ is the centered Gaussian distribution on the plane with variance σ_s^2 , and $k_{\sigma r}(s)$ is the one-dimensional Gaussian distribution with variance σ_r^2; Ω is the support of $k_{\sigma s}(x)$ over which the averaging takes place. $k_{\sigma s}(x)$ and $k_{\sigma r}(s)$ are called the spatial and the range kernel.

Fig. 1. First column original images and second column image of Bilateral Filtering

2.3 The Proposed Method.

Based upon the bilateral filter (BF) and collaborative representation based classification with regularized least square (CRC_RLS) reviewed before, in this section, a new face recognition method is proposed, which is built on combining BF with CRC_RLS to improve the classification accuracy. Specifically, the computation of a bilateral (BF) filter is extremely slow; therefore, a very fast acceleration algorithm is used, keeping the error below a level recognizable by the human visual system. This algorithm was introduced by K. Chaudhury [7], which is called SHIFTABLE-BF algorithm. The detailed procedure of the (BF+CRC_RLS) is described in Algorithm 2.

Algorithm 2. The CRC_RLS Algorithm

1. Normalize the columns of X to have unit l_2-norm.
2. Use SHIFTABLE-BF algorithm to compute the bilateral filter (BF).

3.Code y over X by $\hat{\rho} = Py$ Where $P = (X^T X + \lambda \cdot I)^{-1} X^T y$.

3. Compute the regularized residuals $r_i = \|y - X_i \cdot \hat{\rho}_i\|_2 / \|\hat{\rho}_i\|_2$.

4. Output the identity of y as $Identity\,(y) = argmi_i\{r_i\}$.

3. Experiments Evaluated

In this section, the proposed method is evaluated on two face databases, including Extended Yale B [8][9], AR [10] and compared it with other existing methods, including CRC_LRC [5], SRC [11], SVM, LRC [12] and NN. Three kinds of experiments are performed as follows:

3.1 Gender Classification.

AR database [10] consisting of 50 male and 50 female subjects is utilized. Images of the first 25 males as well as females are used for training and the remaining images for testing. The dimensions of each image, are reduced to 300 by using PCA. A comparison of the performance of the proposed method (BF+CRC_RLS) with the SRC, SVM, LRC and NN, is shown together with the results in Table 1.

Table 1: The Gender Classification Rate Comparison to Several Methods Using (AR) Database.

BF+CRC_RLS	CRC_RLS	SRC	SVM	LRC	NN
98.8%	93.7%	92.3%	92.4%	27.3%	90.7%

Fig. 2. Image variations of samples from the AR database

3.2 Face Recognition.

To verify the effectiveness of the proposed method (BF+CRC_RLS) on FR, two experiments were conducted and Eigenface was used as the face feature. The first one was used on the Extended Yale B [8][9] database which includes 2,414 frontal face images of 38 individuals. Face images were taken under varying illumination conditions, and the database was randomly divided into two sets and the images were cropped and resized to 54×48. In the first set, for each person, 32 images are selected as the dictionary, and the other set was used for testing. Table 2 shows the results versus feature dimension; evidently, the proposed method significantly outperforms NN, LRC, SVM, SRC and CRC_RLS.

Table 2: Face Recognition Rates on the Extend Yale B Database.

Dim	84	150	300
NN	85.8%	90.0%	91.6%
LRC	94.5%	95.1%	95.9%
SVM	94.9%	96.4%	97.0%
SRC	95.5%	96.8%	97.9%
CRL_RLS	95.0%	96.3%	97.9%
BF+ CRL_RLS	**96.7%**	**98.6%**	**100%**

A second experiment was performed on AR [10] database, which contains 50 male subjects and 50 female subjects (with illumination and expression changes only) and cropped to 60×43. From Session 1, the seven images were used for training and from Session 2 the seven images were used for testing. Table 3 shows the comparative results, which establish the superiority of the proposed method as compared with the methods NN, LRC, SVM, SRC and CRC_RLS. It can be seen that BF+CRC_RLS achieves results better than the other methods in all dimensions.

Table 3: Face Recognition Rates on the AR Database

Dim	54	120	300
NN	68.0%	70.1%	71.3%
LRC	71.0%	75.4%	76.0%
SVM	69.4%	74.5%	75.4%
SRC	83.3%	89.5%	93.3%
CRL_RLS	80.5%	90.0%	93.7%
BF+ CRL_RLS	**96.4%**	**95.5%**	**98.8%**

5. Conclusion

In this paper, a method for the face recognition was designed and developed by combining bilateral filter (BF) with collaborative representation based classification and regularized least square (CRC_RLS). Experiments were conducted on representative face image databases: Extended Yale B and AR to evaluate the method . Eigenfaces was first applied to reduce the dimensionality of face images and then the designed method was compared (BF+CRC_RLS) with NN, LRC, SVM, SRC and CRC_RLS, in terms of classification accuracy and yielded very impressive results.

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