Pose Variant Face Recognition using SPARSE l1- Regularized LS

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Summary
As a recently proposed technique, sparse representation based classification (SRC) with l1-normminimization has been widely used for frontal face recognition (FFR). SRC first codes a testing sample as a sparse linear combination of all the training samples, and then classifies the testing sample by evaluating which class leads to the minimum representation error. But, it is really not the l1-norm sparsity that improves the FR accuracy.This paper analyzes the working mechanism of SRC, and indicates that it is the l1-regularized least squares formulation, with nonnegative constraints, that makes SRC powerful for face classification. Consequently, we propose a very simple yet much more efficient face classification scheme, for pose variant database namely ORL database with least square (LS). The extensive experiments clearly show that this scheme has very competitive classification results.

Keywords:
Face recognition, feature extraction, sparse representation, l1 minimization.

1. Introduction

In recent years sparse coding or sparse representation has been widely studied to solve the inverse problems in various image restoration applications [1-2], image recognition and classification applications, due to the progress of l0-norm and l1-norm minimization techniques [3-4]. Sparse representation has also been used in pattern classification.
In [5] sparsely coded a signal over a set of redundant bases and classified the signal based on its coding vector. In [6], a query face image is first sparsely coded over the template images, and then the classification is performed by checking which class yields the least coding error. Such a sparse representation based classification (SRC) scheme achieves a great success in FR, and it boosts the research of sparse based pattern classification. In [7] used the Gabor features for SRC with li1-norm, and in[8] combined sparse coding with linear spatial pyramid matching for image classification.
In sparse representation based FR, usually we assume that the face images are aligned and those images are frontal only, but always this is not the case in practice. Dealing with pose variant is important and challenging. Recently, sparseRepresentation has been extended to solve the misalignment or pose change. The method used in [9] is invariant to image-plane transformation. The method in [10] could deal with misalignment and illumination variation. Pose variant images can be sparsely represented, which is attractive since sparse leads to efficient estimation, dimensionality reduction, and efficient modeling.
The rest of the paper is organized as follows. Sec. 2 discusses Sparse Representation. In Sec. 3, we propose a solution for pose variant face recognition by finding a sparse representation using the l1-regularized least squares. The experiments are described in Sec. 4, where the proposed approach demonstrates excellent performance in accuracy. Section 5 shows experimental results and finally we conclude the paper in Sec. 6.

2. SPARSE Representation

2.1 Background

Sparse representation is the representations that account for most of information with a linear combination of a small number of elementary signals called atoms. Often, the atoms are chosen from a so called over-complete dictionary. Formally, an over-complete dictionary is a collection of atoms such that the number of atoms exceeds the dimension of the signal space, so that any signal can be represented by more than one combination of different atoms. Decoding merely requires the summation of the relevant atoms, appropriately weighted. In other way, the technique of finding a representation with a small number of significant coefficients is often referred to as Sparse Coding.
Sparseness is one of the reasons for the extensive use of popular transforms such as the Discrete Fourier Transform, the wavelet transform and the Singular Value Decomposition. The aim of these transforms is often to reveal certain structures of a signal and to represent these structures in a compact and sparse representation. Sparse representations have therefore increasingly become recognized as providing extremely high performance for applications as diverse as: noise reduction, compression, feature extraction, pattern classification and blind sourceseparation.

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2.2 Representation

Consider a linear system [12] of equations $x = D\alpha$ where D is a $m \times p$ matrix $(m \ll p)$ and $x \in R^m, \alpha \in R^p. D,$ called as the dictionary or the design matrix. The problem is to estimate the signal $\alpha,$ subject to the constraint that it is sparse. The underlying motivation for sparse decomposition problems is that even though the observed values are in high-dimensional (m) space, the actual signal is organized in some lower-dimensional subspace $k \ll m$.

Sparsity implies that only a few components of x are non-zero and the rest are zero. This implies that x can be decomposed as a linear combination of only a few $m \times 1$ vectors in D, called atoms. D It self is over-completes $m \ll p$ .Such vectors are called as the basis of x . However, unlike other dimensionality educing decomposition techniques such as Principal Component Analysis, the basis vectors are not required to be orthogonal.

The sparse decomposition problem is represented as,

$$\min_{\alpha \in R^p} \|\alpha\|_0 \; such that x = D\alpha,$$

Where $\|\alpha\|_0 = \neq \{i: \alpha_i \neq 0, i = 1, \dots, p\}$ is a pseudo-norm, $l_0,$ which counts the number of non-zero components of $\alpha = [\alpha_1, \dots, \alpha_p]^T.$ This problem is NP-Hard with a reduction to NP-complete subset selection problems in combinatorial optimization. A convex relaxation of the problem can instead be obtained by taking the l_1 norm instead of the l_0 norm, where $\|\alpha\|_1 = \sum_{i=1}^{p} |\alpha_i|$ .The l_1 norm induces sparsity under certain conditions[1].

3. Sparse Solution via l1-RLS Minimization

3.1 The Least Square Formulation

The basic Ordinary Least Squares (OLS) problem aims at optimizing:

$$\hat{\beta}_{OLS} = \underset{\beta}{argmin} \|y - X\beta\|^2 \quad (1)$$

Where, $X \epsilon R^{n \times m}$ is the data matrix with $m \in N$ n-dimensional samples and $\beta \in R^m$ is the vector of coefficients from the representation of the query $\in R^n$. If $(X^T X)^{-1}$ exists the algebraic solution is given by:

$$\hat{\beta}_{OLS} = (X^T X)^{-1} X^T y \quad (2)$$

The Representation with RegularizedLeast Squares [11], solves:

$$\hat{\beta}_{OLS} = \underset{\beta}{argmin} \|y - X\beta\|^2 + \lambda_{CR} \|\beta\|^2 \quad (3)$$

Where $\lambda_{CR} \in R$ is a regulatory parameter. The algebraicsolution becomes:

$$\hat{\beta}_{CR} = (X^T X + \lambda_{CR} I)^{-1} X^T \quad (4)$$

WhereI is the m x m identity matrix.

The representation of the sparsityby means of l1-regularization we obtain a Sparse Representation(SR) [6] and solve:

$$\hat{\beta}_{sR} = \underset{\beta}{argmin} \|y - X\beta\|^2 + \lambda_{sR} \|\beta\|_1 \quad (5)$$

Where $\lambda_{sR} \in R$ is the Lagrangian regulatory parameter.For this problem, also known as lasso, we do not knowan algebraic solution.

3.2 Classification Based on Sparse Representation

The information used for classification usually is theresidual corresponding to each class c [6]:

$$r_c(y) = \left\| y - X_c \hat{\beta}_c \right\| \quad (6)$$

Where $\hat{\beta}_c$ and X_c are the coefficients and samples correspondingto class c from the full representation of ydefined by the coefficients $\hat{\beta}$ and the training samplesX. And the classification decision is taken using:

$$class(y) = \underset{c}{argmin} r_c(y) \quad (7)$$

If in eq. (6) $\hat{\beta} = \hat{\beta}_{sR}$, then the resulting decision is theSparse Representation-based Classifier (SRC) decision.

4. Methodology

Here we have used the ORL face database with the same settings as in. There are 40 individualsfor a total of 200 training and 200 testing faceimages of size 112x92. All the features are l1 normalizedbefore and after regularized

(λ= 0.001) projections.SRC uses Least Square algorithm for solving the l1 minimization.Forlow-dimensional data the l1 regularization is much more effective.For theORL dataset, where the features are the grayscale values of down sampled images, 6x4. We have obtained 91% results.

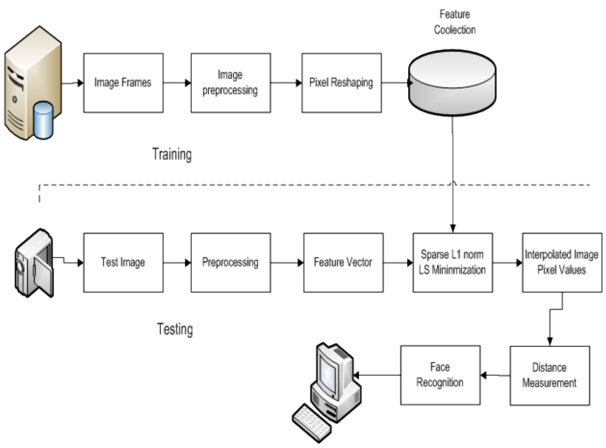

Fig 1: Block Diagram

5. Results & Discussion

In this paper, results were evaluated using MATLAB environment.The experiment involves a set of input test images in different conditions like light, intensity, pose and illumination. The proposed algorithm was tested with two case image added with 10%of white Gaussian noise and images are occluded with 10% of pixels. In both cases weachieved the rate of recognition of 91% and 90%respectively.With 10% Occlusion recognition accuracy achieved is 87%, with 10% Noise accuracy is 90% and with standard data base images of ORL, a very high recognition accuracy of 92% is achieved. The Fig 2 shows the performance obtainedby using different images with added noise and the Fig 5 shows output obtained in MATLAB tool.

Images with variant poses are commomn in today environment where the images with different poses leads to the serious problem in the detection of the faces also with different poses the slight variation in the faces like scars and add ons on the face makes difficult to identify the image to be identified by the normal methods.

Here we have taken care of the slight variation in the face like having a beared or moustache etc and variations like opening or closing of the mouth or eyes by this method It can recognize the face with damage of 50% or if the face is partially covered.

Figure 3 show some of the examples of face detection with small variations in the face.

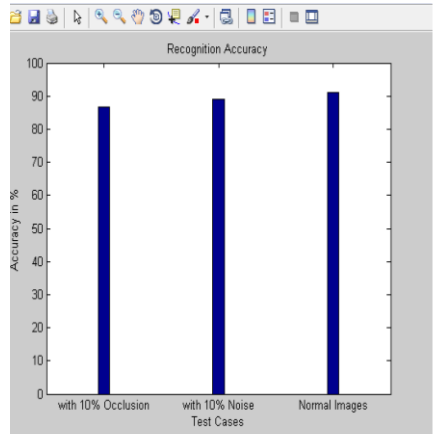

Fig 2: Performance Plot

Fig.3 Faces with small variations in the face

Fig.4 Analysis of images with different pose variation

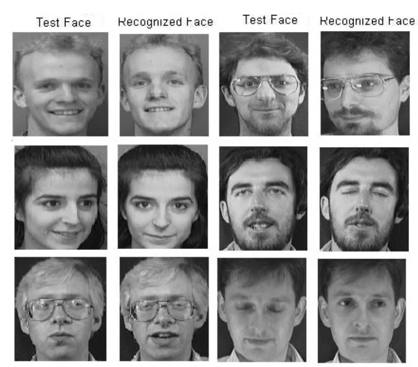

Fig. 5: Results obtained using MATLAB tool.

6. Conclusion

Pose independent face recognition is a one of the challenging area. The paper presents a novel, Sparse based algorithm for pose independent face recognition. The proposed method is less time consuming, which do not use any feature extraction or calculation time. From the test results, the proposed technique was successful in recognizing the pose independent faces with 91% of success rate. This is found to have many advantages over the existing methods.

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