Random Projection on Sparse Representation based Classification for Face Recognition

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***Abstract*—Sparse Representation based Classification for Face Recognition (SRC-FR) has becomes popular, because of its ability to overcome several problems in FR such as occlusion and image corruption. Given this advantages, this method suffers from heavy computational process. In this paper we propose dimensionality reduction of image samples to reduce the computational burden. This reduction is performed by multiplying the feature matrix with random projection matrix (Φ) of smaller size than feature matrix A. Two random projection matrices are generated using Gaussian and Uniform distribution. Several reduction factor in matrix Φ are verified which are from 1 to 256, are evaluated. Higher reduction factor indicates higher dimensionality reduction. As a reference we compared the proposed reduction method to the classical linear down scaling the image. The simulation results on AT&T Dataset that consist of 400 images shows that the proposed method with reduction factor of 8 to 256, achieve recognition rate higher than the classical linear down-scaled method. In addition, the proposed method also shows a better recognition rate up to 5% to the original SRC method.**

***Index Terms*—Compressive Sensing, Sparse Representation, SRC, Face Recognition, Random Projection**

I. Introduction

Face recognition (FR) is a technology for bio-metric recognition based on knowledge of human facial features [1]. This technology has a wide range of applications such as security, personal information access, personal ads and etc. There are several problems of face recognition are identified such as variations in illumination [2], pose variation [3] [4], occlusions [5], human expressions [6], picture alignment [7], and resolution diversity [8]. The requirements for FR in ubiquitous environment demands the ability to handle large database and match within seconds. Also there are several parameters have to be optimized when designing FR system which are storage requirements, computational complexity, and recognition accuracy.

Training and testing phases are the two modes of the FR systems. Each phase is typically comprised of the following fundamental components: pre-processing, feature extraction, and classification. Several algorithms has been proposed for effective and efficient FR. According to Gondhi et al. [9], there are six approaches for FR: knowledge-based, appearance-based, feature invariant, geometry-based, template-based, and model-based methods. Every technique has its own strengths and weaknesses. Despite considerable interest in the past years, existing pattern recognition methods still strive to classify faces in the presence of all kinds of image imperfections [10].

Over the last few years, Compressive Sensing or Compressive Sampling (CS) has been one of the interesting topics in signal processing and optimization, that is popularized by Candés et al. This theory was implemented for the first time in 2006 by Donoho [11]. Using CS, Donoho has revolutionary shifted the paradigm for sensing or sampling that challenges traditional data acquisition knowledge that uses Shannon Theory [12]. The CS theory exploits the fact that many natural signals are either sparse or compressible by selecting right basis [13].

In recent years, several variants of sparse representation methods have been proposed. Huang et al. [14], sparsely coded a signal over a set of redundant bases and classified the signal based on its coding vector. Yang et al. [15], introduced a new approach based on sparse signal representation, to single-image super-resolution. Li et al. [16], present an iterative sparse-representation-based voxel detection algorithm in functional MRI (fMRI) data with task-related information. Guha et al. [17], studied the utility of sparse representations using learned over-complete dictionaries in the context of video-based action modeling and recognition. Wright et al. [18], reported a work using sparse representation for face recognition. This technique is known as Sparse Representation Based Classification (SRC).

The SRC algorithm's main idea is that a face image can be linearly represented by the other samples in the same class. In contrast, the different classes are linearly independent. A face data set consists of some face images, described as a matrix $\mathbf{A} \in \mathbf{R}^{w \times h}$, where w and h represent the height and the width of the face image, respectively. In many face recognition algorithms, the vectorized version of matrix $\mathbf{A}$ denoted by $\mathbf{v} \in \mathbf{R}^m$ and $m = w \times h$ is used to represent the face image data training samples.

The SRC algorithm proposed by Wright et al. provide a complete solution to address FR issues, such as reducing computation complexity by using down-sampled feature extractions methods, handling sample corruption and occlusions, and also combating the image corruption and occlusion. Nevertheless, the extensive database of samples is required to fulfill the sparseness conditions. In addition, more samples are required for pose variations handling. This condition means a bulky sizes of databases. Thus, naturally SRC suffered from high computational complexity.

Many complementary algorithms have been proposed in recent years to improve the accuracy and performance of SRC. Deng et al. [19], proposed extended SRC and applies an auxiliary intra-class variant dictionary to represent the possible variation between the training and testing images. Mi and Liu [20], proposed sparse representation-based classification on k-nearest subspace to lower the computational complexity. Yang et al. [21], discussed fast ℓ_1-minimization algorithms for Robust Face Recognition. Recent review of sparse representation for under-sample data, where very few images of the subject of interest might be captured during the acquisition stage, e.g. passport, driving license, ID Card identification.

Dimensionality reduction of the training samples is one major factor for the practical implementation of SRC. The original size of the training samples is directly affected by the number of computations, hence impacting the algorithm's complexity. Dimension of the raw images $\mathbf{R^m}$ should be reduced to the lower-dimensional feature space $\mathbf{R^d}$ $(d \ll m)$, by trade-off the recognition performance [22]. This dimensionality reduction is also perceived as feature extraction of original sample images.

The dimensionality reduction can be performed by linear transformation such as popular Discrete Cosine Transform (DCT) or more complex transform such as Fast Fourier Transform (FFT) or Discrete Wavelet Transform (DWT) [23]. The dimensionality reduction generally will decrease the recognition performance. On the other hand, Quan et al. [24] suggested that to increase the discriminating power of the SRC, we need to improve the dimensionality of the image database.

In this paper, random projection is reinvented and proposed to perform dimensionality reduction of images or samples for the SRC FR method. The random projection is chosen due to its simple computation process compared to others that use more complex transformations. The idea to use the random projection is derived from compressive sensing method that used the random projection. The existing complex dimensionality reduction is aimed to have good image recovery or recognition by human eyes. In contrast, in face recognition, the objection is emphasized on how the test sample is identified to the correct class or subject based on the training samples of subjects. The notion is that the test sample or training samples themselves do not have to recognizable by naked human eyes as a picture but must be able to detect correctly by the algorithm of face recognition or by the simple statement that mathematically can perform the computation to do the correct classification of a test sample. The random projection has been simulated by Wright et al. [18], using the Gaussian random matrix projection and the result marked that the random faces can be used. In this paper the random projection is studied further, the other distribution function such as Uniform distribution is inspected, and the probability of recognition enhancement when random projection is applied is also inspected. The reinvented proposed random projection sparse representation classification method is abbreviated as RP-SRC.

The proposed RP-SRC performance is compared to classical common linear down-scaled dimensionality reduction that is provided in the Python function. The comparison of these two methods will be on the same reduction factor from the source images $\mathbf{R}^m$ to the extraction image $\mathbf{R}^d$.

II. Random Projection SRC Algorithm

The simple formulation of reduction factor ρ from the sample images $\mathbf{R}^m$ to the extraction image $\mathbf{R}^d$ is as follow [25]:

$$\rho = \frac{m\ (original\ size)}{d\ (projected\ size)} \tag{1}$$

The robust SRC face recognition is formulated by Wright et al. [18] as follow:

$$\mathbf{y} = \mathbf{A}\mathbf{x} \in \mathbf{R}^m \tag{2}$$

In the case of FR, $\mathbf{y}$ represented the image to be recognized, $\mathbf{A}$ is training sample columnwise database matrix and $\mathbf{x}$ is a sparse matrix.

Then the proposed dimensionality reduction using random projection matrix $\mathbf{\Phi}$ transform from $\mathbf{R}^m$ to $\mathbf{R}^d$ $(d \ll m)$:

$$\gamma = \mathbf{\Phi}\mathbf{y} \in \mathbf{R}^d \tag{3}$$

$$\aleph = \mathbf{\Phi}\mathbf{A} \in \mathbf{R}^d \tag{4}$$

$$\gamma = \aleph\mathbf{x} \in \mathbf{R}^d \tag{5}$$

γ is a projected testing samples that is sparse representation of projected training samples $\aleph$. The proposed projection matrix $\mathbf{\Phi}$ is the random matrix. Figure 1 illustrates the matrix multiplication process of equation (2), (3) and (4).

Under generic conditions, the expected sparsest solution $\mathbf{x_0}$ to equation (3) or (4) is unique, and can be solved via a lower complexity convex optimization [26].

$$\hat{\mathbf{x_1}} = \underset{\mathbf{x} \in \mathbb{R}^d}{\operatorname{argmin}} ||\mathbf{x}||_1 \quad s.t \quad ||\mathbf{\Phi}\mathbf{A}\mathbf{x} - \gamma||_2 \leq \varepsilon \tag{6}$$

or s.t

$$\hat{\mathbf{x_1}} = \underset{\mathbf{x} \in \mathbb{R}^d}{\operatorname{argmin}} ||\mathbf{x}||_1 \qquad ||\aleph\mathbf{x} - \gamma||_2 \leq \varepsilon \tag{7}$$

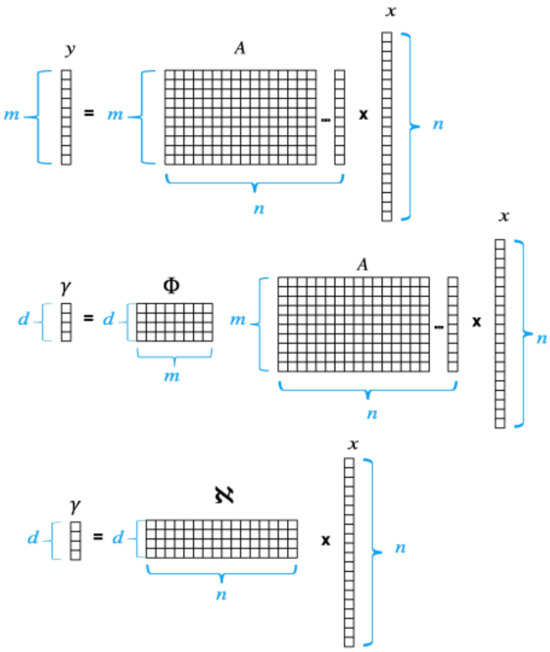

Fig. 1. Matrix Multiplication Illustration

For $\hat{\mathbf{x}_1}$ to have unique solution, then d must not be very small. According to Chen et al. [26], if ς represents the sparseness and η is the number of all training samples, then $\hat{\mathbf{x}_1}$ can be exactly recovered, when the number d fulfills:

$$d \geq O(\eta \log \varsigma / \eta) \tag{8}$$

with overwhelming probability:

$$p \geq 1 - e^{O(-d)} \tag{9}$$

According to Candés et al. [13], this random projection matrix must fulfil the Restricted Isometric Property (RIP) to recover unmeasured data. Several random distribution fulfill the RIP, for example Gaussian and Uniform random distribution. Both distributions are used in this simulation. It also shows a very low coherence with any fixed representation $\mathbf{\Psi}$ [18]. However, the random sensing matrix $\mathbf{\Phi}$ itself, when applied in Random Projected SRC (RP-SRC) equations (3) to (7) randomly hypothetically, may increase the sparsity of the images or subjects in the matrix $\mathbf{A}$ dictionary. Hence it could improve the performance of face recognition itself.

The SRC classical face recognition problem always comes along with any method: image corruption, occlusion, pose variation, and illumination variation. The robust term of [18] is referred to the ability of the SRC method to overcome most of these classical problems. These image inconveniences may affect the representation to deviate from the linear model at equations (1) to (3). The modification of equation due to this occlusion or corruption is as follow:

$$\gamma = \mathbf{\Phi y} + \mathbf{e} = \mathbf{\Phi A x} + \mathbf{e} \tag{10}$$

$$\gamma = \aleph x + \mathbf{e} \tag{11}$$

$\mathbf{e}$ is an unknown vector with nonzero values related to the corrupted pixels in the observation of γ. The errors $\mathbf{e}$ may be significant in magnitude and hence is cannot be neglected. However, like the vector $\mathbf{x}$, in the most cases, $\mathbf{e}$ are sparse, while occlusion and corruption generally affect only a fraction of $\rho < 1$ of the image pixels. Hence, the problem of face occlusion can be solved by the same as sparse representation $\mathbf{x}$ by solving a combined ℓ_1-minimization problem:

$$\hat{\mathbf{x}_1} = \min_{\mathbf{x},\mathbf{e}} ||\mathbf{x} + \mathbf{e}||_{\ell_1} = \min_{\mathbf{x}} ||\mathbf{x}||_{\ell_1} \in \mathbb{R}^{mx(m+n)} \tag{12}$$

$$s.t \quad ||\mathbf{\Phi A x} - \gamma||_2 \leq \varepsilon \tag{13}$$

$$or \ s.t \quad ||\aleph \chi - \gamma||_2 \leq \varepsilon \tag{14}$$

General algorithm of RP-SRC is derived as follow:

Algorithm 1 Algorithm for RP-SRC

Input: a matrix of training samples
$\mathbf{A} = [A_1, A_2, ..., A_k] \in \mathbf{R}^{mxn}$ for k classes.
a test sample $\gamma \in \mathbf{R}^m$ (and optional error tolerance $\varepsilon > 0$)
Output: class $(\gamma) = \operatorname{argmin}_{\mathbf{x}} r_i(\gamma)$
Normalize the column of $\mathbf{A}$ to have unit ℓ_2-norm
Solve the ℓ_1-minimization problem:
$\hat{x_1} = \operatorname{argmin}_{\mathbf{x}} ||x||_1 \quad s.t \quad \mathbf{\Phi A x} = \gamma$
(Or alternatively, solve
$\hat{\mathbf{x}_1} = \operatorname{argmin}_{x} ||x||_1 \quad s.t \quad ||\mathbf{\Phi A x} - \gamma||_2 \leq \varepsilon$
Compute the residuals
$r_i(\gamma) = ||\gamma - \mathbf{\Phi A}\alpha_i(\hat{\mathbf{x}_1})||_2$ for $i = 1, 2, ..., n$

It was observed in [18] [27] that this optimization performs well in correcting occlusion and corruption. For block occlusions that covering up to 20% of the face and random corruptions affecting less than 70% of the image pixels the method can recognize well without error. However, it was also observed, the matrix χ as equation (12) in classical SRC may have in-homogeneous properties that violate the classical conditions for the incoherence criteria and the RIP.

The SRC root problem that also applied to RP-SRC is to find the solution of linear equations by less dimension $(d \ll n)$. There are several well-known methods to solve the classical problems: regular linear programming, convex problem optimization, Orthogonal Matching Pursuit (OMP), and Least Absolute Shrinkage and Selection Operator (LASSO) methods. In this research we used the LASSO algorithm because this method shrinks the regression coefficient of the predictor variable that has a high correlation to exactly zero or close to zero.

In the simulation we compared the performance of RP-SRC with dimensional reduction using random projection to the classical down-scale method. Two parameters are observed which are time computation and recognition rate as function of reduction factors and distribution type. The block simulation diagram depicted in Figure 2.

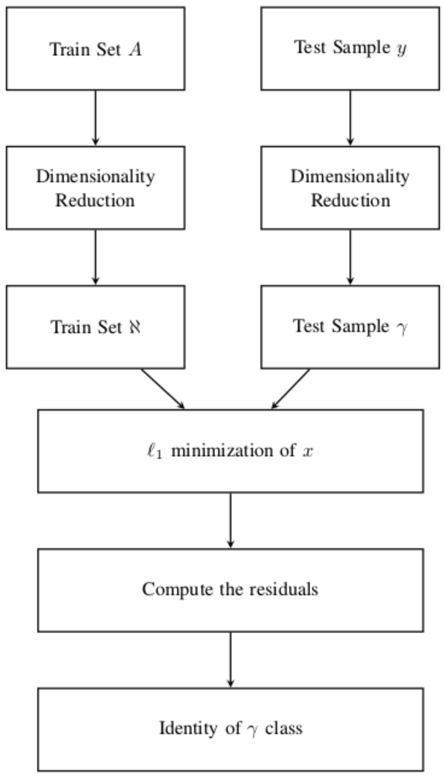

Fig. 2. Simulation Diagram

III. Simulation and Result

This simulation utilizes the most famous face recognition library, which is the AT&T image library. This library contains 400 training images of 40 classes or subjects and 200 samples from the same 40 subjects. The images were taken at different periods, with different lighting, facial expressions (open / closed eyes, smiling / not smiling), and facial details (glasses / no glasses) depicted in Figure 3. The subjects were photographed in an upright, frontal posture against a black, uniform backdrop (with tolerance for some side movement) [28].

The images data of subjects or classes will be stored as training samples after being projected or dimensionality reduced and will be used to identify testing samples. The identification of the training samples is based on solving ℓ_1-minimisation of SRC equation (3) to (7) or equation (10) to (14). The simulation of performance result will be compare accordingly.

Fig. 3. AT&T Dataset [28]

The simulation is performed by changing the sample dimension reduction factor ranging from ρ equals to 1 to 256 times dimensionality reduction. The parameters to be observed are the processing time and the FR performance, which is recognition rate. The simulation of processing time in Table II shows that the processing time is decreasing persistently along with reduction factor ρ increase from 1 to 256, this is applied to both random projection and down-scaled procedures. Figure 4 shows the dimensionality reduction also reduce the computation time.

TABLE I
Dimensionality Reduction vs Processing Time (s)

Reduction	Processing Time (s)		
Factor (ρ)	Downscale	Random Gaussian	Random Uniform
1	696	603	451
2	210	145	125
4	89	72	63
8	40	41	31
16	18	16	13
32	10	11	7
64	8	7	5
128	7	5	5
256	5	4	4

The time constraint result will be helpful for consideration of the application of the size of the dimensionality reduction. Application of recognition process will depend on how human expectation on the process. For example, in real-time electronic transactions, the process under 2 seconds will be acceptable. While for crime identification, there will be no time constraint but accuracy. In contrast, the smaller size of pixels will be preferred for the actual time application and massive implementation. Figure 4 depicted simulation of the time constraint for those 3 (three) simulations. The simulation is performed for 200 test samples. Average per test sample will be under 2 seconds when the reduction factor ρ more than 2.

The recognition rate of linear down-scaled SRC is decrease linearly along with the dimension reduction from about 90% down to 68%. The result of recognition rate on random sensing matrix $\mathbf{\Phi}$ for both Gaussian and Uniform distribution depends on the random matrices generated at the time. The accuracy of random projection is ranged from 71% to maximum 94% most. The simulation showed that for random matrix $\mathbf{\Phi}$

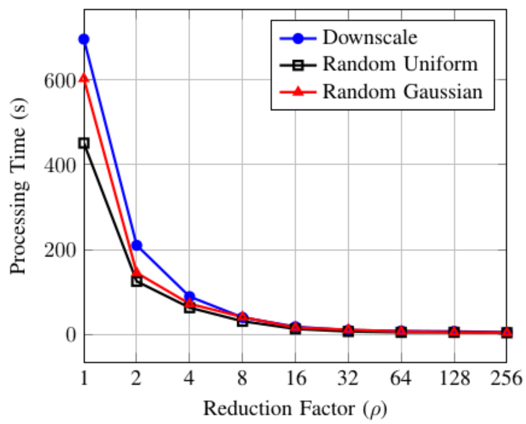

Fig. 4. Processing Time Constraint of Dimension Factor

TABLE II
DIMENSIONALITY REDUCTION VS MAX. RECOGNITION RATE (%)

Reduction Factor (ρ)	Maximum Recognition Rate (%)		
	Downscale	**Random Gaussian**	**Random Uniform**
1	90	91	93
2	90	91	94
4	90	91	94
8	90	90	94
16	88	90	94
32	88	90	94
64	83	84	92
128	76	79	89
256	68	71	77

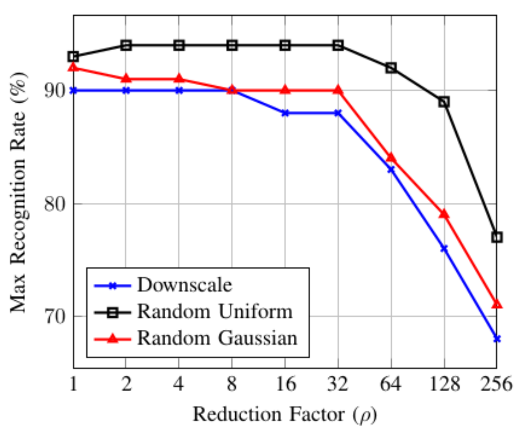

Fig. 5. Maximum Recognition Rate of RP-SRC and Downscaled SRC

could result in maximum 94% accuracy performance while the dimension is reduce from ρ equals to 2 to 64 times dimensionality reduction and then the accuracy performance go down significantly after.

This result apply to both Gaussian and Uniform distribution sensing matrix $\mathbf{\Phi}$, and this means in certain lower dimension the RP-SRC could result a better performance from the common linear down-scaled dimensionality reduction. This happens most probable because of in certain optimum dimension the certain best random sensing matrix the sparsity enhancement happens and the degeneration of dimensionality reduction is overcompensate by random sensing matrix $\mathbf{\Phi}$. This happened randomly but certain best random sensing matrix $\mathbf{\Phi}$ can be sought and stored. Further investigations must be performed and must be test for other data sets.

The result of dimensionality reduction by Python down-scaled function is permanently fixed due to deterministic property and non adaptive process. While the random projection result for best recognition performance is obtained iteratively. The best random sensing matrix $\mathbf{\Phi}$ is sought to have the best performance result by iteration and the best performance result will store the best matrix $\mathbf{\Phi}$. These iterative procedures is performed for both Gaussian and Uniform random distribution matrix and the result in Figure 5. Hence, the maximum performance of certain matrix $\mathbf{\Phi}$ of Gaussian and Uniform and in certain iteration number. These best random matrices is found by direct criteria of recognition performance, there are possibilities to enhance the criteria with other mathematical approach such as sparseness of ℓ_1-minimization solutions, minimum square error of recognition, and discriminant of training samples.

IV. CONCLUSION

The RP-SRC by added the random matrix $\mathbf{\Phi}$ can retain the face recognition performance while dimensionality reduction is significantly applied; hence the computational cost of SRC based-FR calculation can be reduced notably for certain suitable application that requires fast response of face recognition and accept accuracy performance is offered. The best matrix result Φ must be obtained iteratively in a separate effort before use in the main algorithm of CS Based-SRC face recognition application. This best matrix Φ is dynamic to the different groups of samples, or any new samples added into a group can change the best matrix Φ.

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