International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249–8958, Volume-1 Issue-3, February 2012

Face Recognition using Random Projection with Neural Network

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***Abstract:** In the domain of face recognition, many methods are used to reduce the dimensionality of the subspace in which faces are presented. Recently, Random Projection (RP) has emerged as a powerful method for dimensionality reduction. It represents a computationally simple and efficient method that preserves the structure of the data without introducing very significant distortion. Our focus in this paper is to investigate the dimensionality reduction offered by RP and perform an artificial intelligent system for face recognition using back propagation neural network. Experiments show that projecting the data onto a random lower-dimensional subspace yields results and give an acceptable face recognition rate.*

***Index Terms:** Dimensionality reduction; Face Recognition; Sparse Random Projection; neural network.*

I. INTRODUCTION

FACIAL research in computer vision can be divided into several areas, such as face recognition, face detection, facial expressions analysis, among others [7]. In face recognition, the dimension of an input space is so high that the input space has to be compressed into a low-dimensional feature space before classification. The reason is that direct recognition on a high-dimensional input space might arise a heavy burden of computation.

Several methods are used to reduce the dimension of facial data, the most widely used ways are the principal component analysis(PCA)[9]and the Linear Discriminant analysis (LDA)[10]; More recently, frequency domain analysis methods such as discrete wavelet transform (DWT) and discrete cosine transform (DCT) have been adopted in face recognition[8].

Frequency domain analysis methods transform the image signals from spatial domain to frequency domain. Only limited low-frequency components which contain high energy are selected to represent the image. In the last decade, random projection was presented as an efficient method that preserves the structure of the data under random projection without introducing very significant distortion. In this paper we introduce the use of a sparse random projection matrix to reduce the dimension of our facial dataset, and then we perform the task of recognition with a feed forward neural network.

This paper is organized as follows. In section 2 we discuss some related work on random projections in dimensionality reduction. Section 3 presents the projection matrix and the reduced dimension bounds. In section 4, we present our solution for face recognition using random projection with neural network. Section 5 gives the experimental results. Finally, Section 6 gives a conclusion.

Manuscript published on 28 February 2012.
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II. RELATED WORK

Random Projection has been applied on various types of problems like machine learning [1]. Goel.[4] investigates the feasibility of RP for face recognition. In this context, a large number of experiments using three popular face databases have been performed. The experimental results illustrate that although RP represents faces in a random, low-dimensional subspace, it is overall performance comparable to the use of PCA. Bingham. Et al[5] present experimental results on using RP as a dimensionality reduction tool, their application areas were the processing of both noisy and noiseless images, and information retrieval in text documents.

They show that projecting the data onto a random lower-dimensional subspace yields results comparable to conventional dimensionality reduction methods such as PCA and RP is computationally significantly less expensive than it. Also experiments show that using a sparse random matrix gives additional computational savings in random projection. Kurimo[6] applied RP for indexing audio documents, prior to using LSI and Self-Organizing Maps.

III. THE PROJECTION MATRIX AND THE REDUCED DIMENSION BOUNDS

A. Random projection matrix

Dimensionality reduction, refers to the process of taking a data-set with a number of dimension, and then creating a new data-set with a fewer number of dimension.

Let $X \Sigma R^n$ .The method multiplies X by a random matrix

$$RP \; \Sigma \; R^{n*k:} \; Y^k = RP * X$$

The idea is to preserve as much the "structure" of the data while reducing the number of dimensions it possesses; Projections are based on the Johnson-Lindenstrauss lemma

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[12]that states that a set of n points in a high dimensional Euclidean space can be mapped down onto a k>= O(log(n)/Σ²) dimensional subspace such that the distances between the points are approximately preserved (for any 0 <Σ< 1), and provided that RP has i.i.d. entries with zero mean and unit variance[12].

Early projection matrices tried to generate such orthogonal subspaces. Unfortunately, it is not easy to do so. However, the number of nearly orthogonal directions increases in high dimensional spaces, and as a result, it becomes easier to find subspaces that are "good enough".

Initially, random projections were done with a normal matrix, where each entry r_{ij} was an independent, identically distributed N (0, 1) variable with not orthogonal subspace. Achlioptas provided the sparse matrix projection that refer to a powerful concentration bounds [3]

$$r_{ij} = +\sqrt{3}\begin{cases} +1 & p = 1/6, \\ 0 & p = 2/3, \\ -1 & p = 1/6 \end{cases}$$

And

$$r_{ij} = \begin{cases} +1 & p = 1/2 \\ -1 & p = 1/2 \end{cases}$$

Generalize Achlioptas' result by providing the very-sparse projection matrix, they show that s>>3 can be used (for example s=√n or s= n/log (n)) [13].

$$r_{ij} = +\sqrt{s}\begin{cases} +1 & p = 1/2s, \\ 0 & p = 1 - 1/s, \\ -1 & p = 1/2s \end{cases}$$

A. Lowest reduced dimension

As mentioned before, The Johnson-Lindenstrauss lemma proof that we can reduce to k>O (log (n)/Σ²) dimension in order to approximately preserve pairwise distances up to a factor of (1±Σ). Practically it is interested to get some explicit formula for k.

A series of simplifications to the original proof of Johnson and Lindenstrauss, culminating in [11] showed that:

$$k >= \log(n)*4/(\epsilon^2/2 - \epsilon^3/3)$$

This is not a strict lower-bound but deduce that the pairwise distance is probably preserved with the Johnson-Lindenstrauss guarantees.

Other lower-bound are proposed in [2]. We will test in the experimental section how the rate of recognition is affected with different values of k when using sparse random projection and very sparse random projection.

IV. FACE RECOGNITION USING RANDOM ROJECTION WITH NEURAL NETWORK

A. The feature extractor method

RGB color system is mostly used in computers; each of the color components is represented by a number ranging from 0 to 255 with 0 and 255 describing the absence and the full saturation of the color component, respectively.

In the method proposed in this paper, the input data is divided into 3 channels, we assume that R, G, and B are raw vectors. The color image is then expressed as a 3*256 matrix. For each channel we choose an incremental rate p, so the number of sample per channel (numSPC) becomes 256/p then we calculate the result vector for this channel:
For k=0, 1,…, numSPC

$$\{ \quad i = k*p$$
$$\text{result}(k) = \sum_{j=i}^{i+p} \text{hist}(j)$$
$$\}$$

We obtain the extractor vector by concatenating the three result vectors.

B. Random projection with NN

The problem posed by high-dimensional is related to the deeper problem "The curse of dimensionality" that refers that for any data, as the number of dimensions of the data increases, the complexity involved in working with it increases at an exponential rate. It is known that most forms of neural network suffer from the curse of dimensionality and the performance of a network can certainly be improved by reducing the dimension of input variables.

Motivated by this, we study, in this paper, the impact of RP as method of dimensionality reduction to optimize the structure of the network specially the number of neurons in the input and hidden layer; we experiment with Achlioptas's and Li's matrix.

C. The learning Process

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After computation of the reduced vectors of dataset, back propagation algorithm is used to train our neural network.

The process learning is as follow:

- Read data and specify the desired output for each vector.
- Randomly initialize weights and bias.

Then gradually adjust the weights of the network by performing the following procedure for all patterns:

- Compute the hidden layer and output layer neuron activation:
- Calculate errors of the output layer and adjust weights.

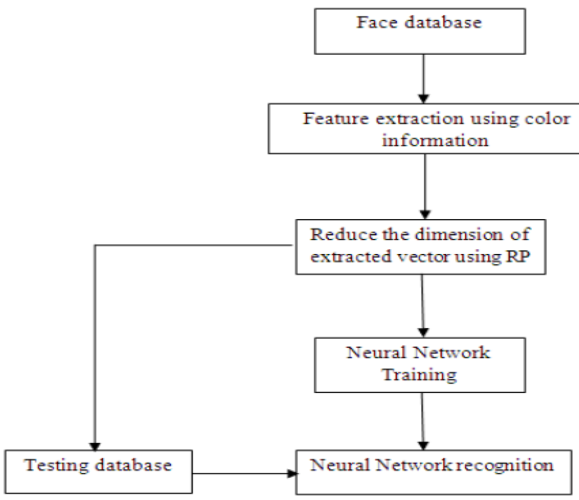
$$w_{ji}(n) = w_{ji}(n-1) + \eta\delta_j(n)y_i(n) + \alpha\Delta w_{ji}(n-1)$$

With:

$$\delta_j(n) = \begin{cases} e_j(n)y_j(n)[1-y_j(n)] & \text{If } j \in \text{output layer} \\ y_j(n)[1-y_j(n)]\sum_k \delta_k(n)w_{kj}(n) & \text{If } j \in \text{hidden layer} \end{cases}$$

η and α are learning rate and momentum factor (0<η,α<1). We repeat these steps on all patterns until minimizing the squared mean error or attend the maximal number of iterations.

D. The system architecture



V. EXPERIMENTS AND RESULTS

A. Description of datasets

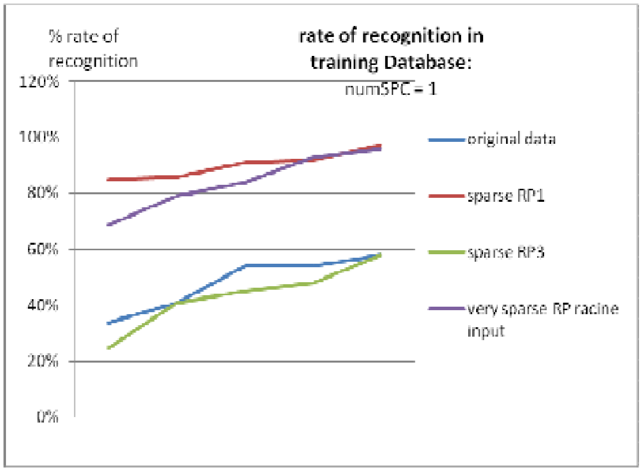
Georgia Tech Face Database

The database contains images of 50 people and is stored in JPEG format. For each individual, there are 15 color images captured. Most of the images were taken in two different sessions to take into account the variations in illumination conditions, facial expression, and appearance. In addition to this, the faces were captured at different scales and orientations.

B. Some experimental results

In our experiment, we evaluate how the rate of recognition is affected using sparse random projection RP1 and RP3 (i.e. s=1 and s=3) and very sparse random projection(s=√n) and also if the lower-bound value proposed by Johnson- Lindenstrauss effectively guarantees good projection. Then we compare the obtained results with results obtained without applying the random projection i.e. using the original data. We implement the algorithm described above; some scenarios of Training with different setups are presented in the following:

Case : numSPC=1→length of the feature vector= 768 and k=100



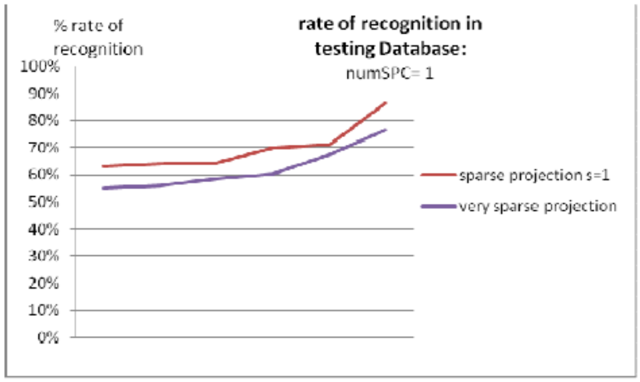
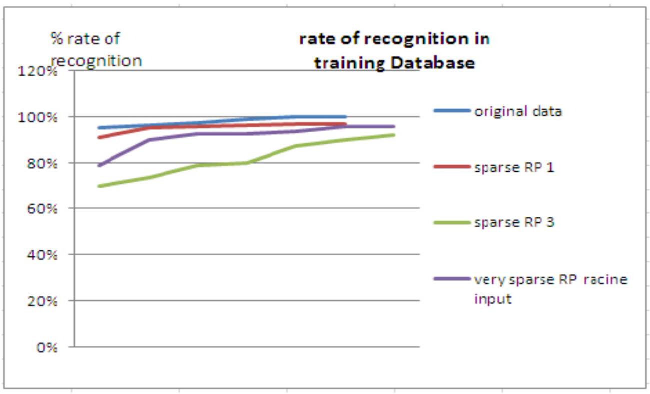


Fig. 1. Rate of recognition when numSPC=1 and k=100

When s=1 and n=768, the rate of recognition with original data do not surpass 60% whereas it attends 97% when introducing RP. Is seems clearly that original data cannot be adopted to train de neural network, even more the rate of recognition in testing data base surpass 60% with sparse RP.

Case : numSPC=8→length of the feature vector= 96 and k= 60



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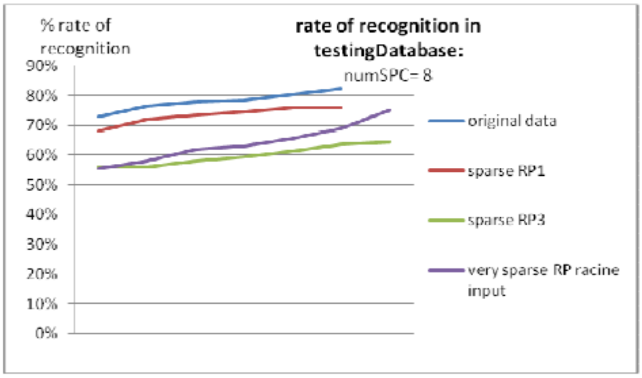
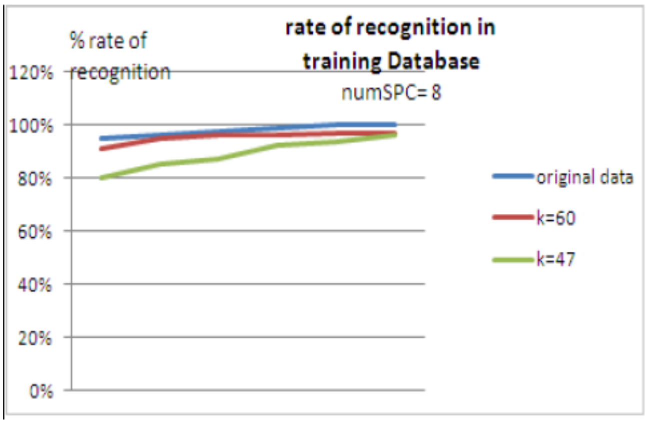


When s=1 and n=96, we observe that the rate of recognition using a sparse RP(s=1) attends 97% in the training data base and 80% in the testing data, whereas a distortion of data is observed when using other matrix of RP. Case : numSPC=8→length of the feature vector= 96 and s=1. We test for two values of the reduced dimensional subspace (k) as illustrated in the curves using Johnson-Lindenstrauss guarantee:

$$K_0 = \log(n)*4/(\epsilon^2/2 - \epsilon^3/3)$$



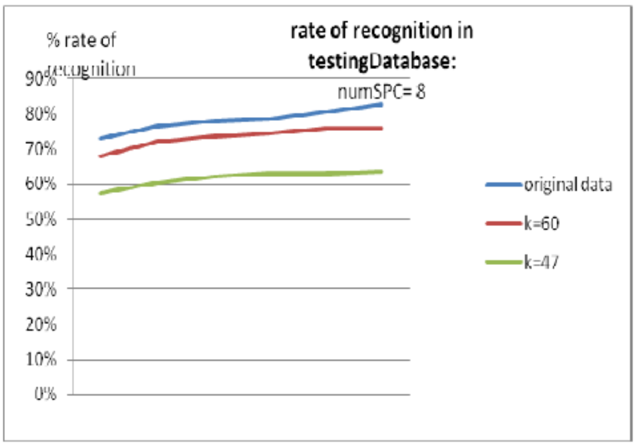


Fig.3. Rate of recognition when numSPC=8 and s=1

VI. CONCLUSION AND PERSPECTIVE

We conclude that random projection is an optimal method of dimensionality reduction. In the case of our study, obtain a higher FR rate depends, among others, on the choice of the random projection matrix and the dimension of the feature vector of original data. As perspective of this work, an extended study will be done to analyze the impact of input distributions on the distortion of the projection for 2D and 3D dimensional data.

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