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# On prediction error compressive sensing image reconstruction for face recognition☆

Suparna Biswas[a,*], Jaya Sil[a], Santi.P. Maity[b]

[a] Department of CST, Indian Institute of Engineering Science & Technology, Shibpur-711103, India
[b] Department of IT, Indian Institute of Engineering Science & Technology, Shibpur-711103, India

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ABSTRACT

This paper explores the scope of spatial domain sparse representation for the application to develop a fast and robust remote end face recognition (FR) scheme in the framework of compressive sensing (CS). At the source end, error images as the difference between the original and the predicted images, are obtained using the different predictors that offer compressive measurements. Sub-sample measurements of the sparse error image and part of the original image are then transmitted. At the destination end, the test image is obtained from its partial information and CS reconstructed error image. Principal Component Analysis is used to extract the important features from the reconstructed image followed by FR. Performance of the proposed method is studied using collaborative representation based classifier with regularized least square method, applied on two databases, AR and ORL and an accuracy of 93.99% for the former and 91.5% for the latter is observed.



## 1. Introduction

Face recognition (FR) offers a cost effective means for identification of individuals using low cost camera and at the same time without using any prior knowledge. Some times FR can be accomplished at lower sampling rate, for example, surveillance in crowded places like railway station, airport and shopping mall that need fast sensing of images in order to recognize the persons with less time and at low space complexity. The other application may be FR at remote end through bandwidth efficient transmission of samples using compressed sensing or compressive sampling (CS) a relatively new technique that appears as a potential solution to sub-sample signal reconstruction.

Literature on FR is quite rich, methods include principal component analysis (PCA), and its various variants, namely symmetrical PCA, two-dimensional PCA [1], weighted modular PCA, various types of linear discriminant analysis (LDA), namely direct-weighted LDA, generalized LDA using singular value decomposition (SVD) [2], local binary pattern (LBP) [3], histogram of oriented gradients (HOG) [4] etc for feature extraction. Researchers apply different types of classifiers, like K- nearest neighbor (KNN) [3], support vector machine (SVM) [5] etc on the feature vectors for FR. Recently sparse representation based classifier (SRC), collaborative representation based classification with regularized least square (CRC_RLS) [6] and CS in kernel based SRC [7] are also used in FR at reduced feature space.

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* Corresponding author.
*E-mail addresses:* suparna_b80@yahoo.co.in (S. Biswas), js@cs.iiests.ac.in (J. Sil).

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In typical application, FR may need to be performed at far end without having access on source data. Here FR system may suffer from limited power and channel bandwidth, hence transmission of full scale image becomes a system limitation. To address the issues, the present work proposes a remote access FR method as a communication problem by utilizing CS principle. Generally, some form of frequency transform methods are applied on the images to sparsify the data which require less transmission bandwidth but computationally expensive. A spatial domain prediction based approach may be a potential solution to generate sparse data at low computation cost and can be sent to the far end with less channel bandwidth.

Rest of the paper is organized as follows: Section 2 presents a brief review on CS-FR. Section 3 presents the various sparse representation methods, while Section 4 describes the proposed FR method. In Section 5 results are discussed followed by conclusion in Section 6.

## 2. Literature review

This section gives a very brief review on FR problem based on CS along with the scope and contributions of the present work.

### 2.1. Related works

Recently CS has been explored a lot in FR, for example, expression invariant FR using reduced feature dimension [8], improved performance over Eigenface, Fisherface and Laplacian based method [9], an infrared method by integrating CS and PCA [10], pose-invariant FR method [11]. Yang et al. [12] proposed a robust sparse coding (RSC) model to improve the robustness on sparse representation. A correntropy based sparse representation (CESR) technique was proposed in [13] to cope up the non-Gaussian noise in FR. FR methods also include discriminative dictionary learning [14], a maximum probability of partial ranking [15], adaptive sparse linear model [16], structured SR [17] etc. Some of the recent works on CS based FR are Histograms of Oriented Gradients-Compressive Sensing (HOG-CS) framework [18] and sparse Fast Fourier Transform (FFT)approach [19].

### 2.2. Scope and contributions

In brief, the literature review highlights the importance of CS on FR to offer benefits of reduced feature space, and a way of bandwidth and energy efficient system design for remote end recognition. Towards this aim, the work employs low cost spatial domain prediction based CS reconstruction for remote signal recognition, in the present case the problem of FR, which prevents accessibility of the source data by unauthorized persons. The major contributions of the work are as follows: i) Remote signal recognition (like FR) from the sub-sampled sparse error image information is done using CS reconstruction. The proposed solution offers improved robustness in FR even at the presence of various degradations. ii) Spatial domain SR, offers benefits in speed and simplicity of the system design. Five prediction algorithms are used such as Autoencoder, Differential Pulse Code Modulation (DPCM), Median Edge predictor (MEP), Gradient Adjustment Predictor (GAP) and Gradient Predictor (GP) to generate the predicted image. Sparse error image is then obtained as the difference between the original and the predicted image. Full scale image is reconstructed from the partial image information and sub-sample measurement of sparse error image followed by solution to FR.

## 3. Spatial domain sparse representation

Here five different prediction methods are discussed.

### 3.1. Autoencoder

An autoencoder is a feedforward neural network [20] with an input layer and output layer having the same no of nodes and one or multiple hidden layers. Autoencoders are trained to reconstruct the inputs through unsupervised learning. Deep Belief Network (DBN) is a machine learning tool, originated from ANN research and is used here as an autoencoder to reconstruct the face image. The architecture of DBN is basically stack of Restricted Boltzmann Machines (RBM), creates a powerful generative model using the training data. Here we develop an autoencoder with three RBM as shown in Fig. 1. The number of input neurons at the first level is 4096 (an image of size $64 \times 64$) and the number of neurons in three layers of RBM are set to 1000, 500 and 250, respectively. An autoencoder consists of encoder and decoder, where the decoder reconstructs the input as the predicted image, $\hat{x}$.

### 3.2. Differential Pulse Code Modulation (DPCM)

In the DPCM based prediction algorithm [21], the image is divided into $(B \times B)$ blocks and is fed to the DPCM encoder, shown in Fig. 2.

For predicting the $j$th block of m samples $y_m^{(j)}$, previously processed block $\hat{y}^{(j-1)}$ is used. The residual vector $d_m^{(j)} = y_m^{(j)} - \hat{y}_m^{(j-1)}$ is quantized to produce the quantization index $i_m^{(j)}$ using function $Q$. The quantized image is coded and ready