# Under sampled Face Recognition via Robust Auxiliary Dictionary Learning

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***Abstract*** — *~~A~~ facial recognition is a computer based application which is capable of identifying or verifying a person from a digital image or video source by comparing facial features from the image and a facial database such as fingerprint or eye iris recognition system. Recently, it is extensively used in various places for authentication and authorisation. Various methods are used in the face recognition such as Correlation, Eigenfaces, Fisher faces, Sparse Representation Coding. In this work, with our proposed approach on two facial datasets which is able to model the above intra-class variations which shows better recognition rate via Dictionary Learning when compared to SRC and Extended Sparse Representation Coding(ESRC).*

***Keywords*** — **Facial Recognition, Eigen Faces, Correlation, Sparse Representation Coding (SRC), Extended Sparse representation Coding (ESRC).**

## I. Introduction

Humans typically use faces to acknowledge people however in today's digital data world authorisation and authentication is very important to maintain the data confidentiality and integrity. Face recognition has always been an interesting topic in this digital world when the data of an image is Undersampled. Various approaches are used in the recognition such as are Correlation[3], Eigenfaces[4], Fisher faces , Sparse representation[12] and Extended Spares Representation [13] since it is challenging in the digitalized world to recognize face images with illumination and expression variations as well as corruptions due to occlusion or disguise. A typical solution is to collect a sufficient amount of training data in advance so that the above intra-class variations can be properly handled. However, in practical data collection in advance which is impossible.

### B. *Major applications of Face Recognition*

Some of the major applications[2] in which face recognition techniques are extensively used are:

- Face Identification
- Security
- Access control
- Surveillance

Let us consider an example[2], In military applications, Data confidentiality and Secrecy are more important for the security of any nation. Face recognition techniques are helpful to scan the person with the facial database of that organization and check whether that particular person is an authorized one or not. If he is an authorized one means that person is allowed to view the Confidential data.

In Medical field, Automatic Face recognition techniques are used to scan the patient and automatically uploads the patient details to hospital server if the patient is visiting the hospital for the first time. If the same patient is visiting the hospital for the second time, the doctor can fetch the previous patient medicine details and compare with the present condition so, that the doctor can give appropriate medicine in time.

C. *Three basic approaches for Face Recognition*

Different approaches of face recognition are classified into three groups based on face representation. They are

1) Holistic approach
2) Feature-based approach
3) Hybrid approach

1) *Holistic Approach*

A holistic approach is an appearance-based approach which uses holistic texture features and is applied to either whole-face or specific regions in a face image. This methodology is predicated on principal part analysis (PCA) techniques which will be wont to scale back the spatiality of the info by holding the characteristics of the dataset. Subspace analysis is done by projecting an image into a lower dimensional subspace formed with the help of training face images and after that recognition is performed by measuring the distance between known images and the image to be recognized. Principal element Analysis (PCA), Linear Discriminant Analysis (LDA) are two algorithms that are extensively used in the face recognition.

2) *Feature-based Approach*

The feature-based approach uses geometric facial features like mouth, eyes, brows, cheeks, etc. and applies geometric relationships between them. Pure geometry, dynamic link architecture. The drawbacks of this method are that it cannot restrain the amendment in element values, if the image is roofed with glasses, mask etc..or disguised.

3) *Hybrid Approach*

The hybrid approach is a combination of both appearances based and feature based approaches. Among the face recognition approaches, appearance-based approaches have been successfully developed and tested in many applications for face recognition. The above approaches also utilize the pixel intensity or intensity-derived features.

## III. LITERATURE SURVEY

From the last two decades Researches have shown their interest in the various Face Recognition techniques under illumination and various facial expressions, developed various algorithms. Some of them is as follows:

In [3] Marios Kyperountas, Anastasios Tefas, Ioannis Pitas has proposed an algorithm in which the test and training faces are projected to a Discriminant face and the data that is projected onto space are partitioned into clusters in multiple steps using the k-means algorithm. Each training data of an image is selected and compared with the test face, repeat the same process until the distance is minimum in between the test and training image. Then that image is matched with the input image.

In [4] M. Turk and A. Pentland has proposed a methodology in which the face images are projected onto feature space. The image is converted into eigen vectors. These eigen vectors are just similar to an low quality image. these eigenvectors one can compare with the training dataset for better recognition purpose.

In [5] Peter N. Belhumeur, Joao P. Hespanha, and David J. Kriegman have proposed an algorithm under varying lighting conditions and facial expressions when the image is subjected in which the face recognition can be possible .

In [7] M. Yang, L. Zhang, J. Yang and D. Zhang have proposed an methodology which is known as Robust sparse coding[12] algorithm in which it eliminates the sparsity-constrained robust regression problem. The RSC enhances the MLE (maximum likelihood estimation) solution of the sparse coding problem in which it is more robust to the corrupted images due to occlusions.

In[10] M. Yang, L. Zhang, X. Feng and D. Zhang have proposed an methodology in which it provides solution for both the discriminative information from the reconstruction error and sparse coding coefficients by utilizing the Fisher discrimination Dictionary Learning method .

In [11] C.-P. Wei and Y.-C F. Wang have proposed an optimization methodology in which the algorithm jointly solves the tasks of auxiliary dictionary learning and sparse-presentation based on the face recognition.

In [12]J. Wright, A. Y. Yang, A. Ganesh, S. S. Sastry, and Y. Ma, have proposed an methodology in which the pixel values are varying in order to recognize the occluded or disguised part in the corrupted image using sparse matrix[12] by linear regression model.

## IV. PROPOSED WORK

The main purpose is to ascertain the establish the question input image y. The gallery D consists of knowledge sets from L categories and auxiliary wordbook learning A is learned from the external data.

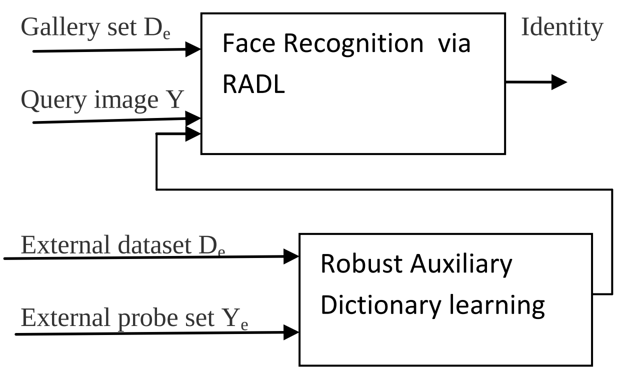


Fig.1 Flow chart for undersampled face recognition

In previous methods residue(ρ) function is introduced for identifying and authentication, but the residue function value has high value for the low and high occlusions which is not suitable for verifying the undersampled data. Our proposed methodology deals with the problems that are occurring frequently due to occlusion and illumination problems.

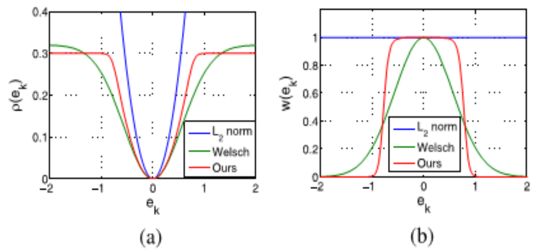


Fig.2 a )Residue function(ρ) and Weight function(W)

### A. *Proposed Algorithms :*

*1) Face Recognition via Robust Auxiliary Dictionary Learning :*

Input: Training data D=[$D_1$,$D_2$....$D_l$] from L subjects, intra-class dictionary A and test input y

step 0 : Normalize y and columns of D to have unit *l*2-norm

step 1 : Initialize W=I

step 2 : Calculate the optimal solution of

$$min\ \rho\ (y - [D\ A][\begin{smallmatrix} x_d \\ x_a \end{smallmatrix}])+\lambda||x||$$

which is denoted by x* and the associated weight matrix W*

while not converged do

x - $argminx\ ||W(y - [D, A]X|| + \lambda||X||$

end while

step 3 : Classify y via weight reconstruction errors

$$l^* = argmin||W^*(y - [D, A][\begin{smallmatrix} \delta_l(x_d{}^*) \\ x^*{}_a \end{smallmatrix}]||$$

output : Identifying test input y from $l^*$

*2) Robust Auxiliary Dictionary Learning (RADL) :*

Input : The gallery matrix $D_c \varepsilon R^{dxp}$ and the probe $Yc \varepsilon R^{dxN}$

Step 0 : Normalize the columns of $Y_c$ and $D_c$ to have unit $l_2$-norm

Step 1 : Initialize $X \varepsilon R^{(p+m)xN}$ and $A \varepsilon R^{dxm}$

Step 2 : Calculate the optimal solution

$$\min_{A,X} \sum_{i=1}^{N} \rho\left(y_e^i - [D_e, \quad A]\begin{bmatrix} X_d^i \\ X_a^i \end{bmatrix}\right) + \lambda \|X^i\|_1 + \eta\rho\left(y_e^i - D_e\delta_{i\ell}(X_d^i) - AX_a^i\right)$$

while not converged do

Sparse Coding Stage : update X

for i = 1: N do

calculate $W_g$ and $W_c$ from

$$W_g = \text{diag}\left(\omega(g_1), \omega(g_2), \ldots, \omega(g_d)\right)^{1/2}$$

$$W_c = \text{diag}\left(\omega(c_1), \omega(c_2), \ldots, \omega(c_d)\right)^{1/2}$$

with g and c

$$g = y_e^i - [D_e, \quad A]X^i$$

$$c = y_e^i - D_e\delta_{i\ell}(X_d^i) - AX_a^i$$

obtain $x^i$ via

$$\min_{X^i} \left\| \begin{bmatrix} W_g y_e^i \\ \gamma W_c y_e^i \end{bmatrix} - \begin{bmatrix} W_g D_e & W_g A \\ \gamma W_c \delta_{il}(D_e) & \gamma W_c \delta_{il} \end{bmatrix} \begin{bmatrix} X_d^i \\ X_a^i \end{bmatrix} \right\|_2^2 + \lambda \|X^i\|_1$$

end for

Dictionary Update Stage : update A

for j = 1: m do

for i = 1 : N do

calculate $\Phi_g{}^i$ and $\Phi_c{}^i$ and $\grave{W}_g{}^i$ and $\grave{W}_c{}^i$

$$\Phi_g^i = W_g\left(y_e^i - D_e X_d^i - \sum_{k \neq j}^{m} \alpha^k x_{a,k}^i\right)$$

$$\Phi_c^i = W_c\left(y_e^i - D_e\delta_{il}(X_d^i) - \textstyle\sum_{k\neq j}^{m} \alpha^k x_{a,k}^i\right)$$

$$\widetilde{W}_g^i = x_{a,j}^i W_g \ \text{ and } \ \widetilde{W}_c^i = x_{a,j}^i W_c$$

end for

obtain $\alpha^j$ via solving

$$\alpha^{j*} = \left(\sum_{i=1}^{N} (\widetilde{W}_g^i)^T \widetilde{W}_g^i + \eta (\widetilde{W}_c^i)^T \widetilde{W}_c^i\right)^{-1} \times \left(\sum_{i=1}^{N} (\widetilde{W}_g^i)^T \Phi_g^i + \eta (\widetilde{W}_c^i)^T \Phi_c^i\right)$$

update the jth column of A i.e. A (: , j) = $\alpha^j$

end for

end while

output = Auxiliary Dictionary (A)

## V. EXPERIMENTAL RESULTS

We have implemented Undersampled Face Recognition in MAT Lab and evaluated the face recognition rate in two different datasets and our experimental results are described as follows

*A. Extended Yale Database*

*1) Pixel based Feature :*

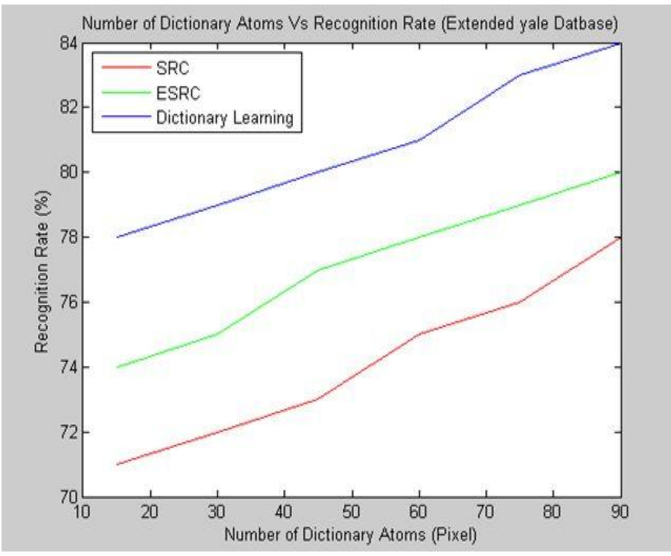


Figure3. Performance comparison on Extended Yale Database using Pixel feature

*2) Gabor Feature:*

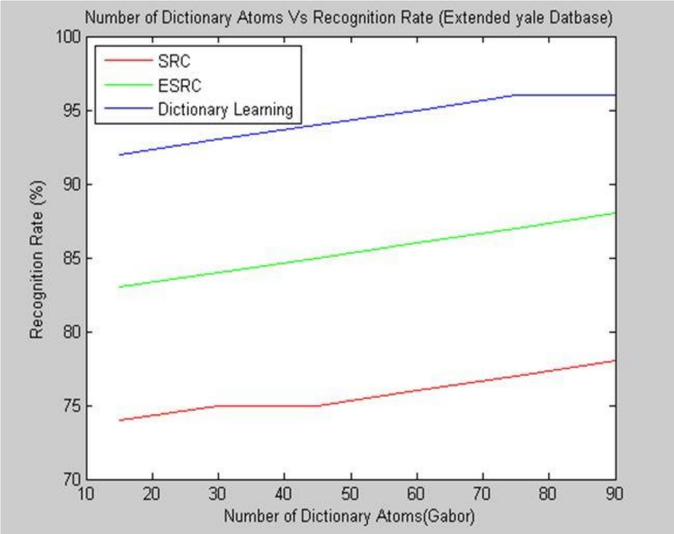


Figure 4. Performance comparison on Extended Yale Database using Gabor feature

From Figures 3and 4 it is clearly shown that Face recognition rate in Extended Yale Dataset via Dictionary Learning is far better than SRC and ESRC.

*B. ORL Database*

*1) Pixel based Feature:*

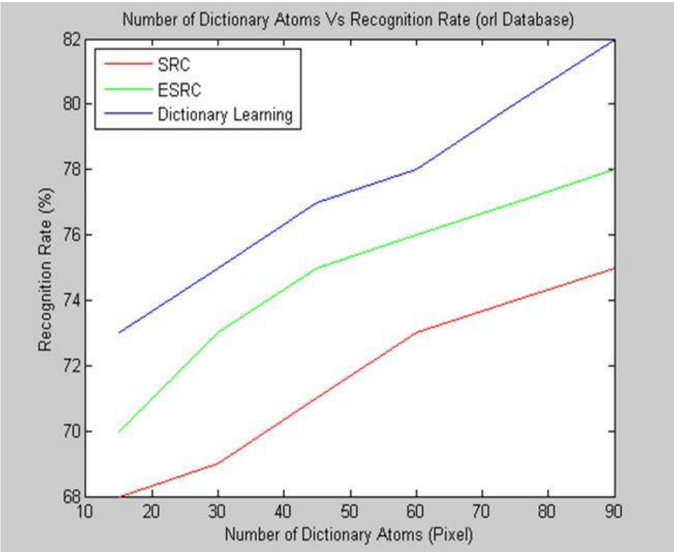


Figure 5. Performance comparison on ORL Database using Pixel feature

*2) Gabor Feature:*

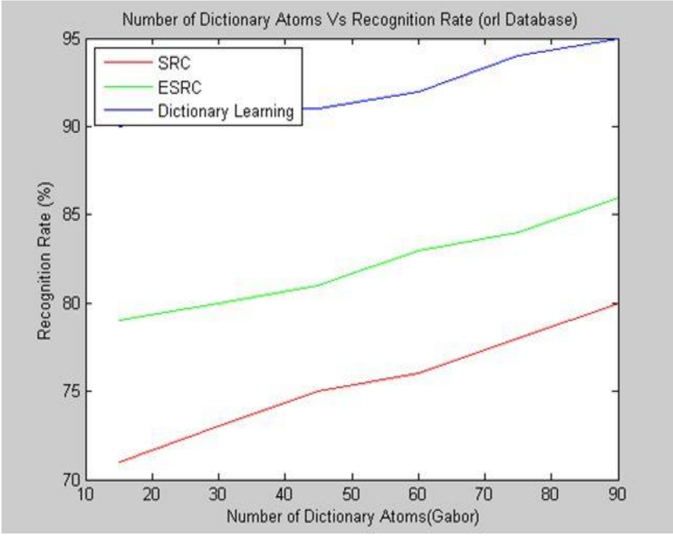


Figure 6. Performance comparison on ORL Database using Gabor feature

From Figures 6 and 7 it is clearly shown that Face recognition rate in ORL Dataset via Dictionary Learning is far better than SRC and ESRC.

## VI. CONCLUSION

Undersampled Face Recognition is a challenging topic in face recognition where the faces are subjected to the occlusion and disguise which are prone to authentication and authorization. In this paper We did a lot of research in this field in order to address the current problems that are facing when undersampled data is present in the database. In this paper we measured the performance comparison of Dictionary Learning , SRC and ESRC and observed that Robust Auxiliary, Dictionary Learning (RADL) method achieved better recognition rate in the facial database than compared SRC and ESRC.

## REFERENCES


[1] Cha Zhang & Zhengyou Zhang (2010) "A Survey of Recent Advances in Face Detection", Tech. Rep., MSRTR-2010-66, Microsoft Research, Microsoft Corporation One Microsoft Way, Redmond, WA 98052, http://www.research.microsoft.

[2] T. Ahonen, A. Hadid, and M. Pietikainen, "Face description with local binary patterns: Application to face recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 12, pp. 2037–2041, Dec. 2006.

[3] Marios Kyperountas, Anastasios Tefas, Ioannis Pitas, "Face recognition via adaptive discriminant clustering" *Reseach gate International Conference on Image Processing*, January 2008. [4] M. Turk and A. Pentland, "Eigen faces for Recognition", *Journal of Cognitive Neuroscience Volume 3, Number 1,1991.*

[5] Peter N. Belhumeur, Joao P. Hespanha, and David J. Kriegman, "Eigen faces vs Fisher faces: Recognition using Class Specific Linear Projection" *IEEE Transactions on Pattern Analysis and Machine Intelligence archive Volume 19 Issue 7, July 1997.*

[6] Y. Su, S. Shan, X. Chen, and W. Gao, "Adaptive generic learning for face recognition from a single sample per person," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2010, pp. 2699–2706.

[7] M. Yang, L. Zhang, J. Yang, and D. Zhang, "Robust sparse coding for face recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2011, pp. 625–632.

[8] M. Aharon, M. Elad, and A. Bruckstein, "K-SVD: An algorithm for designing overcomplete dictionaries for sparse representation," *IEEE Trans. Signal Process.*, vol. 54, no. 11, pp. 4311–4322, Nov. 2006.

[9] M. Yang, L. Van Gool, and L. Zhang, "Sparse variation dictionary learning for face recognition with a single training sample per person," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Dec. 2013, pp. 689–696.

[10 ]M. Yang, L. Zhang, X. Feng, and D. Zhang, "Fisher discrimination dictionary learning for sparse representation," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Nov. 2011, pp. 543–550.

[11]C.-P. Wei and Y.-C. F. Wang, "Learning auxiliary dictionaries for undersampled face recognition," in *Proc. IEEE Int. Conf. Multimedia Expo (ICME)*, Jul. 2013, pp. 1–6.

[12]J. Wright, A. Y. Yang, A. Ganesh, S. S. Sastry, and Y. Ma, "Robust face recognition via sparse representation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 31, no. 2, pp. 210–227, Feb. 2009.

[13]W. Deng, J. Hu, and J. Guo, "Extended SRC: Undersampled face recognition via intraclass variant dictionary," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 34, no. 9, pp. 1864–1870, Sep. 2012.