Robust Face Recognition for Uncontrolled Environment

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Abstract

The aim of this project is face recognition from constraint environment. In this constraint environment various occlusion, different pose variation are exist. Robust Face recognition is needed today, for constrained environment because it used in ATM access, personal identification, Reliable face recognition system mainly depend upon method used for feature extraction and classification. The method used for feature extraction is Eigen Faces and also Sparse Representation based Classification is used .In this Sparse Representation based classification, l1 minimization algorithm is used. Sparse Representation based classification, represent the testing sample as the linear combination of all training sample B=AX, then classify the test sample by evaluating which class leads to minimum sparse representation error. This Sparse Representation based Classification gives best performance for constraint environment with 98% acceptance ratio. SRC based classification is robust to occlusion and gives high recognition rate.

Keywords: Constrained Environment, SRC

I. INTRODUCTION

Face recognition has attracted broad interests in the area of pattern recognition, object detection and recognition from the past 20 years. However, the images taken by the devices under the uncontrolled environments are usually of limited quality. i.e Various human facial expressions, poses, and illumination conditions affect the quality of face images. First, in face recognition, we encounter many of the common variability that outbreak vision systems in general: illumination, occlusion, pose, and misalignment. Second, face recognition has a wide spectrum of practical applications. Indeed, if we could construct an extremely reliable automatic face recognition system, it would have broad implications for identity verification, access control, security, and public safety.

II. RELATED WORK

In[1], used adaptive classification is used .First one based on Sparse representation based Classification ,another one is dense detector, which based on Correlation based image classification .It has good recognition rate for occlusion present, degree of complexity is more and also having low interpretability. In [2], nearest feature line method is used. Two features are extracted from a single class in order to represent it, also using geometric relationship between two features, feature line is formed. During Recognition, using linear model to estimate feature point of class. Advantage is outperforming than nearest neighbor method. In[3], component based method used 14 individual component feature are extracted form face, trained by individual SVM. Very expensive and too slow when compared to global method. In [4], CRC method used, which based on correlation between images, used for classification, it outperform than SRC for input of disguise image.

In [8], hybrid method used for feature extraction i.e extracts both local and global feature from image, combining both feature then Euclidean distance based classifier used separately both local and global feature. If both feature return true means person is accepted. Good recognition rate against different pose variation but not in the case of occlusion. In [9], Histogram of Local Binary Pattern i.e local texture descriptor used as feature for input image. LBP calculated for all non-overlapping local block in face. Euclidean distance based classifier used for recognition, good recognition against misalignment problem, pose variation.

In[10], global method which used Wavelet transformation for feature extraction, it takes whole face for feature extraction. Dimensionality of extracted feature is high; in order to reduce that PCA is used. SVM used for classification, but it does not suitable for real time face recognition, which includes large pose variation, occlusion.

This paper is organized as four parts, first part contains block diagram, second part contains flow chart and method description, third part contains sparse coding algorithm, fourth part contains experiment and results.

III. BLOCK DIAGRAM

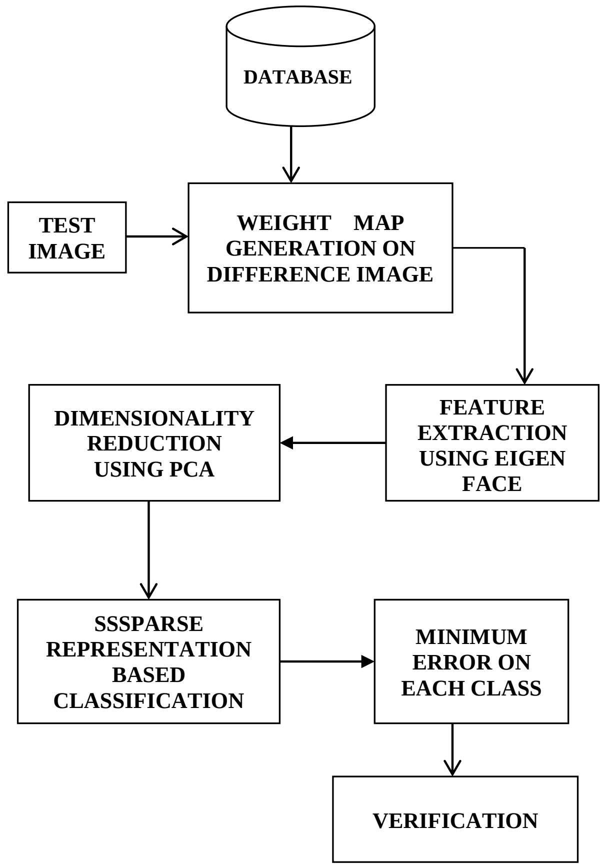

Fig. 1: Block Diagram

Here, this overall outline of the work is showed in Fig 1.First step is feature extraction using Eigen Face .In this method, Eigen value is calculated for entire test image and training image. In this highest Eigen value consist of most predominant information regarding image. Next step is, dimensionality Reduction, which is carried out by PCA. Here, feature selection has taken place. Next step is Recognition, it is done by SRC Sparse Representation based Classification. In this, represent the query image over complete dictionary, so that finding which class leads to minimum error, leading to corresponding correct class for test image.

IV. DATASET

In this AR Data base , provide all images with dimensions of 63*40.so ,Cropping is not needed AR Database is used as training and AR disguise used as testing. AR Database contains totally 700 images. It contains 7 different images per persons, so for 100 persons it contains 700 images, which include different pose variation, lighting condition, occlusion like wearing glass ,wearing scarf. Also AR Disguise data base contains 100 images

Five methods are used in this paper. They listed below

- Weight Estimation Method
- Feature Extraction using Eigen Faces
- Dimensionality Reduction Using PCA
- Classification using Iterative sparse coding
- Minimum Error Calculation
- Verification

Weight Function assign weight on each pixel value for the difference image, which is generated by subtracting mean image with test image. Again this weight value multiplies with test image in order to get weighted test image. Then, feature extraction on weighted test image done by Eigen face, dimensionality Reduction by PCA. After applying PCA, all values are normalized unit l2 norm. This value fed into l1 minimize algorithm for sparse representation of this over complete dictionary.

SRC classify the test sample by evaluating which class leads to minimum sparse representation error .This method is called Robust ,because the test image is occlude or disguise it gives the best recognition.

V. FLOWCHART

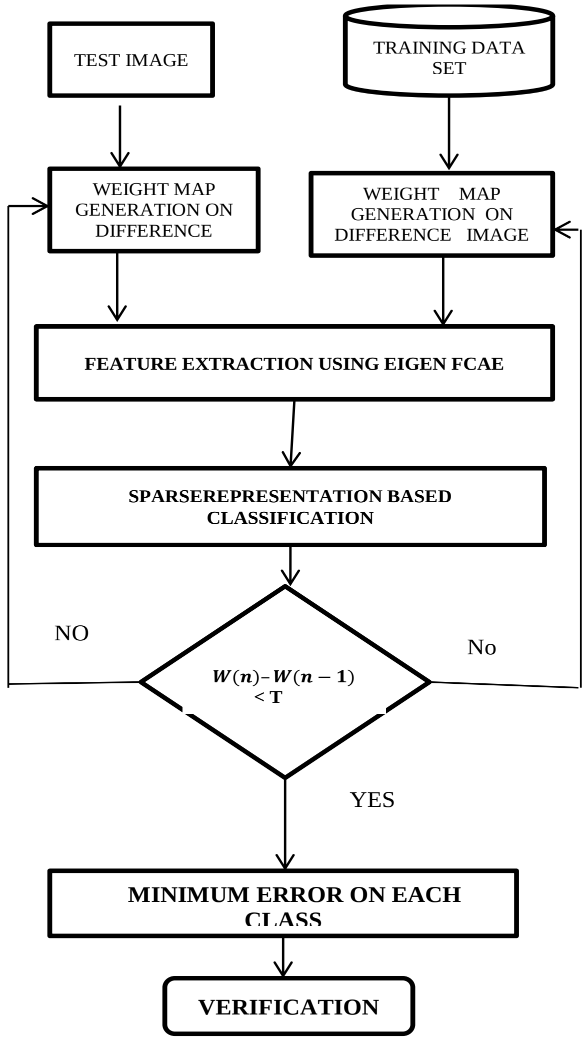

Fig. 2: Flow Diagram for Robust Face Recognition System

VI. FEATURE EXTRACTION USING EIGEN FACE

Following steps are followed for feature extraction

A. Step1: Load Data:

Here, AR database is used in training .The dimension of images used is 60*43 .Represent each image as vector

$$\text{Input data} = x_1, x_2, \ldots, x_M$$

B. Step2: Subtract the Mean:

We calculate the mean of all training data set image. After calculating mean value, this is subtracted from all images.
Compute average face vector

$$\overline{x} = \frac{1}{M}\sum_{i=1}^{M} x_i$$

Subtract the mean vector

$$\{\Phi_i\}_{(N\times 1)} = \{x_i - \overline{x}\}_{(N\times 1)}$$

C. Step3: Calculate the Covariance Matrix:

form matrix $A = [\Phi_1 \quad \Phi_2 \quad .. \quad \Phi_M]_{(N\times M)}$,

find the covariance matrix

$$\{C\}_{(N\times N)} = \frac{1}{M}\sum_{j=1}^{M}\Phi_j\Phi_j^T = \left\{\frac{1}{M}A_{(N\times M)}A^T{}_{(M\times N)}\right\}_{(N\times N)}$$

Using this equation covariance is calculated.

D. Step 4: Calculate Eigen Vectors and Eigen Values of Covariance Matrix Eigen Vector:

First, Eigen vector is calculated from only square matrices. For example,$n \times$ n are square matrix, it has n Eigen vector.

find eigen values of $C : \lambda_1 > \lambda_2 > .. > \lambda_N$

find eigen vectors of $C : u_1, u_2, .., u_N$ Eigen values arranged in decreasing order in order to get best cha

E. Step5: Form Feature Vector:

Here, Eigen vector with highest Eigen value is the principle component of the data set. In general, once eigen vector is calculated from the covariance matrix means, the next step is order them by Eigen value like highest to lowest .This order gives the order of significance.

In this, if we have n dimensions in data, we calculate n Eigen value and n Eigen vector then choose the first p Eigen vector, so finally it has only p dimensions. Form new feature vector, from the set of Eigen vectors

$$\text{Feature Vector} = \left(u_1, u_2, .., u_N\right)$$

VII. DIMENSIONALITY REDUCTION USING PCA

It is the one way of identifying patterns in data and expressing the data in such a way to highlight their similarities and difference. Because, patterns in data can be hard to find in their higher dimension, but PCA is suitable tool for analyze the data. The main advantage of PCA is that is you can compress the data, i.e. by reducing no of dimensions, without loss of information as much.

VIII. SPARSE REPRESENTATION BASED CLASSIFICATION

In face recognition problems, each face is treated as an m$\times$ $n$matrix. There are various methods are available for mapping it to a single vector. This is called feature vector extraction.

One of the most naive feature vector associated with an image is obtained by reshaping the matrix into an m$n \times 1$ vector. Assume there are k distinct classes of face data.

Let $F_i = [f_1 \quad f_2 \dots \dots \quad f_n]$be the collection of feature vectors that represent the ith class. This collection of features form the training set of the i th class. Each vector is called a training vector. Assuming that there is sufficient number of training vectors for all the classes. Given any new arbitrary sample vector of the ith class, it can be approximated by a linear combination of the training vectors. Let T be the new vector, called the test vector, that belong to the ith class. Then T can be expressed as

$$T = \sum_{j=1}^{n} \alpha_j d_j$$

α_j - represent weight coefficient associated with training vectord_j

D = [d_1 , d_2 ,…..,d_m] is the column vector representing training sample of dictionary.

T is the test sample used here,

$$T = DX$$

Here, Sparse coding coefficient used to encode the identity of the test vector T over complete dictionary. Unlike the Nearest Neighbor (NN) classifier or the Nearest Subspace (NS) classifier, SRC uses the entire training set at a time to solve for X. The components of X are zeros except for those associated with the particular class. This used to identify the class to which the test vector belongs , by using minimum residual error .This problem now reduced into linear programming under the linear system of equation T = DX. This solution is Euclidian minimum norm. l_2Solution to the above problem

$$min_x \parallel x \parallel_2 \ subject\ to\ T = DX$$

$l_2$solution is not suitable for this kind of problem. Because, the solution can be dense i.e, there can be a large number of non-zero entries corresponding to coefficients of other classes and hence, may not be of much use in getting the identity of T. So l_2 solution is not suitable for this kind of problem.

Since the test vector is represented using the training vectors from the same class only, we are looking for a sparse solution, i.e., a solution with minimal l_0 norm. The identity of T is determined by the sparsity structure of X. Thus the problem is redefined as:

$$min_x \parallel x \parallel_1 subjectto \ \mathrm{T = DX}$$

These can now be solved using standard techniques like linear programming, Newton interior point algorithm.

IX. ROBUST SPARSE CODING ALGORITHM

Sparse coding modeled as

$min_x \parallel x \parallel_1 subjectto \ \mathrm{T = DX}$ (1)

$min_x \parallel x \parallel_1 subjectto \parallel \mathrm{T - DX} \parallel_2 \leq \varepsilon$ (2)

Here, ε is noise level,ε> 0. T is the test image to be recognized, D is dictionary of training sample

D = [d_1 , d_2 ,…..,d_m] is the column vector representing training sample of dictionary. X is the sparse coding coefficient vector. Residual value e = $\mathrm{T - DX}$ follows Gaussian or Laplacian distribution, when the test images may be have pose variance, occlusions or corruption. In that situation, Eq (1) or (2) becomes useless. To construct robust model for effective face recognition, construct Maximum Like hood Estimation of the coding coefficient.

Dictionary rewritten as

$$\mathrm{D} = [\mathrm{R}_1 \, , \mathrm{R}_2 \, , \ldots\ldots\ldots \mathrm{R}_n \,]. \text{ Here, } \mathrm{R}_i \text{ represent the row vectors of dictionary.}$$

$$e_i = \mathrm{T_i - R_i X}, \quad i = 1, 2\ldots n, \quad e = [\, e_1, e_2 \ldots\ldots e_n \,]$$

Here, e is independently and identically distributed under some function $g_\theta(e_i)$, here θ represent distribution dependent parameter. Maximum Likelihood estimation is modeled as

$$\mathrm{L}_\theta (\, e_1, e_2 \ldots\ldots e_n \,) = \Pi_{i=1}^{n} g_\theta(e_i) \qquad (3)$$

So, objective function for the equation (3) is defined below,

$$\ln \mathrm{L}_\theta = \Sigma_{i=1}^{n} \rho_\theta \, (e_i \,)$$

Here

$$\rho_\theta \, (e_i \,) = -\ln g_\theta(e_i)$$

Maximum likelihood estimation of X for robust sparse coding can be modeled as

$$min_x \Sigma_{i=1}^{n} \rho_\theta \, (\mathrm{T_i - R_i X} \,)$$
$$st \parallel \mathrm{X} \parallel_1 \leq \sigma \qquad (4)$$

Here, σ is constant.

X. WEIGHT ESTIMATION METHOD

Weight matrix has diagonal element W as

$$w_{i,i} = \omega_\theta(e_{0,i} \,)$$
$$= \frac{\rho'_\theta \, (\boldsymbol{e_{0,i}} \,)}{\boldsymbol{e_{0,i}}} \qquad (5)$$

Here, minimization method transformed into weighted iterative method, with w is updated by using last iterative value, this solved by l1- ls newton interior point method. W is the diagonal matrix, its diagonal value $W_{i,i}$ $[i.e(\omega_\theta(e_{0,i} \,))]$ represent the weighted value associated with each pixel value in the query test image.

$$\text{Here,} \quad \omega_\theta(e_i) \quad = \exp(\mu\sigma - \mu e_i^2 \,) \Big/ (1 + \exp(\mu\sigma - \mu e_i^2)) \qquad (6)$$

δ, μ are positive scalar. μ Controls the decreasing rate from 1 to 0. δ Controls the location of change

XI. ITERATIVE WEIGHTED SPARSE CODING METHOD

While testing the face image, initial weight should be calculated based upon the mean image of the all training sample.so, initial error residual value calculated by

$$e = \mathrm{T} - T_{ini}$$
$$T_{ini} = \Sigma_{i=1}^{n} \mathrm{R_i}$$

T_{ini}Represent the mean of all training sample

XII. CONVERGENCE OF ITERATIVE WEIGHTED SPARSE CODING

Convergence can be achieved, when weight value between any two iteration is same.

$$\frac{\| W^{(n)} - W^{(n-1)} \|_2}{\| W^{(n-1)} \|_2} < \gamma$$

Here, γ is small positive value.

XIII. ITERATIVE WEIGHTED SPARSE CODING ALGORITHM

INPUT:
T –test image
D- Training sample
$T_{rec}^{(1)}$ - initialized as T_{ini}
(All inputs should be in l_2 unit norm form
OUTPUT:
X
begin
n = 1
STEP1: compute residual error value

$$e^{(t)} = \mathrm{T} - T_{rec}$$

STEP 2: Estimate weight as

$$\omega_{\theta(e_i^{(n)})} = \frac{exp\left(\mu^{(n)}\delta^{(n)} - \mu^{(n)}({e_i^{(n)}}^2)\right)}{1 + exp\left(\mu^{(n)}\delta^{(n)} - \mu^{(n)}({e_i^{(n)}}^2)\right)}$$

STEP 3: Compute coding coefficient

$$X^* = min_x \Sigma_{i=1}^{n} \| (W^{(n)})^{1/2} (\mathrm{T} - \mathrm{DX}) \|_2^2$$
$$subject \ \ to \ \| \mathrm{X} \|_1 \leq \sigma$$

$W^{(n)}$ is estimated by using equation (5) , (7)

STEP 4: Update coding coefficient
if n = 1 $X^{(n)} = X^*$
else n > 1 $X^{(n)} = X^{(n-1)} + \eta^{(t)}\left(X^* - X^{(n-1)}\right)$
where $0<\eta^{(t)}<1$ is define step size.$\eta^{(t)}$can be searched from 1 to 0 by line search process
STEP 5: compute reconstructed test image

$$T_{rec}^{(n)} = \mathrm{D}X^{(n)}$$
$$\mathrm{n = n + 1}$$

STEP 6: Go To STEP1 until It Convergence

This Iterative Sparse Coding, literately assign weights on test image , and also literately calculate sparse variable X value until weight value between any two iteration is same. By using this sparse variable coefficient only, verification is achieved. Verification is done, based on sparse coefficient concentration within class.

This section contains details about results and comparison

XIV. RESULTS

A. *Input Images:*

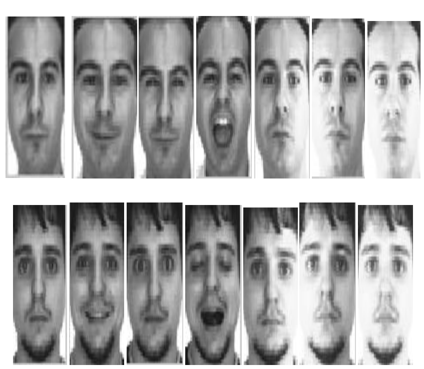

Fig. 4.1: Training Image –AR Database

Here AR Database used .this data set contains totally 700 images. For each person it contains 7 images on different pose variation, various lighting condition.

This AR Database with disguise is used this data set contains totally 200 images. For each person it contains 2 images on different occlusion.

Fig. 4.2: Testing Image using AR Disguise

B. Feature Extraction:

Fig 4.3: MEAN FACE

Mean image is calculated from over all images of all training data set on AR Database (700 images).

XV. EIGEN FACES OF TRAINING DATA SET

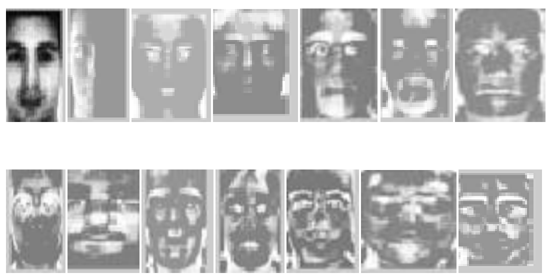

Fig. 4.4:EIGEN FACES

Eigen Faces are calculated from the co variance matrix. It is calculated from a images and the mean of the images .Eigen faces are created by using Eigen values of image set.

XVI. WEIGHT MAP GENERATION FOR TEST IMAGE



Fig. 4.5: Initial Weight Map Fig. 4.6: Weight Map for Test Image on 1^{st} iteration Fig. 4.7: Weight Map for Test Image on 2nd iteration

Weights are calculated by using exponential functions. Here, difference image is calculated between test image and mean image of all training sample. This difference image given input to the exponential function, for weight calculation of test image.

XVII. Graph for Sparse Coding

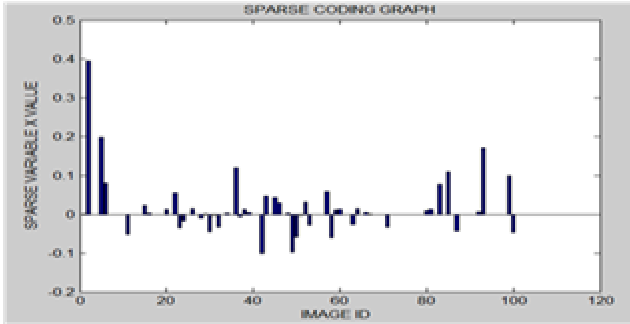

Fig 4.8 Sparse variable X's value on 1st iteration

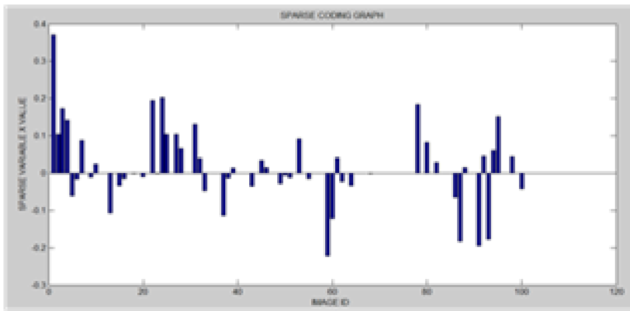

Fig. 4.9: Sparse variable X's value on 2 nd iteration

Sparse Variable X is used to code the identity of test image on over complete dictionary. This value is computed by using l1 minimization algorithms. Then above diagram shows the sparse variable X value on 2nd iterations

XVIII. Residual Error Value on Each Class

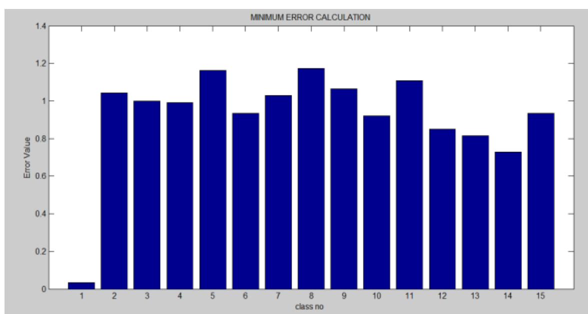

Fig 4.10 Graph for error value on each class

This Graph shows error value is calculated for each class. From the set of class from over complete dictionary, which gives the minimum error, will be consider as test image's class.

XIX. Authentication

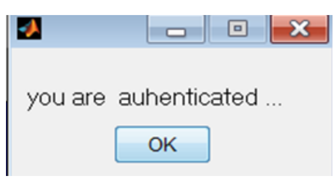

Fig 4.11 Verification Message

By using this sparse variable calculation, authentication message is generated. If the sparse variable having minimum no of nonzero value(<4) only , the person is authenticated.

XX. PERFORMANCE ANALYSIS

For the experimental evaluation, use a PC with Intel(R)Core(TM)2 Due CPU T9550 (2.66 GHz) and 2 GB RAM. All the methods were realized by MATLAB 11.Here, performance analysis of this Robust Face Recognition System, evaluated by means of Acceptance Ratio.

This table shows the recognition rate of Nearest Neighbor, Sparse Representation Based Classification, and Iterative Sparse Coding method on AR Disguise Database. ISC outperforms than other methods, gives 96% recognition rate.

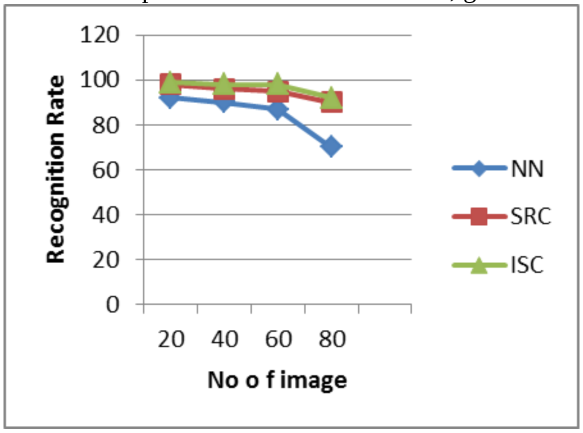

Fig 4.28: Recognition rate of ISC, NN, SRC method on AR Disguise Database (sunglass)

This Graph shows the recognition rate of Nearest Neighbor , Sparse Representation Based Classification , Iterative Sparse Coding method using AR disguise database(wearing sunglass).Recognition rate ISC method is high **(95%)** than other method.

XXI. CONCLUSION

This robust sparse coding (RSC) model is simple and an effective robust method for face recognition. One important advantage of RSC is its robustness to various types of outliers (i.e., occlusion, expression, etc.). This is achieved by using Weight Function .This method is called Robust, because the test image is occlude or disguise it gives the best recognition. The results clearly demonstrated that RSC outperforms significantly previous methods, such as SRC, SVM and other Bayesian classifier while its computational complexity is comparable or less than SRC. It also gives 96 % acceptance ratio when outlier is present. In future, we can apply this method, in video (face recognition in video) in that more occlusion is present when compared to single image. This iteratively reweighted sparse coding (IRSC) algorithm, useful and simple, efficient method for face recognition system in video.

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