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Metaheuristic Algorithms for Verification based on Biometric Features

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Abstract

Most reduction problems of dimensionality are nonlinear and multimodal, under several overlapped constraints. Various targets and objectives are often conflicting. Sometimes, for a single objective, optimal solution may not exist at all and not an easy task. Metaheuristic algorithms used to solve reduction problems of dimensionality in the biometric verification problems. This paper will study some metaheuristic algorithm**s** to solve the biometric verification problems. The boundary energy, HSV histogram features and MultiSVM are used to reduce the dimensionality and improve the performance of user verification. It helps and increases the accuracy factor of security recognition in identity verification.

Keywords: Features reduction, dimensionality, verification, biometric authentication, metaheuristic algorithms.

INTRODUCTION

The algorithms optimization are classified into two types. First type is the exact methods but second type is the metaheuristic optimization methods. Exact methods guarantee finding the exact global optimum for small sized problems. The instances of medium-sized problem oftentimes become tenacious, It cannot be resolved any more using exact techniques. Hence, exact optimization methods cannot be useful in our feature selection problem. On the other hand, metaheuristic optimization methods have local search or an imitation of a natural process, such as annealing or biological evolution. Then, they are more appropriate for solving large dimensionality problems[1]. Single solution and population based algorithms are the two common typesof metaheuristic optimization. Single solution based techniques are related to local search techniques which give a single optimized solution like Simulated Annealing. Population based methods can capture multiple optimal solutions. Hence they are appropriate to our case of study. Evolutionary algorithms such as GA and swarm intelligence algorithms such as PSO are represented a type of this techniques.

In the case of current problem, the objective is to determine the classes of individuals such that the intra-variation is minimized and the inter-variation is maximized. So, instead of optimizing only one measure of classification, we will concurrently optimize two different measures of classification by means of the search ability of Multi-Objective Optimization (MOO). The major objective of MOO is to make a Pareto front of non-dominated solutions in feature subsets forms [1].

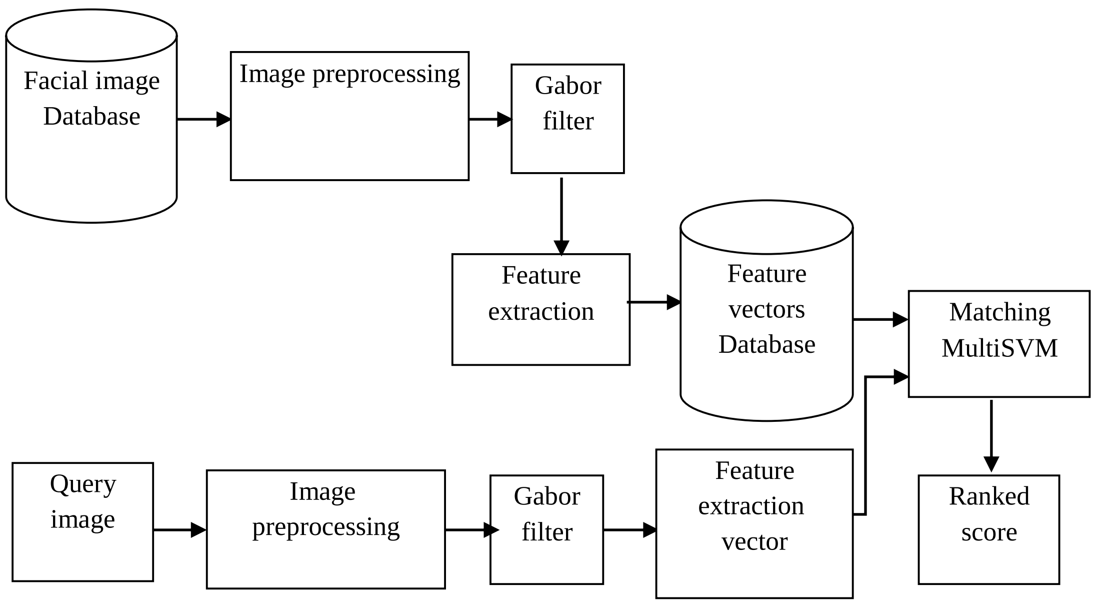

Figure 1. The flowchart of the authentication method.

The main benefit of current approach is the automatic and quick retrieval process of images rather than the conventional keyword-based approach which require much potential and is time consuming as it employs annotations such as explanation or clue of database sets. The traditional approach would seek for basics things for the search of image in the database i.e. the textual data which includes all the information i.e. creation of file, author of the file, date of creation, need of creations and much more. This all information would lead to more confusion if the amount of data stored is huge. The other technique which is more beneficial and less consuming is the searching on basis of content i.e.(shape, texture and color). The mechanism which would be applied in this paper is extraction of the histogram from image with the hue saturation and value (HSV) features and furthermore matching it with the MultiSVM algorithm. MultiSVM means speeded up robust feature which would increase the retrieval accuracy. It is interest point detector and descriptor generally used in computer vision application and deals with gray scale images.

The system of individual verification depends on 4 major phases: facial image enhancement, Gabor filter for feature extraction, establishing of feature vectors database and MultiSVM matching as illustrated in Figure 1. Every image in certain class is represented a vector. The vector consists of six types of features. The features are extracted from HSV histogram, boundary energy, color auto Correlogram, color moments, mean amplitude and wavelet moments.

HSV HISTOGRAM FEATURES:

HSV is a color model that is more intuitive to humans. To specify a color, one color is chosen and amounts of black and white is added, which gives different shades, tints and tones. The parameters of color are represent by saturation, hue and value. In a three-dimensional representation, as shown in Figure 2, hue is the color and is represented as an angle between 0 and 360. The saturation varies from 0 to 1 and is the purity of the color, for example is a pale color like pink less pure than red. Value varies from 0 at the apex of the cone, which stands for black, to 1 at the top, where the colors have their maximum intensity.

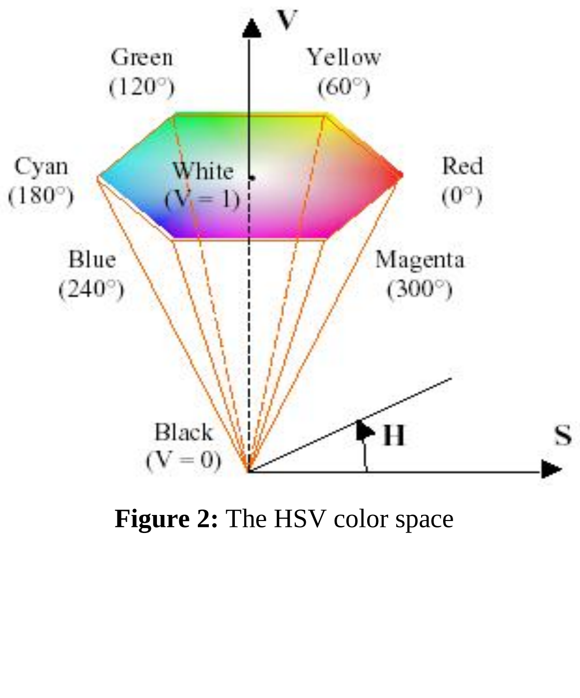

Figure 2: The HSV color space

The HSV color pattern matches better to how people experiment color than the RGB color pattern worked. The HSV color space is used to be called the hex-cone color model. The origin point in the hex-cone corresponds to "black", and both H and S are meaningless. Relatively, the end point (V = 1 and S = 0) is considered to be "white", and H is undefined.

$$H = arccos\left(\frac{(R-G)+(R-B)}{2\sqrt{((R-G)^2+(R-B)(G-B)}}\right) \quad (1)$$

$$V = \frac{1}{3}(R+G+B) \quad (2)$$

$$S = 1 - 3\frac{min(R,G,B)}{R+G+B} \quad (3)$$

Several studies display that HSV is never changing to highlights at white light roots, to ambient lighting and non-shiny surfaces. Nevertheless, hue discontinuities and the calculation of the luminance composition struggle severely with the color visibility properties. The periodic nature of Hue-Saturation spaces also specifies it disadvantageous for parametric skin color patterns that requirement a tight cluster of skin execution for optimum achievement [2].

Procedure hsvHistogram

input: read RGB image Im to be quantized in hsv color space into 8×2×2 equal bins

output: 1×32 vector $hsvHist$ indicating the features extracted from HSV color space.

begin

1- Convert Im in RGB into Im in HSV form with size rows r and columns c.

2- Split image into H,S and V planes

i.e. $h = Im(:,:,1)$, $s = Im(:,:,2)$ and $v = Im(:,:,3)$

3- Find $maxh$, $maxs$ and $maxv$ are the maximum values in H,S and V respectively.

4- Specify the number of quantization levels. Quantize each h, s,and v to 8×2×2. $nLh = 8$, $nLs = 2$ and $nLv = 2$ are numbers of levels for H,S and V respectively.

5- Initialize HSV- histogram matrix, $hsvHist$ of size 8×2×2 to zeros.

6- Create c vector of indexes for later reference. initialize $index$ with size $c.r$ rows and 3 columns to zeros.

7-Put all pixels into one of the number levels, and calculate quantization levels:

k = 1;

for i = 1 to $length(h,1)$

for j = 1 to $length(h,2)$

$quantizedh(i,j) = \lfloor nLh \times h(i,j)/maxh \rfloor;$

$quantizeds(i,j) = \lfloor nLs \times s(i,j)/maxs \rfloor;$

$quantizedv(i,j) = \lfloor nLv \times v(i,j)/maxv \rfloor;$

$index(k, 1) = quantizedh(i,j);$

$index(k, 2) = quantizeds(i,j);$

$index(k, 3) = quantizedv(i,j);$

$k = k + 1;$

end

end

8- Put 1 to matrix $hsvHist(h,s,v)$, if the values of h, s, v are nonzero.

for i = 1 to $c.r$

$i1 = index(i,1)$; $i2 = index(i,2)$;$i3 = index(i,3)$;

if ($i1 \neq 0$ && $i2 \neq 0$ && $i3 \neq 0$) then

$hsvHist(i1,i2,i3) = hsvHist(i1,i2,i3) + 1;$

end

end

9- Convert $hsvHist$ to vector, and normalize all values in its positions to unit sum.

BOUNDARY ENERGY AND GABOR WAVELET

The energy amount needed to adjust the contour shape to its lowest level of energy is called as boundary energy, with the same circle perimeter as the central objective.

The concept of boundary energy originated from the theory of elasticity and was first applied in biological shape characterization [3, 4]. Since then it has been widely used as a global shape measure for classification of a variety of shapes. Boundary energy is defined as follows:

$$B_{a,k} = \frac{1}{N}\sum_{n=0}^{N-1} c(a,n)^2 \qquad (4)$$

where $B_{a,k}$ denotes the boundary energy of a signal at scale a along the dimension k, c is the curvature at point n, $n = 1,2,\dots,N$; and N is the discrete observations number. The boundary energy is detailed in [5].

A low-pass filter is applied on series data to present the multi-scale dimension of boundary energy by calculating boundary energy of filtered series data separately.

Gaussian filter is the most common one and the value of 'sigma' in the Gaussian expression is changed gradually from low values to very high values. As a result the curvature of a series data is calculated at various values of sigma, i.e., at various analyzing scales leading to a multi-scale representation of the series data [5, 6]. When apply successive low-pass filtering on a sets data with changing rate of sigma, effect in an energy multi-scale characterization contained in the sets data.

Gabor filters types such as wavelets and kernels have a strong tool for extraction of facial feature because of their strong in the problems of illumination alterations, image noises, and to natural image changes like backgrounds variation. Both scopes illustrate complicated band-restricted filters with reserve an optimum values. In the current approach we have calculated the measure echoes of an image filtrated with a filter bank of compound Gabor filters as indicated in [4,7]. The common format of two-dimension Gabor filters in local area can be defined as:

$$\Psi_{u,v}(x,y;\theta,k,\gamma) = \frac{f_u^2}{\pi k\gamma}\exp(-f_u^2 x'^2/k^2 - f_u^2 y'^2/\gamma^2).\exp(i2\pi f_u x') \qquad (5)$$

and

$$\frac{dx}{d\theta} = y\sin(\theta_v) + x\cos(\theta_v), \quad \frac{dy}{d\theta} = y\cos(\theta_v) - x\sin(\theta_v) \qquad (6)$$

where $f_u = 2^{-u/2} f_{\max}$, and $\theta_v = v\pi/8$. Gaussian kernel function modified by compound plane wave can be utilize in Gabor filter form with orientation θ_v and centre frequency f_u. The parameters k and γ determine the ratio between the centre frequency and the size of the Gaussian envelope. If $I(x,y)$ denote a grey scale per-ocular region image, the complex Gabor filtering output can be defined as:

$$G_{u,v}(x,y;\theta,k,\gamma) = \Psi_{u,v}(x,y;\theta,k,\gamma) * I(x,y) \qquad (7)$$

The magnitude response,

$$A_{u,v}(x,y) = \sqrt{(\mathrm{Im}[G_{u,v}(x,y)])^2 + (\mathrm{Re}[G_{u,v}(x,y)])^2} \qquad (8)$$

Gabor_Wavelet procedure:

Inputs: Number of wavelet scales, Number of filter orientations

Outputs: calculates Gabor features: mean-squared energy and mean amplitude for every scale and orientation is computed.

1- Get arguments and/or default values such as image , number scale, n orient , min wave length, sigma and theta on sigma and k,

2- Using the filters constructed in the frequency plane, calculate the standard deviation of the angular Gaussian function.

3- Compute Fourier transform of facial image.

4- Construct energy matrix for collecting values of weighted phase congruency.

5- Construct matrix for collecting filter values of response amplitude.

6- For every pixel, the orientation and maximum energy value are saved in a matrix.

7- Construct cell array of convolution results and array of inverse FFTs of filters.

8- Establish X and Y matrices with ranges normalized to -/+ 0.5.

9- Matrix values contain × normalized× radius from Centre, radius $= \sqrt{x^2 + y^2}$.

10- Theta values are store in polar angle matrix, since positive anticlockwise angles are presented by $-y$, theta $= \tan^{-1}(x, -y)$.

11-Filters are constructed in terms of two components, by multiply the radial component and angular component together.

12- Using amplitude as even filter and median as odd filter to convolve image and return the result in EO.

13- Estimate of noise energy.

I. Color Moments and Color Properties Features

In this procedure, read the color image in R,G,B channels. It extract two first moments R,G,B channels to output the color moments , 1x6 vector of color moments contains mean and standard deviation of R, G,B channel, respectively. The mean and standard deviation of R ,G and B are stored as the vector of color moments and the feature vector represent by 64 items of color properties.

Color Properties Features Procedure

Input: image in uint8 form, from which to extract the color properties.

Output: 1x64 feature vector containing the color properties.

1- Quantize image Im into 64 colors = 4×4×4, in RGB space. i.e. converts the RGB image to an indexed map image using minimum variance quantization. map contains at most 64 colors.

2- Converts the matrix Im and corresponding color-map map to RGB (true color) format rgb.

3- Predefined distances dis=[1,3,5,7] between neighbor pixel intensities.

4- Calculate the features color properties depending on rgb, map, and dis as follows:

[m, n]=length (rgb);

Initialize the counter of color CountCcolor to zero;

Initialize colori with length of map to zero;

for x = 2 to m increasing by step ⌈m/10⌉ {

for y = 2 to n increasing by step ⌈n/10⌉{

Ci = img(x, y); Cn = get neighbors of (x, y) depending on the dis;

for jj = 1:length(Cn){

Cj = img(Cn{1, jj}(1), Cn{1, jj}(2));

for i= 1:length(map){

if isequal(map(i),Ci) && isequal(map(i),Cj)

{ CountCcolor = CountCcolor + 1; colori (i) = colori (i) + 1; }

}}}}

for ii = 1:length(color){ colori (ii) = double(colori (ii) / countColor); }

} correlogram = color; }}

II. Classification

Classifiers are trained using DT, ANN and SVM to learn the following mapping from the labeled training data:

$$\{x_{l,1}, B_{l,1}, x_{l,2}, B_{l,2}, \dots x_{l,K}, B_{l,K}\} \rightarrow C_i \quad (9)$$

where l = index of instances, $l = 1,2, \dots, nj$., and nj is the number of instances in Sj;

K = number of dimensions (signals).

$B_{l,k}$ = Boundary energy at point l in dimension k for input variable $x_{l,k}$.

The classifier (Eq.10) learns to classify each instance. Finally the mapping (2) is ensured by compacting the classes of instances within a segment. This is required due to the reason that frequently within a series data there could be instances (measurements) that obviously belong to the class C1 but are within the segment corresponding to another class C2 and should be attributed to the class C2.

The compaction algorithm assigns weights to the classes determined by the PC unit. The weights w_i are computed as points on a Gaussian curve with zero mean and standard deviation = 2 , and the compact class C_p is determined by:

$$\bar{C_p} = w_i C_p \sum_{i=1}^{nj} w_i \quad (10)$$

where nj = number of instances in a segment and C_p is the class for the ith instance.

Outline of MultiSVM Procedure

Inputs: training matrix T, group C and testing matrix Test

Outputs: Resultant class itrfin

1- Initialize itrfin=empty, Cb=C and Tb=T;

2- For tempind=1 to size (Test) with each class :

Find svm Struct by using rbf kernel function in svm train of new Class and T.

Find classes by using svm Struct in svm classify function with tst.

3- Reduction of Training Set, for all i in new Class and reduction of group.

4-Use Condition max(C)-min(C) for avoiding group to contain similar type of values and the reduce them to process. This condition can select the particular value of iteration base on classes.

5- Apply the logic Cb==u(itr)condition to allow classification of multiple rows testing matrix, and return itrfin position value.

EXPERIMENTAL ANALYSIS AND RESULTS

The experiments have been performed on IIT-KANPUR Database, It contains human face images that are taken in the campus of Indian Institute of Technology Kanpur [8].

Figure 3. Sample of an individual faces of IIT database

It consists of images of 61 folders ,39 males and 22 females, distinguished subjects with 11 various poses for each folder. In this way, every individual has the various in pose, images with 4 emotions - laughter, smile, neutral, sad/disgust. For each individual, database included the following pose for the face: facing front, facing right, facing left, facing down, facing up, facing up towards right, facing up towards left. For some entities, a small number of extra images are also included if available. The background selection for all the images is bright identical and the persons are in a straight, frontal situation. Some sample faces are shown in Figure 3.

Eigen faces are calculated by using PCA algorithm. The algorithm is developed in MATLAB 17b. Figure 4 illustrate the interface of the program.

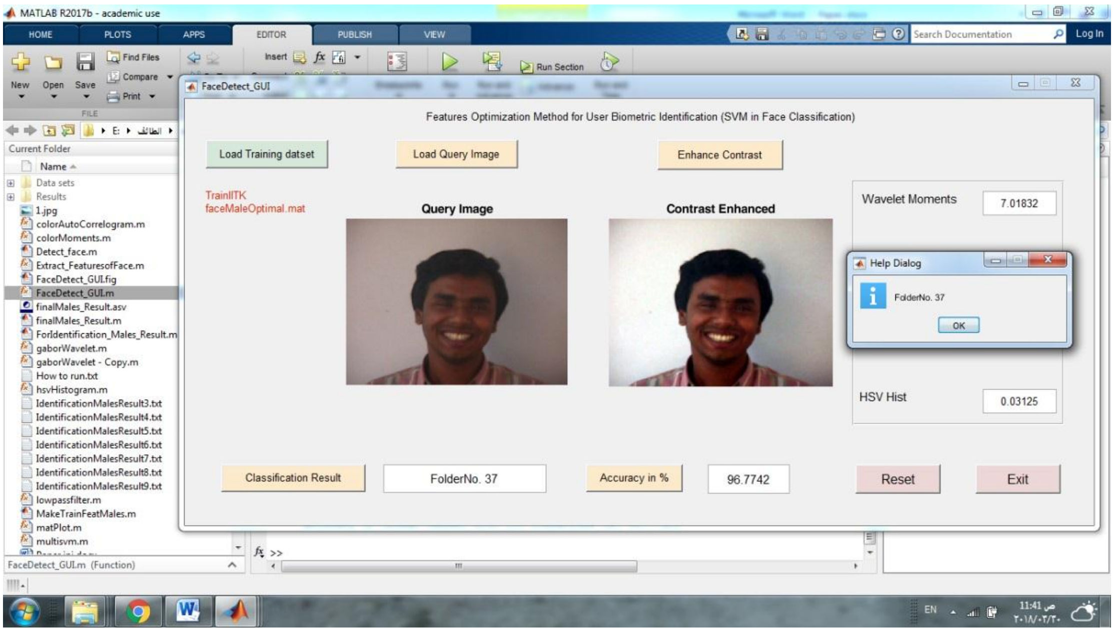

Figure 4. The interface of the program developed in MATLAB

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The comparison between the current method and other methods such as PCA, Normalized PCA (NPCA) [9], Gabor Nearest Neighbor(GNN), Gabor Parzen Probabilistic Neural Network (GPPNN)[10], SIFT Local matching(SIFTL), SIFT Global matching (SIFTG)[11], DWT Nearest Neighbor(DWTNN) and DWT Parzen Probabilistic Neural Network (DWTPPNN)[10] is given. The approach shows significant accuracies over the databases. The experimental result shows that as the number of training images increases, efficiency of the system increases. See Table 1 and Figure 5.

Table 1: Verification Accuracies (%) on IITK database

The method	Recognition rate	Error rate
PCA	72.2	27.8
NPCA	74.6	25.4
GNN	82	18
GPPNN	84.5	15.5
SIFTL	95.8	4.2
SIFTG	93.2	6.8
DWTNN	62.8	37.2
DWTPPNN	81.8	18.2
Proposed	96.2	3.8

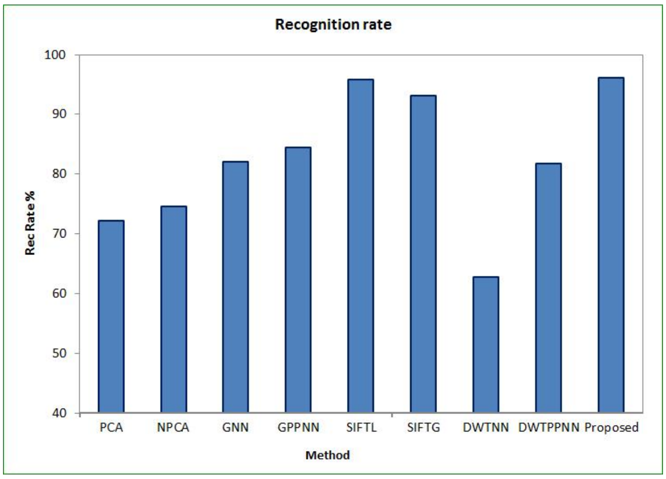

Figure 5. The average of performance of the method and some techniques.

CONCLUSION

In this work, we studied some metaheuristic algorithms to solve the biometric verification problems. The boundary energy, HSV histogram features and MultiSVM are employed to improve the performance of user verification. Next, the comparison between proposed method and other state of the art methods (PCA, DWT, and Gabor Nearest Neighbor) is given.

REFERENCES

[1] M. A. El-Sayed and M. A. Abdel-Latif," Optimization methods for identity verification system using biometric features", Int. J. of Applied Engineering Research, 12(18), 7143-7153, 2017.

[2] V. Vezhnevets, V. Sazonov, and A. Andreeva, "A Survey on Pixel-Based Skin Color Detection Techniques". In GraphiCon, Moscow, Russia, Sept. 2003.

[3] I.T. Young, and T.W. Calvert, "An analysis technique for biological shape", Information and Control, vol. 25, pp. 357-370, 1974.

[4] M. A. El-Sayed, M. Hassaballah, M. A. Abdel-Latif, "Identity verification of individuals based on retinal features using Gabor filters and SVM", J. of Signal and Information Processing, 7, 49-59 ,2016.

[5] L.F. Costa, and R.M. Cesar, Shape Analysis and Classification:Theory and Practice, Boca Raton, Florida: CRC Press, 2001.

[6] M. A. El-Sayed, S. F. Bahgat, and S. Abdelkhalek, "New approach for identity verification system using the vital features based on entropy", Int. J. of Computer Science Issues, 10(6), 2, 11-17, 2013.

[7] V. Štruc, N. Pavešic, "The Complete Gabor-Fisher Classifier for Robust Face Recognition," EURASIP Advances in Signal Processing, vol. 2010.

[8] V. Jain, A. Mukherjee. The Indian Face Database.www.cs.umass.edu/~vidit/IndianFaceDatabas , 2002.

[9] A. K. Bansal, P. Chawla, "Performance Evaluation of Face Recognition using PCA and N-PCA", International Journal of Computer Applications Vol. 76,No.8, 14-20, 2013

[10] A. Joshi, A. Gangwar, R. Sharma, A. Singh, Z. Saquib "Periocular Recognition Based On Gabor And Parzen Pnn" Conference ICIP 4977- 4981, 2014·

[11] D. R. Kisku, M. Tistarelli, J. K. Sing and P. Gupta. "Face Recognition by Fusion of Local and Global Matching Scores using DS Theory: An Evaluation with Uni-classifier and Multi-classifier Paradigm", Computer Vision and Pattern Recognition Workshops, 2009. CVPR Workshops 2009.