IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)
e-ISSN: 2278-2834,p- ISSN: 2278-8735.Volume 11, Issue 4, Ver. I (Jul.-Aug .2016), PP 34-44
www.iosrjournals.org

Improved Face Recognition Rate Using HOG Features and SVM Classifier

Harihara Santosh Dadi, Gopala Krishna Mohan Pillutla

Abstract: *A novel face recognition algorithm is presented in this paper. Histogram of Oriented Gradient features are extracted both for the test image and also for the training images and given to the Support Vector Machine classifier. The detailed steps of HOG feature extraction and the classification using SVM is presented. The algorithm is compared with the Eigen feature based face recognition algorithm. The proposed algorithm and PCA are verified using 8 different datasets. Results show that in all the face datasets the proposed algorithm shows higher face recognition rate when compared with the traditional Eigen feature based face recognition algorithm. There is an improvement of 8.75% face recognition rate when compared with PCA based face recognition algorithm. The experiment is conducted on ORL database with 2 face images for testing and 8 face images for training for each person. Three performance curves namely CMC, EPC and ROC are considered. The curves show that the proposed algorithm outperforms when compared with PCA algorithm.*

IndexTerms: *Facial features, Histogram of Oriented Gradients, Support Vector Machine, Principle Component Analysis.*

I. Introduction

Face recognition has been an important topic of research originated way back in the year 1961. Numerous algorithms are developed on face recognition particularly in the last two to three decades. Improving the Face recognition rate is always the challenge ever since the first algorithm was developed. In 1991, Alex Pentland and Matthew Turk [1] – [2] applied Principal Component Analysis (PCA) which was invented in 1901 to face classification. This has become the standard known as the eigenface method and is today an inspiration for all face recognition algorithms evolved [3]. Gheorghita Ghinea *et. al.* [4] first made an attempt in integrating the Hausdorff Distance (HD) and Schur decomposition for dimensionality reduction based face recognition. The Schur faces have the high discriminative power and performed well over the standard face recognition methods. Still it is in need of some kind of preprocessing step and an enhanced recognition engine for better face recognition performance. Navneet Dalal *et. al.* [5] made a paradigm shift by introducing Histogram of Oriented Gradient (HOG) features instead of Eigen faces which are in the standard PCA algorithms[18] – [19]. HOG features being dense overlapping grid gives very good results for person detection. HOG features have the advantage of fine orientation binning, fine scale gradient, relatively course spatial binning and high quality local contrast normalization which are important for good performance. Paola Campadelli *et. al.* [6] developed feature base face recognition. This is an automatic face recognition which localizes the facial features. The author considered 16 fuducial points. This can be more effective if the geometry and position of the intermediate points are also considered.

The remainder of this work is prepared as follows. Section II reminds the related work. Section III presents methodology of extraction of HOG features and about SVM classifier. Section IV shows the experimental results. Conclusions are finally stated in Section V.

II. Related Work

Face recognition methods mainly deal with images which are of large dimensions. This makes the task of recognition very difficult. Dimensionality reduction is a concept which is introduced for the purpose of reducing the image dimensions. PCA is the most widely used dimensionality reduction and also for subspace projection. PCA can supply the client with a lower-dimensional picture, a projection of this object when seen from its informative view point. This can be achieved by taking only the starting few principal components in such a way that the dimension of the transformed data is minimized. The linear combinations of pixel values here in PCA are called Eigen faces. PCA is an unsupervised and it ignores all the class labels. It treats the entire data as a whole. It uses SVD for dimensionality reduction.

III. Face Recognition Algorithm

A typical face recognition algorithm is presented in this section. For any face recognition algorithm, there are two phases. One is training phase and the other is the testing phase. In the training phase, the features of all the faces in the gallery are found and stored in the data base. The features could be the standard Eigen features or the HOG features. HOG features are taken in the sample face recognition algorithm shown below in the figure 1. In the testing phase, the features of the probe are calculated. These features and the features of the gallery are given to any of the classifier. SVM classifier is taken as example in the figure. SVM classifier looks for optimal hyper plane as a decision function. The HOG features of the probe and the Gallery are taken by the SVM. The classifier looks for the closest feature matching face from the gallery with the probe and gives that face as output. Fig.1 shows the sample face recognition algorithm block diagram.

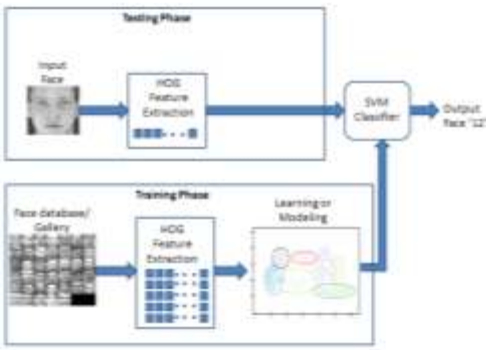


Fig.1 existing face recognition system

Here for experiment purpose the simple database AT&T ORL data base has been taken. There are 40 set of faces in the data base and each set has 10 images. The first 8 images from each set are considered for training and the remaining two images from the data set are considered for testing purpose. The total number of images considered for training are 320 and for testing are 80. The features of all the face images in the training group are extracted using HOG feature extraction. This HOG feature extraction preserves the edges and also the directionality of the edge information. In this the whole image is divided in to cells. Each cell has a matrix of pixels. Each pixel casts a weight vote for an oriented based histogram channel. Histogram channels are evenly spread over 0 to 360 degrees. The best thing is unsigned gradient with 18 channels for human face recognition. Ones the features are extracted, these features are to be classified using any machine learning classifier. Here SVM classifier is used. This is a non probabilistic binary classifier which looks for optimal hyperplane as a decision function. In the testing phase, the test image is taken and given to the SVM classifier for classification.

The face recognition rate is calculated as

$$\frac{\text{Total number of images in the data set which are properly matched}}{\text{Total number of persons in the dataset}} * 100 \qquad (1)$$

The images considered in the numerator of (1) are the test images. These images are excluded from the dataset of the denominator.

A. Histogram of Oriented Gradients

The Histogram of Oriented Gradients (HOG) is a feature based descriptor which used in image processing and computer vision for the purpose of detecting the objects.

1) Gradient computation

Calculation of gradient values is the first step in computation. The first method is to apply 1D derivative masks both vertical and horizontal directions. The dimensions of the masks here we used are 1X3 and 3X1. Specifically, this method requires filtering the color or intensity data of the image with the following filter kernels:

$$D_x = \begin{bmatrix} -1 & 0 & 1 \end{bmatrix}$$

$$D_y = \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} \qquad (2)$$

Where D_x in (2) is the horizontal kernel mask and D_y is the vertical kernel mask.

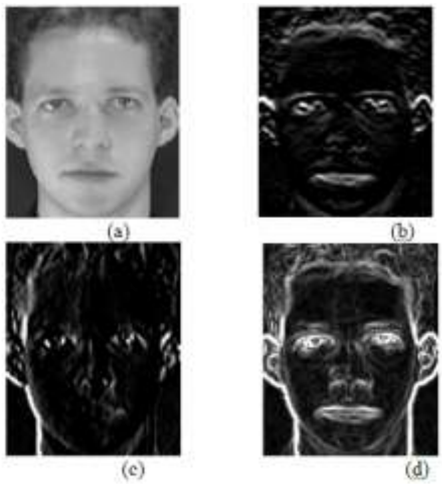
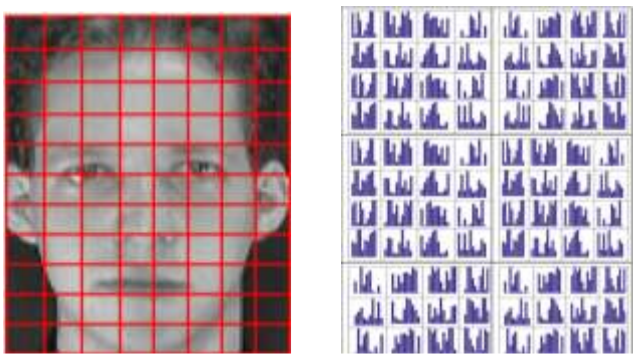


Fig. 2. (a) Sample face from ORL database. (b) Horizontal gradient masked face image. (c) Vertical gradient masked face image. (d) Combination of horizontal and vertical gradients masked face image. **Figure 2(b)** and 2(c) are the application of horizontal and vertical kernels on 2(a). Figure 2(d) is the application of both horizontal and vertical masks.

2) Orientation binning

Orientation binning is the second step in extracting the HOG features. Based on the number of values obtained in the gradient computation, each pixel within the cell casts a weighted vote for a histogram channel which is based on the orientation. The cells can be either radial or rectangular shape and channels are spread over 0 to 360^0 or 0 to 180^0 and it depends on whether the gradient is signed or unsigned. Dalal *et. al.* observed that 9 histogram cannels used in conjunction with unsigned gradients performed best for experiment conducted for human detection. The contribution of pixel can either be the magnitude of the gradient itself, or some kind of the function of the magnitude. In general, in tests the gradient magnitude produces excellent results. Other alternative for the voted weight could be the square or the square of the gradient, or some kind of clipped version of the magnitude.

Figure 3(a) shows the orientation binning operation. The sample face image is divided in to cells. Figure 3(b) is the corresponding histograms of the cells.



(a) (b)

Fig. 3. (a) Division of face image into cells. (b) Histograms for each cell in the image.

3) Descriptor blocks

The strengths of the gradient must be normalized locally in order to account the changes in contrast and illumination. This requires grouping of cells into larger and spatially connected blocks. The Histogram of Oriented Gradients descriptor is obtained by concatenating the components of the cell histograms which are normalized from all the block regions. These blocks overlap typically, means that every cell contributes to the final descriptors at least more than once. There are two kinds of block geometries: Rectangular HOG and Circular HOG blocks. R-HOG blocks are rectangular or square grids, which are characterized by three parameters: cells per each block, pixels per each cell and the channels per each histogram. In the human face detection experiment conducted by Dalal *et. al.*, the most favorable parameters were observed to be four number of 8X8 pixel cells per each block (16X16 pixels per block) with 9 histogram channels. The R-HOG blocks are quite similar to the SIFT descriptors.

4) Block normalization

Dalal and Triggs explored four different methods for block normalization. Let '*v*' be the non-normalized vector containing all histograms in a given block, $\|v\|_k$ be its *k*-norm for k=1,2 and 'e' be some small constant. Then the normalization factor can be one of the following:

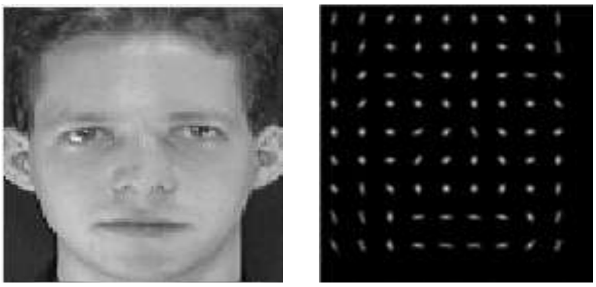
L2-norm: $$f = \frac{v}{\sqrt{\|v\|_2^2 + e^2}} \qquad (3a)$$

L2-hys: L2-norm followed by clipping (limiting the maximum values of v to 0.2) and renormalizing, as in

L1-norm: $$f = \frac{v}{\sqrt{\|v\|_1 + e}} \qquad (3b)$$

L1-sqrt: $$f = \sqrt{\frac{v}{\|v\|_1 + e}} \qquad (4a)$$

In addition, the scheme L2-hys can be computed by first taking the L2-norm (3a), clipping the result, and then renormalizing. In their experiments, Dalal and Triggs found the L2-hys, L2-norm, and L1-sqrt (4a) schemes provide similar performance, while the L1-norm (3b) provides slightly less reliable performance; however, all four methods showed very significant improvement over the non-normalized data.



(a) (b)

Fig. 4. (a) Sample image from the ORL database. (b) HOG features of the image (a)

Figure 4(a) shows the sample image from the ORL database and figure 4(b) shows the HOG features of figure 4(a).

B. Support Vector Machine

Let the training dataset of 'n' points of the form

$$(\vec{x}_1, \vec{y}_1), \ldots\ldots, (\vec{x}_n, \vec{y}_n) \qquad (4b)$$

where the y_i are either 1 or −1, each indicating the class to which the point $\vec{x}_i$ belongs. Each $\vec{x}_i$ is a *p*-dimensional real vector. We want to find the "maximum-margin hyperplane" that divides the group of points $\vec{x}_i$ for which $y_i = 1$ from the group of points for which $y_i = -1$, which is defined so that the distance between the hyperplane and the nearest point $\vec{x}_i$ from either group is maximized.

Any hyperplane can be written as the set of points $\vec{x}$ satisfying

$$\vec{w}.\vec{x} - b = 0 \tag{5}$$

Where $\vec{w}$ is the (not necessarily normalized) normal vector to the hyperplane in (5). The parameter $\frac{b}{\|\vec{w}\|}$ determines the offset of the hyperplane from the origin along the normal vector $\vec{w}$.

1) Soft-margin

To extend SVM to cases in which the data are not linearly separable, we introduce the *hinge loss* function,

$$\max(0,1 - y_i(\vec{w}.\vec{x}_i - b)) \tag{6}$$

This function (6) is zero if the constraint in the equation (7)

$$y_i(\vec{w}.\vec{x}_i - b) \geq 1 ......forall.....1 \leq i \leq n \tag{7}$$

is satisfied, in other words, if $\vec{x}_i$ lies on the correct side of the margin. For data on the wrong side of the margin, the function's value is proportional to the distance from the margin. We then wish to minimize

$$\left[\frac{1}{n}\sum_{i=1}^{n}\max(0,1 - y_i(\vec{w}.\vec{x}_i - b))\right] + \lambda\|\vec{w}\|^2 \tag{8}$$

2) Gaussian radial basis function

$$k(\vec{x}_i, \vec{x}_j) = \exp(-\gamma\|\vec{x}_i - \vec{x}_j\|^2, \text{ for } \gamma > 0. \tag{9}$$

Sometimes parameterized using $\gamma = 1/2\sigma^2$ (10)

3) Computing the SVM classifier

Computing the (soft-margin) SVM classifier amounts to minimizing an expression of the form

$$\left[\frac{1}{n}\sum_{i=1}^{n}\max(0,1 - y_i(w.x_i - b))\right] + \lambda\|w\|^2 \tag{11}$$

4) Primal

Minimizing (11) can be rewritten as a constrained optimization problem with a differentiable objective function in the following way.

For each $i \in \{1,\ldots n\}$ we introduce the variable ζ_i, and note that

$$\zeta_i = \max(0,1 - y_i(w.x_i + b)) \tag{12}$$

if and only if ζ_i is the smallest nonnegative number satisfying

$$y_i(w.x_i + b) \geq 1 - \zeta_i \tag{13}$$

Thus we can rewrite the optimization problem (11) as follows
minimize

$$\frac{1}{n}\sum_{i-1}^{n}\zeta_i + \lambda\|w\|^2 \tag{14}$$

Subject to $y_i(x_i.w + b) \geq 1 - \zeta_i$ and $\zeta_i \geq 0$, for all *I* (15)

This is called the *primal* problem.

5) Dual

By solving for the Lagrangian dual of the above problem, one obtains the simplified problem
maximize

$$f(c_1....c_n)=\sum_{i=1}^{n}c_i-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}y_ic_i(x_i.x_j)y_jc_j, \quad (16)$$

Subject to

$$\sum_{i=1}^{n}c_iy_i=0 \quad (17)$$

and

$$0\le c_i\le\frac{1}{2n\lambda} \text{ for all i} \quad (18)$$

This is called the *dual* problem. Since the dual minimization problem is a quadratic function of the c_i subject to linear constraints, it is efficiently solvable by quadratic programming algorithms. Here, the variables c_i are defined such that

$$\vec{w}=\sum_{i=1}^{n}c_iy_i\vec{x}_i \quad (19)$$

Moreover, c_i=0exactly when $\vec{x}_i$ lies on the correct side of the margin, and $0<c_i<\frac{1}{2n\lambda}$ when $\vec{x}_i$ lies on the margin's boundary. It follows that $\vec{w}$ can be written as a linear combination of the support vectors. The offset, 'b', can be recovered by finding an $\vec{x}_i$ on the margin's boundary and solving

$$y_i(\vec{w}.\vec{x}_i+b)=1\Leftrightarrow b=y_i-\vec{w}.\vec{x}_i \quad (20)$$

6) Kernel trick

Suppose now that we would like to learn a nonlinear classification rule which corresponds to a linear classification rule for the transformed data points $\varphi(\vec{x}_i)$ Moreover, we are given a kernel function 'k' which satisfies $k(\vec{x}_i,\vec{x}_j)=\varphi(\vec{x}_i).\varphi(\vec{x}_j)$. (21)

We know the classification vector $\vec{w}$ in the transformed space satisfies

$$\vec{w}=\sum_{i=1}^{n}c_iy_i\varphi(\vec{x}_i) \quad (22)$$

where the c_i are obtained by solving the optimization problem
maximize

$$f(c_1.....c_n)=\sum_{i=1}^{n}c_i-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}y_ic_i(\varphi(\vec{x}_i).\varphi(\vec{x}_j))y_jc_j$$

$$=\sum_{i=1}^{n}c_i-\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}y_ic_ik(\ \vec{x}_i,\vec{x}_j)y_jc_j \quad (23)$$

$\sum_{i=0}^{n}c_iy_i=0$ and $0\le c_i\le\frac{1}{2n\lambda}$ for all *i*.

The coefficients c_i can be solved for using quadratic programming, as before. Again, we can find some index '*i*' such that $0<c_i<\frac{1}{2n\lambda}$, so that $\varphi(\vec{x}_i)$ lies on the boundary of the margin in the transformed space, and then solve

$$b=\vec{w}.\varphi(\vec{x}_i)-y_i=\left[\sum_{k-1}^{n}c_ky_k\varphi(\vec{x}_k).\varphi(\vec{x}_i)\right]-y_i$$

$$=\left[\sum_{n=1}^{k}c_ky_kk(\vec{x}_k,\vec{x}_k)\right]-y_i \quad (24)$$

Finally, new points can be classified by computing

$$\vec{z} \mapsto \operatorname{sgn}(\vec{w}.\varphi(\vec{z})+b) = \operatorname{sgn}\left(\left[\sum_{i=1}^{n} c_i y_i k(\vec{x}_i, \vec{z})\right] + b\right) \tag{25}$$

Fig. 5. First face image of all 40 people in the ORL database

IV. Experimental Results

For experiment ORL database is used [11].The first two face images are considered for testing and the remaining eight images are considered for training. Table I and Table II shows the comparison of output face images for test face 1 and test face 2 respectively. Green color indicates that the output face images is showing wrong using PCA algorithm and is rectified using HOG-SVM based algorithm. Orange color indicates that the output face image is wrong by using both the algorithms namely PCA and the proposed. Red color indicates that the output face image is showing right using PCA and is showing wrong using proposed algorithm. Table I shows that the face images S5, S9, S13, S20 and S34 are rectified by using the proposed algorithm. S16 and S19 are showing wrong even in the proposed algorithm. S28 is showing wrong using the proposed algorithm and is showing right using the PCA algorithm. Table II shows that the face images S1, S14, S15, S17, S36 and S37 are rectified by using the proposed algorithm. S10, S19, S29 are showing wrong even in the proposed algorithm. S8 is showing wrong using the proposed algorithm and is showing right using the PCA algorithm. There is an improvement of 8.75% face recognition rate using the proposed algorithm when compared with PCA based face recognition algorithm.

Table I : Outputs Of Different Face Recognition Algorithms For Test Face 1

Face 1		
Original AT&T Database	PCA Algorithm	Proposed Algorithm (HOG-SVM Based)
S1	S1	S1
S2	S2	S2
S3	S3	S3
S4	S4	S4
S5	S17	S5
S6	S6	S6
S7	S7	S7
S8	S8	S8
S9	S22	S9
S10	S10	S10
S11	S11	S11
S12	S12	S12
S13	S40	S13
S14	S14	S14
S15	S15	S15
S16	S1	S1
S17	S17	S17
S18	S18	S18
S19	S19	S19
S20	S22	S20
S21	S21	S21
S22	S22	S22
S23	S23	S23
S24	S24	S24

S25	S25	S25
S26	S26	S26
S27	S27	S27
S28	S28	S1
S29	S40	S40
S30	S30	S30
S31	S31	S31
S32	S32	S32
S33	S33	S33
S34	S1	S34
S35	S35	S35
S36	S36	S36
S37	S37	S37
S38	S38	S38
S39	S39	S39
S40	S40	S40

Table II: Outputs Of Different Face Recognition Algorithms For Test Face 2

Face 2		
Original AT&T Database	PCA Algorithm	Proposed Algorithm (HOG-SVM Based)
S1	S40	S1
S2	S2	S2
S3	S3	S3
S4	S7	S4
S5	S5	S5
S6	S6	S6
S7	S11	S7
S8	S8	S39
S9	S9	S9
S10	S40	S40
S11	S11	S11
S12	S12	S12
S13	S13	S13
S14	S30	S14
S15	S40	S15
S16	S16	S16
S17	S21	S17
S18	S18	S18
S19	S16	S16
S20	S20	S20
S21	S21	S21
S22	S22	S22
S23	S23	S23
S24	S24	S24
S25	S25	S25
S26	S26	S26
S27	S27	S27
S28	S28	S28
S29	S40	S40
S30	S30	S30
S31	S31	S31
S32	S32	S32
S33	S33	S33
S34	S34	S34
S35	S35	S35
S36	S40	S36
S37	S22	S37
S38	S38	S38
S39	S39	S39
S40	S40	S40

Table III shows the list of face database used in this experiment. Table IV shows the comparison of PCA algorithm face recognition rate with the proposed algorithm.

Table III: Different Datasets And Their Total Number Of Images And Persons

Data base	Total number of persons	Pose, Illumination and facial expression variations	Total number of face images
Color FERET [7] – [8]	1199 individuals 365 duplicates	9	14126
Yale Database [9]	15	11	165
Yale Face Database 'B' [10]	10	64 illumination 9 poses	5760
BioID [12] – [13]	23	60-70	1521
Georgia Tech [14]	50	15	750
FEI [15]	2000	14	17000
Labeled faces in the wild [16] – [17]	5749	1-20	13233

Table IV: Comparison Of Hog – Svm Based Algorithm And Pca Base Face Recognition Algorithm

Database	Total number of people considered	Total number of faces per person	Faces considered for testing	Faces considered for training	Face recognition rate (in %)	
					Principle Component Analysis Algorithm	HOG features with SVM classifier
Color FERET	40	9	8	1	61.0	68.5
Yale Database	5	11	9	2	88.26	92
Yale Face Database 'B'	10	10	8	2	80.01	88.6
BioID	20	20	16	4	66.36	75.67
Georgia Tech	50	15	13	2	81.63	81.25
FEI	50	14	12	2	77.89	80.13
Labeled faces in the wild	40	10	8	2	61.0	64.6

In case of testing images taken are more than one, then the face recognition rate is calculated by taking the average of the face recognition rates of all the testing images.

The proposed algorithm is also compared with the PCA algorithm with respect to the performance curves namely CMC, EPC and ROC. These curves are shown in the figures 6, 7 and 8 respectively. The performance curves show that the proposed algorithm is superior to the standard PCA algorithm.

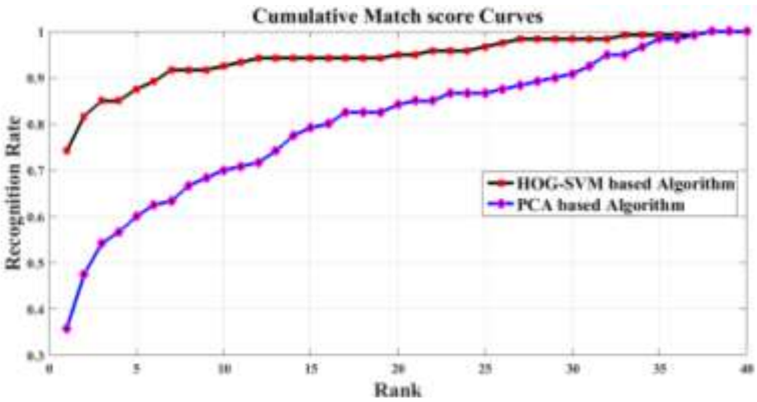


Fig. 6. CMC curves for both the PCA and the proposed algorithms.

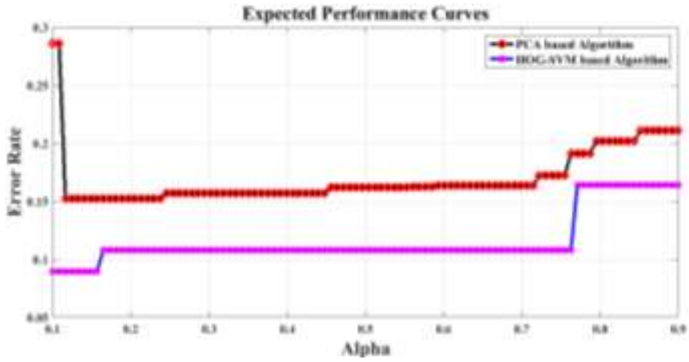


Fig. 7. EPC curves for both the PCA and the proposed algorithms.

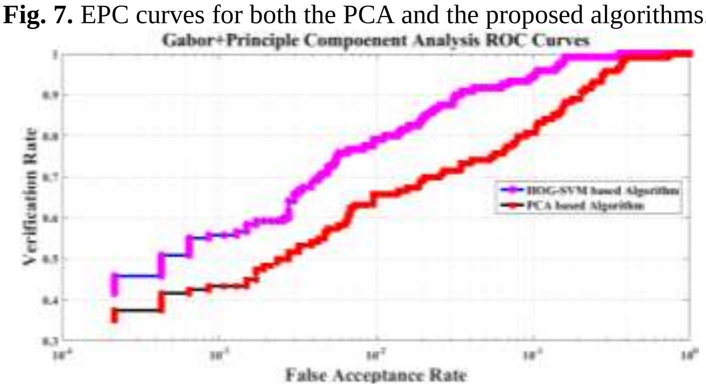


Fig. 8. ROC curves for both the PCA and the proposed algorithms.

V. Conclusions

In this paper, HOG features and SVM classifier based face recognition algorithm is introduced. This proposed algorithm is compared with standard Eigen feature based PCA algorithm. Results show that the proposed algorithm is having an improved face recognition rate of 8.75% on ORL database. The proposed algorithm is also verified on seven other face data sets. Results show that the proposed algorithm outperforms when compared with PCA algorithm for all the datasets.

Acknowledgments

Portions of the research in this paper use the FERET database of facial images collected under the FERET program, sponsored by the DOD Counterdrug Technology Development Program Office.

References

[1]. M. Turk and A. Pentland (Jun. 1991). "Face Recognition Using Eigenfaces." *Proceedings of CVPR IEEE Computer Society*. [Online]. pp. 586-591. Available: https://www.cs.ucsb.edu/~mturk/Papers/mturk-CVPR91.pdf.

[2]. Georghiades A.S., Belhumeur P.N., and Kriegman D.J., "From Few To Many: Illumination Cone Models For Face Recognition Under Variable Lighting and Pose," *IEEE Trans. Pattern Anal. Mach. Intelligence*, vol. 23, no. 6 pp. 646-660 Jun 2001.

[3]. Hailing Zhou, Ajmal Mian, Lei Wei, Doug Creighton, Mo Hossny, and Saeid Nahavandi (December 2014). "Recent Advances on Single Modal and Multimodal Face Recognition: A Survey." *IEEE Transactions on Human-Machine Systems.* [Online]. 44(6) pp.701-716. Available: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6876188.

[4]. Gheorghita Ghinea, Raj kumar Kannan, and Suresh Kannaiyan (2014). "Gradient – Orientation – based PCA Subspace for Novel Face Recognition." *IEEE Access.* [Online]. (2) pp. 914-920. Available: http:// ieeexplore. ieee. org/xpl/ abstractauthors. jsp?reload=true&arnumber=6878464.
[5]. Navneet Dalal and Bill Triggs (Jun. 2005). "Histograms of Oriented Gradients for Human Detection." IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05). [Online]. 1, pp. 886-893 Available: https:// lear .inrialpes. fr/ people/triggs/pubs/Dalal-cvpr05.pdf.
[6]. Paola Campadelli, Raffaella Lanzarotti, Chiara Savazzi. "A Feature-Based Face Recognition System." [Online]. Available: https://homes.di.unimi.it/~campadel/Articoli/ICIAP2003.pdf.
[7]. P.J. Phillips, H. Wechsler, J. Huang, and P. Rauss. (1998). "The FERET Database and Evaluation Procedure for Face Recognition Algorithms." *Image and Vision Computing Journal.* [Online]. 16(5) pp.295-306. Available: http:// biometrics. nist. gov/ cs_links/ face/frvt/feret/feret_database_evaluation_procedure.pdf.
[8]. P.J. Phillips, H. Moon, S.A. Rizvi, and P.J. Rauss, "The FERET evaluation methodology for face recognition algorithms," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 22, no. 10, pp. 1090-1104. Dec. 2000.
[9]. Yale face database. [Online]. Available:http://vision.ucsd.edu/datasets/yale_face_dataset_original/yalefaces.zip.
[10]. Yale face B database. [Online]. Available: http://vision.ucsd.edu/~iskwak/extyaledatabase/extyaleb.html.
[11]. ORL Database. *AT&T Laboratories, Cambridge*. [Online]. Available: http:// www. cl.cam. ac.uk/ Research/ DTG/ attarchive: pub/data/att_faces.zip.
[12]. O. Jesorsky, K. Kirchberg, R. Frischholz, In J. Bigun and F. Smeraldi, editors. "Face Detection Using the Hausdorff Distance." *Audio and Video based Person Authentication - AVBPA 2001, pages 90-95. Springer, 2001.* [Online]. Available: https:// www.bioid.com/download?path=AVBPA01BioID.pdf.
[13]. Bio ID Face Database. [Online]. Available: https://www.bioid.com/About/BioID-Face-Database.
[14]. Georgia Tech Face Database. [Online]. Available: http://www.anefian.com/research/gt_db.zip.
[15]. FEI Face Database. [Online]. Available: http://fei.edu.br/~cet/facedatabase.html.
[16]. Gary B. Huang, Manu Ramesh, Tamara Berg, and Erik learned-miller. (October 2007). *Labeled faces in the wild: a database for studying face recognition in unconstrained environments. University of Massachusetts, Amherst, technical report 07-49*. [Online]. Available: http://people.cs.umass.edu/~elm/papers/lfw.pdf.
[17]. Labeled Faces in the Wild. [Online]. Available: http://vis-www.cs.umass.edu/lfw/.
[18]. Harihara Santosh Dadi and P G Krishna Mohan, "Performance Evaluation of Eigen faces and Fisher faces with different pre-processed Data sets," *International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)*, vol. 4, no. 5, pp. 2110 – 2116. May 2015.
[19]. Harihara Santosh Dadi and P G Krishna Mohan, "Enhancement of Face Recognition Rate by Data Base Pre-processing," *International Journal of Computer Science and Information Technologies, IJCSIT,* vol. 6, no. 3, pp. 2978-2984. Jun. 2015.

Mr. D. Harihara Santosh obtained his B. Tech. and M. Tech degrees from JNT University, Hyderabad in the year 2005 and 2010. Presently he is pursuing Ph.D, in Video Processing at JNTU, Hyderabad. He is presently pursuing his Ph.D. under the Guidance of Dr. P.G. Krishna Mohan. He is presently working as Associate Professor in AITAM, Tekkali in the department of ECE. He has 12 publications in both International and National Journals and presented 22 papers at various International and National Conferences. His areas of interests are Image and Video Processing.

Dr.P.G.Krishna Mohan presently working as Professor in Institute of Aeronautical College of Engineering, Hyderabad. He Worked as Head of ECE Dept. , Member of BOS for ECE faculty at University Level, Chairman of BOS of EIE group at University level, Chairman of BOS of ECE faculty for JNTUCEH, Member of selection committees for Kakitiya, Nagarjuna University, DRDL and convener for Universite a Hidian committees. He has more than 46 papers in various International and National Journals and Conferences. His areas of interests are Signal Processing, Communications.