Face Pose and illumination Normalization for Unconstraint Face Recognition from Direct Interview Videos

T. Shreekumar, K. Karunakara

Abstract— The Posture variation and the Lighting sets in the vicinity problem are the two major challenges in Facial parameters identification. We use Local Linier Regression (L.L.R) and Discrete Cosine Transform for Posture and Lighting set correction. In this publication Principal Composition Exploration (P.C.A), Fisher's Linier Discrimination examination (F.L.D.A) and the combined score of P.C.A and L.D.A are castoff to articulate the single layered sped forward Neural Network. During the testing portion Posture and the Lighting sets in the vicinity normalization are carried out using L.L.R and D.C.T respectively. Then the combined score of P.C.A and L.D.A of test image is used to recognize the image using the trained Neural Network. We further use the Support Vector Machine (S.V.M) to train and recognize the Face images replacing Neural Network. We are able to obtain more improvement in the results such as computational complexities and computation speed.

Index Terms— Artificial Neural Network, Support Vector Machine,Discrete Cosine Transform, Fisher Linear Discriminant Examination, Linear Facial parameters identification, Principal Compound Investigation, Local Linear Regression.

1. INTRODUCTION

Facial parameters identification technique is one of the best technique when implementing a stored data structures technology where faces discriminates and disintegrates individuals in specified form of still or video image. It has numerous reliable applications involving both human cum computer device interaction system, substantially authentication techniques, global security management, and domestic cum commercial surveillance sectors. The predominant types of facial parameters identification strategies include (i) feature-based (ii) appearance-based. In the former method geometrical parameters pertaining to the facial part measurements are used, whereas in the latter, intensity derivative parameters are used.

The already performed researches have focused on functional parameters like pose, lighting sets in the vicinity, hair style, make-up, facial expression, identity, aging and so on. Out of these of these facial parameters identification, lighting sets in the vicinity and Posture are the two major bottlenecks which completely influence the technique. The storage of a huge number of photographic views for each facial image is a challenging factor in Pose-invariance recognition. Hence it becomes inapplicable in circumstances where different images to be included. Varying lighting sets in the vicinity faces computational cost as the major drawback apart from its technical incapability. Various algorithms are being developed continuously by research scholars for facial parameters identification to solve these critical problems, still in vain due to its computational complexity in investigation, huge cost incurred and huge memory space requirements. To overcome all these hitches and to make the best use of the approach we recommend a new facial recognition system involving video images clipped with variable Posture and varying lighting sets in the vicinity conditions.

Here the facial parameters identification comprises of two predominant stages (i) training section (ii) testing section. Section (i) focuses on training the database by implementing P.C.A, F.L.D.A and Neural network where, dimensionality of the image is reduced through P.C.A while feature vector is acquired with F.L.D.A. The combined score of P.C.A and L.D.A together is implicated in training the neural Network. On the contrary, section (ii) uses the video clipping of the sample personnel to be recognized to be the input which may or may not have the Posture variation and lighting sets in the vicinity fluctuation as only a standardized image of the personnel is acquired using L.L.R and D.C.T techniques .Consequently these reduced dimensions and features attained using P.C.A and F.L.D.A are converted and recognized by Neural Network.

The experiment is further carried out by selecting S.V.M in place of Neural Network. The combined score of P.C.A and L.D.A are used to train the S.V.M. The test image is standardized using the L.L.R and D.C.T. The dimensionality redued using P.C.A and the same is represented using L.D.A.Then the score is used to recognize the image. The statistical parameters such as Sensitivity, Specificity, Accuracy etc and the computation speed are recorded. In the next experiment the S.V.M with RBF kernel is used to test and recognize the image.

A brief research related views of Facial parameters identification is illustrated in Section II. The suggested video facial parameters identification system is elaborated section III with its experimental results in Section IV and the work is concluded with the possible Future Enhancement in Section V.

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2. RELATED WORK

Aishat Mahmoud Dan-ali and Mohamed Mustafa [1] have proposed a five lighting sets in the vicinity normalization techniques using Euclidean distance and Cosine distance. Experiments were performed on three different face databases -CAS PEAL Database, Extended Yale Database and AT&T database. The Anisotropic Smoothing method (AS) is used as a smoothing technique. The above techniques are used along with the distance classifiers resulting ten combinations. The Results shows an improved recognition rate when applied appropriately using the right classifier.

Jianke Le et al. [2] gives a novel approach for facial parameters identification using P.C.A, L.D.A and S.V.M. The S.V.M is appointed for classification. Geometric normalization of the face image was performed prior to feature extraction to eliminate redundant information. The experiment is conducted on ORL face database which consists of 40 individuals, 10 images of each individual. Positive and Negative sample images were taken as input to control and regulate a S.V.M classifier in the hyper plane. The experiment is conducted with three methods: P.C.A+ Standardized Cross Correlation (NCC) where NCC and S.V.M were used as classifiers. Recognition rates for all three methods were evaluated. P.C.A+L.D.A+S.V.M gave higher recognition quotient in the outcome.

R.Rajalakshmi and M.K.Jeyakumar [3] have proposed an automated recognition system to identity of the individual from images that were not used during the training phase. Posture and Lighting set variations were taken into consideration in the system. Dimensionality reduction and feature extraction was done using Principal Component Investigation and Linear Discriminant Investigation respectively. K- Nearest Neighbour algorithms were used to illustrates the performance of the system. Results showed that when L.D.A+P.C.A combination were used as feature extractors along with S.V.M as classifier, it gave the best recognition rate of 96%. It also deduced that classifier with supervised learning method such as S.V.M is better when compared to unsupervised methods.

Cemil Tosik et al. [4] proposed a method which deals with lighting sets in the vicinity variation. The proposed system investigated different pre-procedural stepsing algorithms for lighting sets in the vicinity normalization with front face images of 10 subjects each with 64 different lighting sets in the vicinity and evaluated the Yale Face Database B. Later these pre procedural stepsing algorithms were cascaded to measure recognition rates. Experimental results showed that Steerable Gaussian Filter and combination of Histogram Equalization with Steerable Gaussian Filter gave the best outcomes.

N.Pattabhi Ramaiah et al. [5] proposed a prototype for facial parameters identification with varying lighting sets in the vicinitys with Convolution Neural Networks (CNN). CNN is capable of detecting native patterns from input data to differentiate images. This approach employs Back Propagation Algorithm using 5 fold cross validation method. Here horizontal reflection of images is considered in the training dataset which gives additional information on appearance of shadow on only one side of the face. This step improves the performance of the system by 4.96% from 89.05%. During testing, the maximum value of a given facial image is considered to determine the output class. All experiments are conducted on Extended Yale Face Database B. It also concluded that the CNN is computationally expensive to train when the input database size is Large.

Virendra P. Vishwakarma et al. [6] proposed a framework for lighting sets in the vicinity normalization in D.C.T domain by down scaling of D.C.T Coefficients. Lighting sets in the vicinity variation is compensated by scaling down low frequency D.C.T coefficients. These images were fed to the classifiers. The classifiers used were K-Nearest Neighbourhood(k-NN) and Nearest Mean Classifier(NMC) with distance metrics as correlation coefficient and Euclidean distance. The database used here was Yale Face Database B. The proposed method claims 100% recognition rate without any error.

Chande Anita and Shah Khushbu [7] proposed an invariance in lighting sets in the vicinity of facial parameters identification system using Discrete Cos Transform (D.C.T), Principal Component Investigation and the Artificial Neural Networks (A.N.N). Initially the input image is given to a logarithm transform. This logarithmic image is given to D.C.T. Using D.C.T for removing the low frequency components, then the high frequency components are scaled and the P.C.A is employed to extract important facial features by reducing the dimensionality. Experiments were conducted using Euclidean distance and BPNN as classifiers with Modified D.C.T, D.C.T and D.C.T without normalization on Yale database. The modified D.C.T with BPNN gives better result than the modified D.C.T with Euclidean Distance.

3. VIDEO FACIAL PARAMETERS IDENTIFICATION SYSTEM UNDER POSTURE AND LIGHTING SET FACTORS

The video facial parameters identification system is an appearance based approach for documentation of faces under Posture and Lighting set variation. The procedural steps performed illustrated in Fig.1. Let $D = \{D_i \mid i = 1,2,3\cdots, N\}$ denote the training data sample sets with 'N' number of images and $X = \{x_{ij} \mid i = 1,2,3\cdots, n; j = 1,...N\}$ Where, x_i is a face vector.

A. Feature implied Learning (Training)

Techniques and methodologies such as Principal Compound Investigation (P.C.A), Fisher Linear Discriminant Investigation (F.L.D.A) and Artificial Neural Network (A.N.N) are utilized in the training section. The functional parametric vectors that best illustrate distribution of face image representation within the entire image representation P.C.A is determined using the Fisher Linear Discriminaation Investigation (F.L.D.A). Let $\hat{R} = \{R_i \mid i = 1,2,3\cdots, n; j = 1,23...N\}$ and the threshold value used be λ .

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B. Video Face Recogntion System - Testing

Let 'T' be the testing video streams, $\widehat{F}=\{f_i\ ,|\ i=1,2,3,\cdots,.N\ \}$ be the produced frame set of 'T and $M=\{m_i\ |\ i=1,2,3\cdots,N\ \}$ be the masked images of the frameset $\widehat{F}$ .Let $P=\{p_i\ |\ i=1,2,3\cdots N\ \}$ be the frames set on which the posed invariant procedural steps must be performed and $L=\{l_i\ |\ i=1,2,3\cdots N\ \}$ be the sampled frames set on which the lighting sets in the vicinity invariant procedural steps must be performed. The optimum representation criterion of P.C.A and the discriminant criterion of F.L.D.A are united to the Neural Network predicting a threshold value λ .

1) Dealing with Posture Invariant Procedural steps Using L.L.R

Linear Regression procedural steps is employed on the current frame sets cumulatively. If the lighting source (x,y,z) is permanently fixed, then the strength of each surface point is independent of the perspective location and it can be evaluated as,

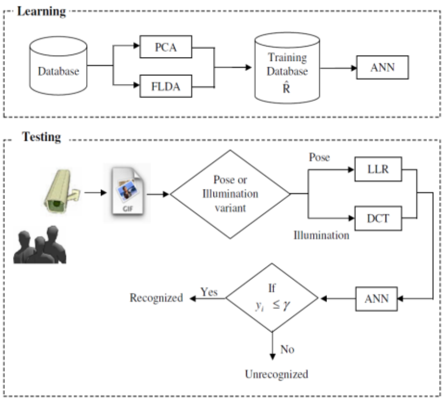

Fig. 1: Procedural steps of Proposed System

$$\delta(x,y,z)=\gamma(x,y,z)\cos\alpha \tag{1}$$

Where, δ is a vector that joins the intensity of the surface points in a specific scan-line sequence, $\gamma(x,y,z)$ is the albedo of the specified point and α is the angle between the normal vector $\vec{n}(x,y,z)$ and the lighting direction vector $\vec{s}(x,y,z)$.

Apparently, the operator is subjective to both the viewpoints and the 3-D structure of the specific face image. If the j^{th} point in δ is visible from the viewpoint Q and it is anticipated as the i^{th} pixel in I , then $D_{ij}=1$, otherwise $D_{ij}=0$.

The frontal image vector (I_0) and the non-frontal image vector (I_P) are evaluated as follows,

$$I_0=D_0\delta \tag{2}$$

$$I_P=D_P\gamma \tag{3}$$

Predicting I_0 from I_P necessitates recovery of δ from I_P and m is always less than n. The skipped data a blocked version δ can be determined as,

$$\delta'=D_\gamma^\delta I_\gamma=D_\gamma^\delta D_\gamma\delta \tag{4}$$

In eqn. (4), $D_P^T I_P$ is a $m\times n$ identity matrix adapted by changing the i^{th} "1" in diagonally

$$\bar{\delta}=D_\gamma^\delta I_\gamma+\Re I_\gamma=(D_\gamma^\delta+\Re)I_\gamma \tag{5}$$

where, $\Re$ is the $n\times m$ neighborhood relation matrix. Finally we get,

$$I_0=D_0((D_\gamma^\delta+\Re)\cdot I_\gamma)=(D_0D_\gamma^\delta+D_0\Re)\cdot I_\gamma \tag{6}$$

Eqn. (6) can be rewritten to obtain the estimation of I_0 as,

$$\tilde{I}_0=A_\gamma I_\gamma \tag{7}$$

$$A_\gamma=D_0D_P^T+D_0\Re \tag{8}$$

. As The patches $I_\gamma=(I_{(1,\gamma)}\ I_{(2,\gamma)}\ \cdots\ I_{(M,\gamma)})$. of the i^{th} frontal patch $I_{(i,0)}$ that corresponds to the i^{th} non frontal patch involves two steps

Step 1: Determine the reconstruction coefficients for the i^{th} patch in $I\gamma$ as

$$\alpha_i=\varpi_{(i,\gamma)}^{\perp}I_{(i,\gamma)} \tag{9}$$

$\Phi_{(i,\gamma)}=\left(I_{(i,\delta)}^1\ I_{(i,\gamma)}^2\ \cdots\ I_{(i,\gamma)}^N\right)$ contains the i^{th} patch from the training images with pose P .

Step 2: Determine the virtual frontal patch as,

$$I_{(i,0)}=\varpi_{(i,0)}\alpha_i \tag{10}$$

where, the matrix $\varpi_{(i,0)}=\left(I_{(i,0)}^1\ I_{(i,0)}^2\ \cdots\ I_{(i,0)}^N\right)$ contains the i^{th} patch sampled from the frontal training images with pose γ . The mean of the specified pixels in these overlapping patches is calculated as follows,

$$g_0(x,y)=\frac{\sum_{m=1,\cdots M} g_{(m,0)}(x,y)}{\sum_{m=1,\cdots M} Index_{(m,0)}(x,y)} \tag{11}$$

where, $Index_{(m,0)}(x,y)=\begin{cases}1, & if(x,y)\in I_{(m,0)},\\ 0, & otherwise\end{cases}$ and the acquired intensity value $g_{(m,0)}(x,y)$ for the pixels that corresponds to the m^{th} patch $I_{(m,0)}$ is assigned 0 if the point (x,y) is not present in the m^{th} patch.

2) Dealing with Lighting sets in the vicinity Invariant Procedural steps using D.C.T

The major cause for the problems associated with lighting sets in the vicinity variation for face images is the different appearance of the 3D shape of human faces under different direction lighting sets in the vicinitys is given as $I_f(x,y)$ and can be regarded as the product of reflectance $RR(x,y)$ and luminance $LL(x,y)$ as given in eqn (20).

$$I_f(x,y)=RR(x,y)LL(x,y) \tag{12}$$

logarithmic transform on eqn. (20),

$$\log I_f(x,y)=\log RR(x,y)+\log LL(x,y) \tag{13}$$

The linear equation (12) shows that the logarithm transform of the illuminated image and the logarithmic transform of luminance in (13). The homogeneously

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illuminated image, l_o, can be expressed as in (14). where, $LL(x,y)$ and $LL_o(x,y)$ are the incident luminance and the uniform luminance respectively. The luminance component indicates the lighting sets in the vicinity variation.

$$\log LL_o(x,y) = \log LL(x,y) + c(x,y) \tag{14}$$

Low frequency components of D.C.T do lighting sets in the vicinity normalization as follows,

The 2D D.C.T for an $N \times N$ image is obtained as,

$$C(x,y) = \sum_{x=0}^{N-1}\sum_{y=0}^{N-1} I(x,y)\cos\frac{\pi(2x+1)u}{2N}\cos\frac{\pi(2y+1)}{2N} \tag{15}$$

where υ, $v = \{0,1,2,\cdots,N-1\}$ are the horizontal and vertical components respectively and $l_f(x,y)$ is the pixel value at coordinate (x,y). The square root of the sum of v^2 and u^2, yields the frequency. The inverse 2D D.C.T is obtained as,

$$l(x,y) = \sum_{u=0}^{N-1}\sum_{v=0}^{N-2}\left((u,v)\cos\frac{\pi(2x+1)u}{2N}\right) \tag{16}$$

From (16), by adding a compensation term, luminance component can be obtained from the original image. First, an $r \times c$ image is reconstructed and its mean is calculated from the low frequency components of D.C.T as follows,

$$m = \frac{1}{r \times c}\sum_{x=1}^{c}\sum_{y=1}^{r}\log LL(x,y) \tag{17}$$

Then from each pixel we get,

$$c(x,y) = 0.5*(m - \log L(x,y)) \tag{18}$$

The $\log LL(x,y)$ is estimated using the low frequency components of D.C.T. Negative value points indicate dark and positive value points indicate bright ones. By adjusting each pixel as shown in eqn. (18).the difference between the pixel value and mean value are halved. Lighting sets in the vicinity normalization is performed using the odd and even D.C.T components in horizontal direction

In this part, to eliminate the shadows and specularities and store the original features which use the properties of odd and even D.C.T components we proPosture an lighting sets in the vicinity correction method. Variable lighting sets in the vicinity produces odd D.C.T components hence eqn (12) can be changed as,

$$I(x,y) = idct(En\,DCT\,comp) + idct(Od\,DCT\,com) \tag{19}$$

Here, an even and odd D.C.T components manipulation based lighting sets in the vicinity compensation method is proposed.

First, two new images l_{odd} and l_{even} are reconstructed from the odd and even D.C.T components in the horizontal direction of the original images..

$$l_c(x,y) = 0.5*(l_{odd}(x,c+1-y) - l_{odd}(x,y)) \quad 1 \le y \le \frac{c}{2} \tag{20}$$

$$l_c(x,c+1-y) = 0.5*(l_{odd}(x,c+1-y) - l_{odd}(x,y)) \quad \frac{c}{2} < y \le c \tag{21}$$

Both pixels will be modified according to the following equations if the right side pixel is negative and the corresponding left side pixel is positive.

$$l_c(x,y) = 0.5*(l_{odd}(x,y) - l_{odd}(x,c+1-y)) \tag{22}$$

$$l_c(x,c+1-y) = 0.5*(l_{odd}(x,y) - l_{odd}(x,c+1-y)) \tag{23}$$

The new pixel intensity for the compensated image is determined using the following equation.

$$l(x,y) = l_c + l_{even} \tag{24}$$

The lighting sets in the vicinity changes are greatly diminished while preserving the significant facial features. The output images may contain adverse effects. All the images are standardized for a mean of 0.6.

3) P.C.A Based Dimension Reduction

Functional parametric vectors that best represent distribution of face images within the entire image space can be found out using the Principal Component Investigation technique.. The sub space of the face images called eigen face space is defined by these functional parametric vectors.. Let $D = \{D_I \mid i = 1,2,3\cdots,N\}$ be the training data set that has 'N' number of images. Let $X = \{x_{ij} \mid i = 1,2.3\cdots,n; j = 1,2,3...N\}$ be the n*N data matrix where each x_I is an 'N' dimensional face vector joined from $P*Q$ face image and $n = P.Q$ signifies the total number of pixel in the face image can be represented as a linear transformation (1) i.e.,

$$F = E^T X \tag{25}$$

F - feature vector matrix of dimension m × N

m-feature vector

E is a transformation matrix of dimension N ×m

$$\beta v_i = S v_i. \tag{26}$$

Here, the entire scatter matrix S and mean image of the entire samples are determined as follows,

$$S = \sum_{i=1}^{N}(x_i - \varphi)(x_i - \varphi)^T \quad \text{and} \quad \varphi = \frac{1}{N}\sum_{i=1}^{N}x_i. \tag{27}$$

The scatter transformed feature functional parametric vector constraint $\{f_1, f_2, ...f_N\}$ after the application of linear transformation E^T, is $E^T SE$. In P.C.A, determinant that maximizes the total scatter matrix of the projected samples is selected.

$$E_{opt} = \arg\max_w \left|E^T SE\right| = [E_1, E_2....E_m] \tag{28}$$

where $\{E_i \mid i = 1,2,........m\}$ is the set of n dimensional eigen functional parametric vectors of 'S' corresponding to the m biggest eigen values.

4) Feature Vector Generation - Fisher Linear Discriminant Investigation

Considerably alienated classes of environment generated through extreme lighting conditions and facial expressions changes accomplished by F.L.D in a low-dimensional subspace. Linear Discriminant Investigation (L.D.A). P.C.A of the mean of specific variables, exploiting the class information can be useful for the identification tasks.

Let c represent N face images. The face images functional parametric vectors of dimension n within-class scatter be maximized by the W selected by L.D.A in (5)

$$P_i = E^T Y_i \tag{29}$$

Assuming that S_j is non-singular the first l eigenfunctional parametric vectors with the largest eigen values of $S_W^{-1} S_G$ are represented by the basis functional parametric vectors in W. S_G between-class scatter matrix and S_W the within-class scatter matrix are determined by

$$S_W = \sum_{i-1}^{c} \sum_{Y_k} (y_k - \varphi_i)(y_k - \varphi_i)^T, \varphi_i = \frac{1}{N_i} \sum_{k=1}^{N_i} Y_k \tag{30}$$

$$S_G = \sum_{i-1}^{c} N_i (\varphi_i - \varphi)(\varphi_i - \varphi)^T \tag{31}$$

In the above expression, N_i c, φ_i and Y_k number of training samples in class Y_i, number of unique classes, mean vector of samples belonging to class Y_i and the samples belonging to class Y_i. The optimal projection of E_{opt} is selected as,

$$E_{opt} = \arg\max_{w} \frac{E^T S_G E}{E^T S_W E}, \ i = 1, 2, \ldots..l$$

$$[E_1 E_2 \ldots\ldots\ldots E_m] \tag{32}$$

where the set of n–dimensional eigenfunctional parametric vectors of S $\{E_i \mid i = 1,2,\ldots\ldots\ldots m\}$ represents the m biggest eigen values.

5) Neural Network Based Recognition Using P.C.A and F.L.D.A

By providing the combined scores obtained by P.C.A and F.L.D.A to the neural network whether the video is recognized or not can be decided.

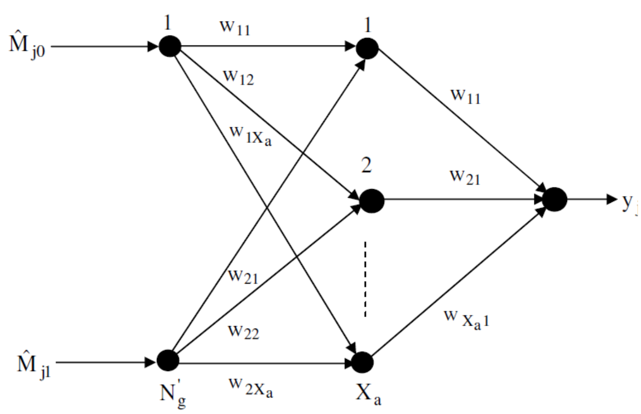


Fig. 2: two inputs-1 output Neural Network

N, represented as $\hat{M}_{jo}$ and $\hat{M}_{j1}$ exists in the artificial neural network characteristics presented in this Fig.2. A weight represented as $w_{11}, w_{12}, \cdots, w_{1N}$ assigned to each line that links these input units to their respective neuron parameters. λ Represents the threshold in artificial neuron is determined implementing the below formulae for the activation.

$$y_j = \alpha + \sum_{k=0}^{N_g'-1} w_{jk} \hat{M}_{jk} \qquad 0 \le j \le N_s' - 1 \tag{33}$$

$$g(y) = \frac{1}{1+e^{-y}} \tag{34}$$

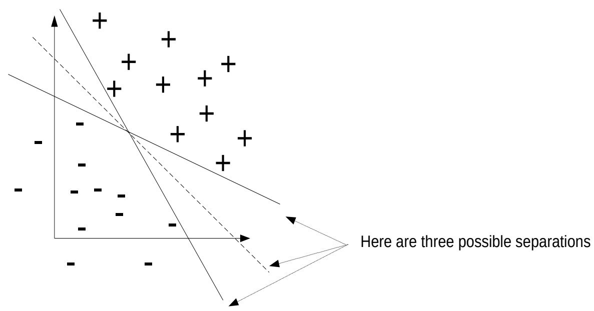
$$g(y) = y \tag{35}$$

The basis functionis given in Eq. (33) is selected for the hidden/with held output layer are given by Eq. (34) and Eq. (35) respectively. In Eq. (33), $\hat{M}$, α and w_{jk} are the feature extracted by Fisher Linear Discriminant Investigation(F.L.D.A) and Principal component investigation(P.C.A), bias and the weight of the neurons respectively. The hidden channels and output layers normally employ the basis functional elements given in Eqn. (33). The outcomes from N_p A.N.Ns is resolved by illustrating $\hat{M}$ as input. A singlular value y_i is acquired by by combining both the weighted values. Finally, the out come is cross checked with the corresponding threshold value for distinguishing the face image. If $y_i \le \lambda$, t. A selected network will be reported as the host of the input face if its output passes a predefined threshold and otherwise it will be added to the face library and reported as unknown.

6) Support Vector Machines with P.C.A and F.L.D.A

S.V.M is used widely in most of the classification and regressions classification and even for unsupervised learning applications because of its efficiency and computational speed. It also exhibits more accuracy in most of the cases comparable to Multilayer Perceptrons.

presuming training variable $D = \{(\vec{x}_i, y_i), i = 1 \ldots N\}$ $y_i \in \{-1,+1\}$ separated by means of a hyper plane.



Here we can get the answer for what is the best linear classifier of the type

$$f(\vec{x}) = \vec{w}^T \vec{x} + b \quad (= w_1 x_1 + w_2 x_2 + w_3 x_3 + \ldots + w_n x_n + b).$$

Infinitival hyperactive planes can accomplish nearly 100% accuracy on data specified for the training , the question is what hyper plane is the optimal with respect to the accuracy on test data?

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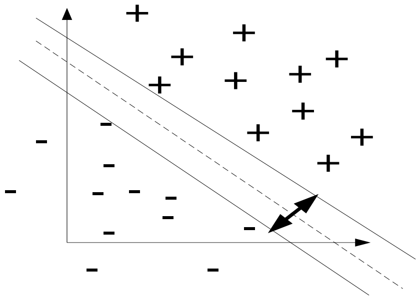
The classification for Given f(x), is

$$\hat{\mathbf{y}} = sign(f(\mathbf{x})) = \begin{cases} +1 & f(\mathbf{x}) > 0 \\ -1 & f(\mathbf{x}) < 0 \end{cases}$$

Here different values of w and b can also result ilead to identical classification.

Increase the maximum margin between positive and negative feature points so



In the Fig 1 when we replaced A.N.N with S.V.M we observed greater improvement in accuracy, specificity and other statistical measures this is shown in our experimental result.

We also observed improvement in the performance of S.V.M by selecting proper kernel function. Here we have selected Radial basis function for kernel optimization.

IV. EXPERIMENTAL RESULTS

The Video facial parameters identification system is instigated through MATALB and assessed with the four dataset of UPC Face Database [19]. Fig.3 shows standard sample frame setset from the existing database.

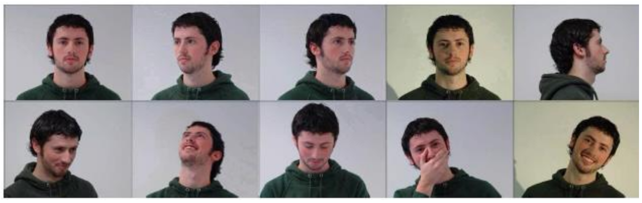


Fig. 3: The standard sample frame sets

Fig. 4 portrays the masked portraits of the standard sample set of frames of fig.3. Fig 5(a) represents the standard sample frame sets with varied lighting sets in the vicinity and 5(b) represents the standard sample frame sets set with varied poses.

Fig. 4: Masked image of Fig.3.

Fig. 5(a): Sample frames with varied Lighting sets in the vicinity

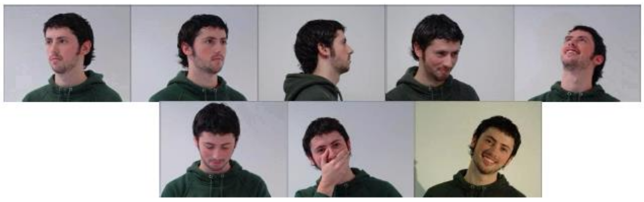


Fig. 5 (b) Standard sample frame sets with varied Posture

In the lighting sets in the vicinity invariant procedural steps the standardized frames are obtained by D.C.T procedural steps of Posture invariance procedural steps the standardized portraits are obtained by L.L.R. Fig.6 (a) portrays the standardized portrait post lighting sets in the vicinity variance and Fig.6 (b) portrays the standardized portrait after the Posture variance.

(a)

(b)

Fig. 6(a): Standard image post D.C.T implementation (b): Standard image post L.L.R implementation

The scores acquired using the P.C.A and F.L.D.A are collectively fed to the concerned neural network to check if the video has been captured and acknowledged (i.e.) yielding a single output with the threshold data values =.6. The image is acknowledged is authenticated if , otherwise unauthorized if .

Further the Face database is trained and tested using S.V.M as indicated in Table 1.Here we are able to obtain more accuracy of 85% , 10% more accuracy than Neural Network. The S.V.M kernel parameters are then optimized using RBF. Hence we are able to get 5% more accuracy yielding 90% accuracy on selected dataset.

Experimental result shows more improved statistical measures and Computational speed as indicated in Table 2.

A. Performance Assessment

The performance is assessed by statistical parametric variables namely, sensitivity and specificity. The output of may be dependent on the recognized image. The output may or may not match with the original position of the personnel. Hence we enumerate the following criteria for the statistical purpose.

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Truly Positive (TP): Authorized personnel appropriately recognized to be the authorized.

Falsely Positive (FP): Un-authorized personnel inaccurately recognized to be the authorized.

Truly Negative (TN): Un-authorized personnel appropriately recognized to be the un-authorized.

Falsely Negative (FN): Authorized personnel inaccurately recognized to be the un-authorized.

Sensitivity values illustrate the percentage of facial posture recognition with respect to that of actual values. Specificity exemplifies the proportion of facial posture recognition with respect to actual negatives.

The following Table 1denotes the arithmetical parameters and Fig 7. Show the graphical representation for the same dataset.

Sensitivity denotes the percentage of actual recognition while Specificity is the percentage of negative recognition.
Accuracy denotes the highest possible degree of nearness of dimensions of any magnitude to its actually present (true) value or ideal value.

V.RESULTS & DISCUSSIONS

Table 1: Statistical measures for proposed UPC Face Database [19]

Measures	Proposed method with A.N.N	Proposed method with S.V.M	Proposed method with RBF kernal
True Positive	7	9	9
True Negative	8	8	9
False Positive	2	2	1
False Negative	3	1	1
Sensitivity	70.00	90.00	90.00
Specificity	80.00	80.00	90.00
Precision	77.78	81.82	90.00
N.P.V	72.73	88.89	90.00
F.P.R	20.00	20.00	100.00
F.D.R	22.22	18.18	100.00
F. N.R	30.00	10.00	100.00
Accuracy	75.00	85.00	90.00
F1 Score	73.68	85.71	90.00
MCC	50.25	70.35	80.00

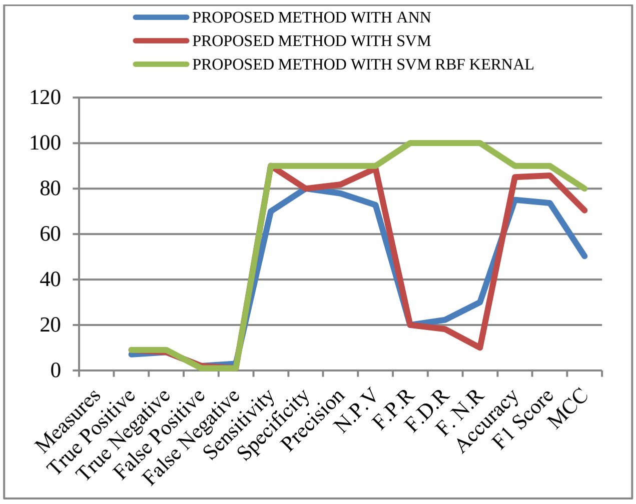

Fig.7. Graphical Representation of various Statistical measures.

Table II: Time taken for recognition

Experimental setup (TRAINING+TESTING)	PROPOSED METHOD WITH A.N.N classifier	proposed method with S.V.M classifier	proposed method (OPTIMIZED S.V.M WITH RBF KERNAL)
1	8.13 Sec	4.67 Sec	4.50 Sec

VI. CONCLUSION AND SCOPE FOR FUTURE ENHANCEMENT

The methodology is implemented directly and their performance characteristic is assessed concurrently using MATLAB. From the experimental result it is clear that L.L.R is a powerful and reliable technique for generating virtual front view of the facial image when there is an issue with Posture variation by just using non frontal sequence and further D.C.T gives moderate performance in eliminating the lighting sets in the vicinity problem. From the investigation it is clear that the S.V.M based Recognition system gives better result compared to A.N.N. We can improve the recognition performance of S.V.M by optimizing the kernel parameters. The future work will be optimizing the kernel parametric variables of the S.V.M during training to improve the Facial parameters identification technique thereby increasing its performance factors.

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