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Identifying the Faces from Poor Quality Image / Video

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Abstract—Face biometric is becoming more popular because of its wide range of applications in authorizing the person either from an image or from the video sequence. The bottleneck in face recognition is Pose angle variation, varying light condition, Partial Occlusion, Blur in the image or Noise. The proposed method first removes the noise from the image using Adaptive Median Filter (AMF) then Discrete Cosine Transform(DCT) is applied to normalize the illumination problem. The algorithm is further used to remove the motion blur using Lucy Richardson's method by calculating the Point Spread Function (PSF). The Pose variation problem is then addressed with Global Linear Regression(GLR). Then the Principal Component Analysis(PCA) and Linear Discriminant Analysis(LDA) are applied to the normalized image to get the feature vector. This combined feature score is used to recognize the image using K-Nearest Neighbor (K-NN). The result shows a maximum accuracy of 92% and 87.5% with Pose angle variation between (0°, 22°) and (22°, 40°) respectively. The pose variation greater than this shows an average accuracy of 77.5%. The result also shows a maximum computation speed of 0.018 Seconds.

Keywords: Face Recognition, Linear Regression, Principal Component Analysis.

I. INTRODUCTION

The present trend expects enhancement in the protection process for each and everything which are used in real-time. The improvement in the secured accessing product is much more valued in limited surroundings like, mobile phone access, laptops access, shops, entering group which calls for an extremely high-level authentication, nearly every location in which the security is playing the main role. By providing that the security measures for the daily issues the subscribers can lead a calm as well as a protected lifestyle without being concerned about the confidential information they have to stay protected.

For authorized access to confidential information, determining the people's identity is vitally important. The identification of an individual is utilized for a valuable objective. In the recognition of the person, the biometrics plays a significant role in meeting the security must-have.

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The different biometrics include the private ID number, iris identification, fingerprint recognition, palm print identification, etc. These are the physiological attributes that are worn in identifying patterns for offering security to these biometric engineering. Face recognition is regarded as the prominent technology utilized at determining an individual.

Face Bio metric is starting to be common in Bio metric identification process since it's robust and non-intrusive. Face recognition gets tough due to Light variation, occlusion, pose variation, sound, and so on, when captured in a cluttered history (subway, airport). Uncontrolled Face recognition product must be in a position to identify the faces from shot picture, extract the functions of its and then identify it still from a most difficult environment.

The quality of the image is extremely important in Face Recognition. The recognition process is actually going to be difficult when the image under consideration is actually under the influence of degradation. The degradation is primarily because blur and noise. The typical type of blur is actually motion blur. The motion blur is actually because of camera or maybe object action while capturing the image. For restoring the picture ,it is crucial to discover the degree of the blur and blur perspective length. The blur perspective as well as the blur length ,then utilized for calculating the Point Spread Function (PSF). Proper kernel functionality could be used on PSF for getting rid of the blur.

Out of various challenges that influence the face recognition rate , the pose variation plays an important role. Common method to overcome the problem of Pose variation, first the pose and the illumination variations are normalized and then the image is used in recognition. Various algorithms have been developed for normalizing the Pose and illumination variations. But still some drawbacks exist in the recognition process, and to overcome these drawbacks we propose a new face recognition system for video images under a variety of viewpoint and Illumination conditions.

II. LITERATURE SURVEY

Recognizing faces appropriately under different illumination conditions is an extremely challenging problem in the field of face recognition. This is because same person's face appearance changes under different illumination conditions. Over the years, different algorithms have been developed to solve this illumination variation problem.

Aishat Mahmoud Dan-ali and Mohamed Mustafa [1] have proposed various illumination normalization techniques for face recognition.

Here, five pre-processing techniques were compared and analysed with the help of Euclidean distance and Cosine distance. Experiments were performed on three challenging face databases. The normalization techniques employed here were GIC, DCT, Histogram Remapping techniques like HRN, HRL and AS method. These techniques along with the distance classifiers resulted in ten types of combinations. It was observed that GIC gave good performance on all databases except CAS PEAL. It worked best when employed with Euclidean distance.

In [2] Jianke Le et al. used PCA, LDA and SVM for face recognition. Combining PCA and LDA is better for feature extraction and SVM for classification. PCA is appropriate for image reconstruction and LDA is used to make up for the deficiency of PCA. Geometric normalization of the face image was performed prior to feature extraction to eliminate redundant information. Experiments were conducted on ORL database which consisted of 40 individuals; each person's 10 images were captured. Among these 10 images, 5 images were considered for training samples and remaining 5 for test samples. 5 images of each person were marked as positive samples and remaining images of other samples were considered negative samples. Both positive and negative samples of the images were considered input samples to train SVM classifier. Experiments were conducted for three types of methods- PCA with NCC, PCA with LDA and NCC, PCA combined with LDA and SVM where NCC and SVM were used as classifiers. Recognition rates for all three methods were evaluated. Combination of PCA, LDA and SVM gave high recognition rate.

Shreekumar T and Nagaratna.P.Hegde [3] proposed a video based face recognition by considering pose and illumination factor. The proposed system consisted of two sections- training phase and testing phase. Techniques such as PCA, FLDA and Neural Network were used during the training phase. PCA was used for dimensionality reduction and FLDA was used for representing the feature vector space. During the testing phase normalized frames were obtained using FFD (Frontal Face Detection) and DCT (Discrete Cosine Transform). FFD performed the pose invariant process and DCT performed the illumination invariant process. Both PCA and FLDA scores were combined and given to Neural Network. Finally using Neural Network, image was classified as authorized image or unauthorized image. Experiments were conducted on UPC face database. This system was implemented with the help of MATLAB 7.10 and it could successfully recognize the face from video. System performance was evaluated by employing some statistical measures. The final result was compared with those obtained from DWT based technique.

In [4] R.Rajalakshmi et al. proposed an automated face recognition system. This system recognizes the identity of an individual from images which weren't used during the training section. Pose and illumination variations were taken into consideration in the system. Dimensionality reduction and feature extraction were done by means of PCA and LDA respectively. Different classifiers such as ANFIS, NN, SVM and K-NN algorithms were employed to analyse and evaluate performance of the system. Results showed that when LDA+PCA combination were used as feature extractors along with SVM as classifier, it gave the best recognition rate of 96%. It also deduced that SVM classifier is better than K-NN.

In [5] CemilTosik*et al.* investigated different pre processing algorithms like HE, DCT and SGF to solve the illumination variation problem. PCA was used as feature extractor. Frontal face images of 10 subjects each with 64 different illumination conditions was used for evaluation on Yale B face database. In the experiments conducted, five sets were considered for training and remaining sets were taken for testing. Combination of PCA with Euclidean distance was also conducted as an experiment to measure recognition rate. But later other pre processing methods were applied alone or cascaded to measure recognition rates. Experimental results showed that Steerable Gaussian Filter and combination of HE with Steerable Gaussian Filter (SGF) gave high recognition rate under varying illumination.

In [6] Shermina.J conducted experiments by employing DCT and PCA in their face recognition system to solve the problem of illumination. Initially the input image was subjected to logarithmic transform. It is a product of reflectance and luminance and was employed to expand dark pixel values. Then illuminated images were normalized by means of low frequency DCT components. Odd and even components of DCT were used in compensation of illumination variation and finally recognition of the face image was done using PCA. The proposed approach was implemented with the help of MATLAB and accuracy of the system calculated using statistical measures such as FAR and FRR. The performance of the system was evaluated on Yale B face database which gave a good recognition rate with the proposed approach.

Chande Anita and Shah Khushbu [7] employed DCT, PCA and ANN in their face recognition to solve the problem of illumination variation. Here initially an input image was given to logarithm transform to expand dark pixel values. This logarithmic image was given to DCT. Using DCT, low frequency coefficients were removed and high frequency coefficients were scaled. Then PCA was employed to extract important facial features. These extracted features were given to BPNN. PCA with BPNN gives better and faster result than PCA with Euclidean Distance. Experiments were conducted on Yale Face B database. Experiments were conducted using Euclidean distance and BPNN as classifiers with Modified DCT, DCT and DCT without normalization. Here modified DCT with BPNN gives better result than modified DCT with Euclidean Distance.

Virendra P. Vishwakarma*et al.* [8]focussed on illumination normalization in DCT domain by down scaling of DCT Coefficients. Initially HE was applied on the input image for contrast stretching. On output of HE, DCT was applied to switch from space domain to frequency domain. Illumination variation was compensated by scaling down low frequency DCT coefficients. Then inverse DCT is applied on these coefficients to generate illumination normalized images. These images were then fed to the classifiers.

The classifiers used were k-NNC and NMC along with distance metrics as correlation coefficient and Euclidean distance. The database used here was Yale Face Database B. The proposed method gives 100% recognition rate without any error.

N.PattabhiRamaiah*et al*. [9] concentrated on non uniform illumination by employing CNN technique. CNN learns local patterns from input data to differentiate facial images. In the proposed approach, CNN is trained using Back Propagation Algorithm and evaluated using 5 fold cross validation method. Horizontal reflection of facial images was considered in the training dataset which gave additional information about the shadow on one side of the face. This step improves the performance of the system by 4.96% from 89.05%. Therefore, total average obtained is 94.01%. Training dataset will be enhanced when horizontal reflection of facial image is considered. During testing, maximum value of a given facial image was considered to determine the output class. Experiments were carried out on Extended Yale B database. It also deduced training CNN is time consuming when size of input image is large.

Yan Gang *et al.* [10] presented a survey on illumination problem in face recognition. They have classified existing methods into three main categories namely invariant feature extraction, pre-processing and normalization and finally face modelling. They discussed various algorithms and analysed their merits and limitations. They pointed out that face recognition technology developed from two dimensional model to three dimensional model. Therefore it was better to combine the advantages of both 2D and 3D approaches to find an efficient way solve the illumination problem in face recognition system. This paved the way to combine with other approaches like pose and expression to develop a robust face recognition system.

SwetaTakur*et al.* [11] proposed a new method for recognizing faces by means of FLDA and SVM. Here the facial features were extracted with the help of FLDA and about 90 features were extracted. SVM was employed for classification of images. The proposed method was experimented on ORL face database which contained 400 gray scale images of 40 persons. The average recognition rates from the proposed system was found to be 96.30%, 97.95% and 97.31% for training set s=4, 5, 6 respectively. They also performed the N-Fold Cross validation test. In this case, the face database was divided into 10 folds; taking one image into a fold. They also compared the performance of the new approach with other FLDA based methods and found that the proposed system gave the best result.

Swati Manhotra and Dr.Reecha Sharma [12] proposed a hybrid framework for illumination invariant face recognition along with combination of two feature extraction techniques LBP and LTP. Combining information from two different feature extraction technique provides more discriminative information about the face image. LBP describes texture and shape information and is invariant to monotonic variations in gray scale images. LTP is an extended version of LBP. It uses threshold constant to change neighbourhood pixels into binary pattern. ANN is used for classification of face image due to iterative learning process and efficient performance. ROC curves were plotted for AR database and Extended Yale B database. It showed that compared to other existing techniques like gradient faces, weber faces etc; the proposed method occupied largest area under the ROC curve. Therefore fusion of two feature extraction techniques LBP and LTP resulted in better performance compared to the existing techniques. It had higher TPR values and low FPR values.

Kong Rui, Cheng Lin, JieYingda [13] proposed a novel approach for varying illumination in a face recognition system. Here illumination insensitive representation of the face image was extracted which is based on the ratio of gradient amplitude to the original image intensity. Initially face image was normalized and noise removed from the image using a Gaussian filter. Then the illumination insensitive feature was extracted. Then NS-LDA approach was employed to extract the discriminative feature from the image. Finally nearest neighbour classifier based on Euclidean distance was employed to classify and recognize the image. Experiments were conducted on three databases namely CAS-PEAL, Yale and Extended Yale B. Results obtained were compared with LBP, weber faces and gradient faces. It showed that proposed methodology performed better than the existing methods and had higher precision value. Recognition rates of the proposed method on CAS-PEAL, Yale and Extended Yale B databases were 96.39%, 99.01% and 99.29% respectively.

AlmabrokEssa and Vijayan K. Asari [14] presented a new technique for achieving illumination invariant face recognition system named as Local Boosted Features (LBF). LBF extracts facial features from two different neighbourhood configurations. A histogram is then built from each of those neighbourhood configurations. Two histogram feature vectors are combined to form final LBF vector for each image. A library of Support Vector Machines (LIBSVM) is used as the classifier to define similarity between a test feature vector and other feature vectors. Performance evaluation in the proposed system was carried on two datasets- Extended Yale B and ORL face dataset. Results obtained from the experiment were compared with other techniques like LTP, LBP, LDP, Weber face and gradient face. The proposed system gave a recognition rate of 99.21% using Extended Yale B dataset and 98.75 % on the ORL dataset.

In [15] DayronRizo Rodriguez *et al.* gave a new approach for illumination invariant face representation based on quaternion number structure. Goal of their system was to compare the performance of quaternion correlation filters taking different image representations. Four different face descriptors namely DCT, DWT, DIF and LBP were used to construct quaternion representation. Experiments were conducted on XM2VTS and Extended Yale B database. Results reveal that LBP exhibited the best results on the both the datasets whereas DCT performed the worst. They concluded that quaternion algebra on combining with existing techniques gave good results. It gave more discriminative information about face images. Therefore quaternion algebra is a great tool which can give outstanding results in face recognition problems.

III. FACE RECOGNITION

In situations, the face images are degraded because of the introduction of Noise or blur .This may be due to some electro-magnetic interference, or because of camera or object motion while capturing the image/video. In this system the image is restored by eliminating the noise as well as Blur effectively using AMF and Lucy Richardson's blur removal technique. The blur removal procedure includes blur angle estimation as well as blurs length estimation. Right after estimating these 2 variables Point Spread Function (PSF) is calculated. The PSF is applied with Lucy Richardson's Kernel to recover the image. By this preprocessing stage of picture restoration by taking out the Noise as well as the blur, the recognition efficiency is improved.

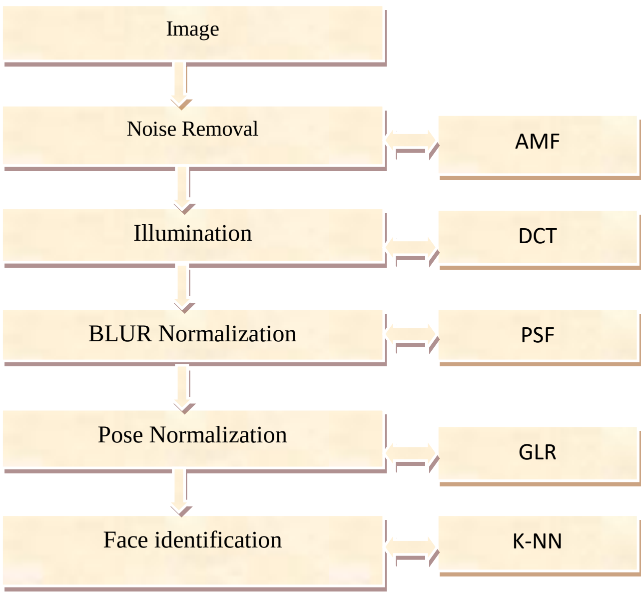

Fig.1: Process of the Proposed System

Next, the Illumination problem is addressed using Discrete Cosine Transform (DCT). The outcome of DCT is a illumination normalized image. Then the normalized image is given Global Liner Regression(GLR) for Pose normalization. After the pose normalization PCA and LDA is applied to find the feature vector from the image. This feature vector is used to identify the image using K-NN.

3.1 Noise Removal with AMF

In video face recognition, first we carry out the preprocessing process on the given input video frames. Here we have to exploit an adaptive median filtering (AMF) to remove the noise from the video frames. Let us consider the given set of training and testing images,

$$D_i^{tr}(a,b), D_j^{te}(a,b); a=0,1,\Lambda\ A-1, b=0,1,\Lambda\ B-1$$
$$and\ \ i=1,2,\Lambda\ M, j=1,2,\Lambda\ N \qquad (1)$$

In Equ. (1), $D_i^{tr}(a,b)\ and\ D_j^{te}(a,b)$ represents training and testing images with the size of $A\times B$, whereas i,j is the number of training and testing images. These numbers of training and testing images are given to the adaptive median filtering technique for preprocessing and these preprocessed video frames are given to feature extraction. The preprocessed images from the adaptive median filtering are represented as $D_i^{tr}(a,b)'\ and\ D_j^{te}(a,b)'$.

3.2 Illumination Normalization using DCT.

The major cause for the problems associated with illumination variation for face images is the different appearance of the 3D shape of human faces under different direction illuminations . Each frames in the frames set L is given as input to this process. Normally the illuminated face image $l_f(x,y)$ can be regarded as the product of reflectance $RR(x,y)$ and luminance $LL(x,y)$ as given in eqn (10).

$$l_f(x,y)=RR(x,y)LL(x,y) \qquad (2)$$

eqn. (2), can be we written as,

$$\log l_f(x,y)=\log RR(x,y)+\log LL(x,y) \qquad (3)$$

The linear equation got by employing logarithmic transform on equation (2) shows that the logarithm transform of the illuminated image can be obtained by adding the logarithmic transform of reflectance and the logarithmic transform of luminance as shown in (3). The illuminated image, l_o, can be expressed with the parameters $LL(x,y)$ and $LL_o(x,y)$. Where $LL(x,y)$ is incident luminance and $LL_o(x,y)$ is uniform luminance . The intensity across all of the images is normalized by finding the mean value of LL_o.

$$\log LL_o(x,y)=\log LL(x,y)+c(x,y) \qquad (4)$$

The illumination normalization for the Low frequency components of DCT is shown below,

The two dimensional DCT for an image $N\times N$ is derived as,

$$C(x,y)=\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}I(x,y)\cos\frac{\pi(2x+1)u}{2N}\cos\frac{\pi(2y+1)}{2N} \qquad (5)$$

where υ, $v=\{0,1,2,\Lambda\ ,N-1\}$ 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 DCT is obtained as,

$$I(x,y)=\sum_{u=0}^{N-1}\sum_{v=0}^{N-2}\left((u,v)\cos\frac{\pi(2x+1)u}{2N}\right) \qquad (6)$$

By adding a compensation term in the equation(6), the uniform luminance component can be obtained from the original image. First, an $r\times c$ image is reconstructed by calculating the mean as follows,

$$m=\frac{1}{r\times c}\sum_{x=1}^{c}\sum_{y=1}^{r}\log LL(x,y) \qquad (7)$$

Then by subtracting each pixel from the mean we get ,

$$c(x,y)=0.5*(m-\log L(x,y)) \qquad (8)$$

The low frequency components of DCT is obtained as $\log LL(x,y)$. Negative value points indicate single pixels that are dark and positive value points indicate single pixels that are bright.

By adjusting each pixel as shown in eqn. (8).the difference between the pixel value and mean value are halved. Illumination normalization is performed using the odd and even DCT components in horizontal direction

To eliminate shadow and specularities , the eqn (2) can be re written using odd and even DCT component as,

$$I(x,y)=idct(En\ DCT\ comp)+idct(Od\ DCT\ com) \quad (9)$$

The odd and even DCT is used here to obtain two new images I_{odd} and I_{even} by applying DCT in horizontal direction. The left half pixels and the right half pixels then compared with one another. Before calculating the compensating term, I_C, both the pixel values are modified as follows (if the right side pixel is positive but corresponding left side pixel is negative).

$$I_c(x,y)=0.5*(I_{odd}(x,c+1-y)-I_{odd}(x,y))$$

$$1\le y\le\frac{c}{2} \quad (10)$$

$$I_c(x,c+1-y)=0.5*(I_{odd}(x,c+1-y)-I_{odd}(x,y))\ \frac{c}{2}<y\le c \quad (11)$$

Both side pixels are modified according to the below equations (if the right side pixel is negative and the corresponding left side pixel is positive),

$$I_c(x,y)=0.5*(I_{odd}(x,y)-I_{odd}(x,c+1-y)) \quad (12)$$

$$I_c(x,c+1-y)=0.5*(I_{odd}(x,y)-I_{odd}(x,c+1-y)) \quad (13)$$

The following equation(14) is used to determine the new intensity value of compensated image.

$$I(x,y)=I_c+I_{even} \quad (14)$$

Here All the images are normalized for a mean of 0.6.

3.3 Blur Removal

The efficiency of any restoration algorithm[1] depends on the amount of blur present in the image and the same is the function of parameters. The algorithm is used to estimate the blur parameters , blur angle and blur length. By visualizing the blurred image in frequency domain, the blur parameters are easily estimated.

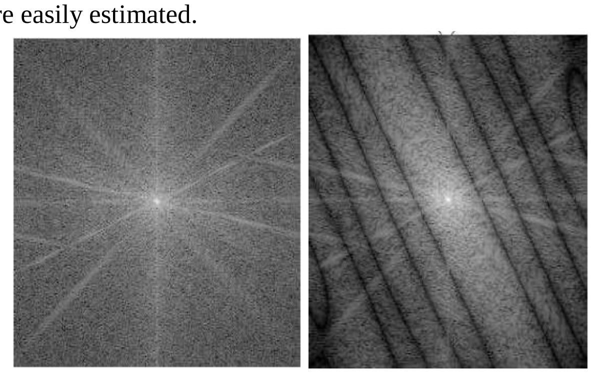

Fig. 2: Fourier spectrum without blur, Fourier spectrum with motion length 10 pixel and motion orientation 30°.

Fig. 3: Face images with blur and Pose variation

3.3.1 Motion Blur angle estimation using Hough Transform

Hough transform is used for the finding the orientation of these parallel lines. Which is indirectly used to find the factors that affects the blur. The Hough transform is used to applied for the patterns such as circles, eclipse, lines for the finding the line. The points in the lines are easily detectable using Hough transform.

$$p = x \cos \theta \quad (15)$$

Where (x, y) point at a particular point on the line; θ is the angle between line and origin in the x-axis and ρ is the length of the perpendicular. Thus (ρ, θ) depict the line.

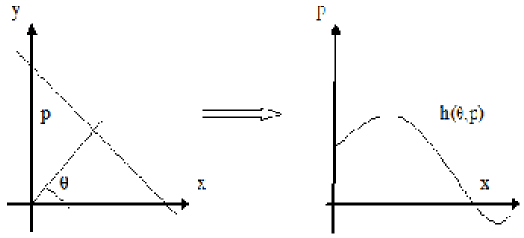

Fig.4: Image domain to hough domain

For using the Hough transform when the image is converted into the Fourier transform. When this is converted it should be into the log spectrum. The direction of the lines shows the direction of the blur. The motion blur image is perpendicular to the blur direction. The accumulator is used for the collection of all the predefined values. The direction of the blur is obtained by taking the higher values in the accumulator array. That maximum values forms the blur direction.

Algorithm:

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1. The blurred image is converted into grayscale.
2. The hann window is passed through the image to eliminate boundary artifacts.
3. Fourier transform of the image from step2.
4. Log transform of the image from step3.
5. Inverse Fourier transform of the image from step4.
6. Compute the cepstral domain to find edge map.
7. αmin and αmax are the minimum and maximum values of blur angle.
8. Accumulator is initialized.
9. Repeat it for every edge point.
10. Find the peak in the accumulator.

3.3.1 Motion Blur Length Estimation using Ceptral Method

The cepstral method[1] is used for the division of blur factors and image components. The motion blur has the periodic patterns in the frequency domain. This makes the negative peaks in the cepstral method. From these negative peaks it is possible to calculate the motion blur. From the calculated blur angle the image is rotated at that particular angle later average of the column is calculated then the distance between origin and first negative peak is calculated forms the blur length.

Algorithm:

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1. The blurred image is converted into the gray scale.
2. Hann Window is scanned through the image to remove artifact.
3. Fourier transform of the image from the step2.
4. Log spectrum of the image from the step3.
5. Inverse Fourier transform of the image from the step4.
6. The image is rotated into the angle in inverse direction.
7. The first peak in opposite place forms the blur length.

3.3.4 Lucy Richardson Filter

The Lucy Richardson filter[1][9] is the de-convolution filter which works based on the number of iterations. After the calculation of the blur angle and blur length. These two parameters are used to calculate the point spread function of the pixel. The point spread function is successfully incorporated into the filter for the efficient de-blurring of the image. The point at a particular image shows the spreading of the pixels rather than appearing as the single point source. The pixels in the non-point sources are the summation of the many single points. The pixel value de-blurred image is presented as

$C_i = \Sigma_i p_{i,j} u_j$ (16)

Where$p_{i,j}$is the point spread function, $u_j$is the pixel valueat location j, $C_i$is the pixel value observed at location i.

The simple de-convolution method is done by using the calculated PSF value with blurred image. This filter is very efficient to reconstruct the image to the original stage. These non-linear pixel value are not always guessable this algorithm forms the maximum formulation. It is a non-linear method since it performs the value without dependent on the other values.

3.4 Virtual Virtual Frontal View Generation

Provided a non frontal Face image[22] , our goal is to generate the virtual frontal view of the person with the help of a training set. We produce this problem mathematically as a regression process. Formally, it's referred to as follows:

Let the training set X^{P_0}, X^{P_k} , which is composed of frontal pose samples P_0 and non-frontal pose P_k . The training set $X^{P_0} = (X_1^{P_0}\ \ X_2^{P_0}\ \ X_3^{P_0}\ \ ...X_N^{P_0})$ denotes the frontal face set and $X^{P_k} = (X_1^{P_k}\ \ X_2^{P_k}\ \ X_3^{P_K}\ \ ...X_N^{P_k})$ is the corresponding non-frontal face set under pose P_k of N known individuals.Note that $X_i^{P_k}$ is the counterpart image of $X_i^{P_0}$ coming out of precisely the exact same person however with different pose. Then there should be a mapping,

$$f: X^{P_k} \rightarrow X^{P_0} \quad (17)$$

which can generate a virtual view $X^{P_0}$from non-frontal face X^{P_k} . Here, the mapping can be written as:

$$X^{P_0} = QX^{P_k} \quad (18)$$

Where **Q** is a linear operator and the linear mapping Q can be estimated by the following linear regression equation:

$$Q = X^{P_0}(X^{P_k})^{\perp} \quad (19)$$

$$(X^{P_k})^{\perp} = ((X^{P_k})'(X^{P_k}))^{-1}(X^{P_k})' \quad (20)$$

Where $(X^{P_k})^{\perp}$is the pseudo of X^{P_k}

Once the function Q is calculated , then the virtual frontal view from image X^{P_k} with pose P_k can be generated as:

$$X^{P_0} = QX^{P_k} = X^{P_0}\,(X^{P_k})^{\perp}\, X^{P_k} \quad (21)$$

the equation (21) can be written as:

$$X^{P_0} = X^{P_0}\alpha \quad (22)$$

where

$$\alpha = (X^{P_k})^{\perp} X^{P_k} \quad (23)$$

Consequently the virtual view generation may be decomposed into 2 steps: first one is solving the reconstruction coefficients in the P_k pose image by the equation (25). The second step is predicting the final virtual frontal view with the equation (24). After Minimizing the following residue function:

$$\varepsilon(\alpha) = \left\| X^{P_k} - X_{Rec}^{P_k} \right\|^2 \quad (24)$$

$$X_{Rec}^{P_k} = X^{P_k}\,\alpha = \sum_{j=1}^{N} X_j^{P_k} \;- \alpha_j \quad (25)$$

is the projection of X^{P_k} in the P_k pose image space.

3.5 Global Linear Regression

Based on the above mentioned analysis, we are able to quickly derive the virtual frontal perspective from the one non frontal face image by using equation (9). Remember that, when this particular treatment is implemented, one must thoroughly align the face image. As well as well recognized in face recognition region, one can just arrange the faces based on the eye centers. Then the normalized image in an entire are used for prediction. We call this particular implementation as Global Linear Regression (GLR).

However the face is not planar in whole, that is to say, the absolute linear mapping between two different views of a person does not exist. Therefore, both the reconstruction of the input image in pose image space and the prediction in the frontal image space are not as precise as expected.

IV. EXPERIMENT AND RESULTS

The proposed video face recognition system deals with the noise and eliminates it from the image initially , as a pre-processing step.For dealing with the noise the AMF is used. As shown in the Fig.4 , Hough transform is applied to calculate the blur angle and the blur length is calculated with Ceptral method as discussed in[1].The calculated blur angle and length then used to calculate PSF. The PSF is used with Lucy Richardson's technique to remove the blur from the image.

The Fig 5 shows image with motion blur in the very first row. The very next row shows the images of the same individuals after removing the blur and Noise.The images shown in the second row of the Fig.5 still faces the illumination and Pose problem. Initially DCT is applied to normalize the Illumination and then the GLR is used to generate the virtual frontal view from the non-frontal counterpart. The virtual view of the same individual is shown in Fig.6.

(a) (b) (c) (d)

Fig.5: input image, restored image and face recovered

The results show that our approach has an encouraging performance and that the approach of LLR with FLDA improves the accurate recognition rate in face recognition. The sample output obtained from the pose Invariant process is shown in Fig.6.

Fig. 6: Virtual Frontal View generated using GLR

The following Table 1 and Fig.8 represents the statistical measures of the proposed system and Analysis of the measures respectively for the selected datasets.

Table 1: Statistical measures for proposed system for different degree of Pose angle variation

Statisticsl measures	(0°,22°)	(22°,40°)	40°>
Sensitivity (TPR)	0.9200	0.8800	0.8000
Specificity	0.9200	0.8700	0.7500
Precision	0.9200	0.8713	0.7619
Negative Predictive	0.9200	0.8788	0.7895
False Positive Rate	0.0800	0.1300	0.2500
False Discovery Rate	0.0800	0.1287	0.2381
False Negative Rate	0.0800	0.1200	0.2000
Accuracy	0.9200	0.8750	0.7750

The face recognition is efficient for the pose angle between(0°,22°) is 92.5%. (22°,40°) is 87.5%. The pose angle greater than this will have an accuracy 77.5%.

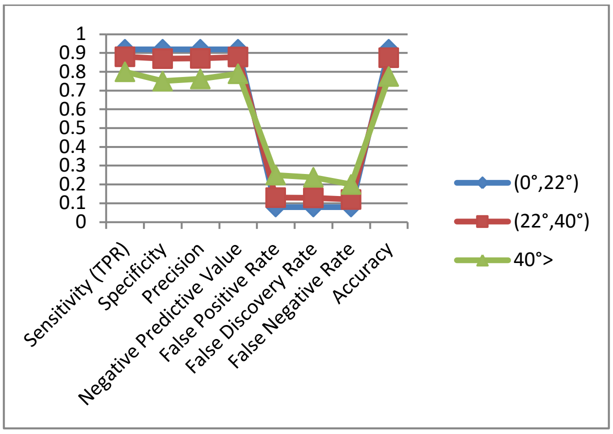

Fig 8:Analysis of different statistical measures on the dataset

Table 2 shows the recognition speed of the algorithm on six different experiments.The speed is recorded in Seconds.Since we are using K-NN, the training is not required**.**

Table 2:Computation speed in Seconds

Experiment No.	Computation Time
1.	**0.0194**
2.	**0.0207**
3.	**0.0186**
4.	**0.0211**
5.	**0.0189**
6.	**0.0184**

V. CONCLUSION

This paper introduced a simple face recognition method form poor quality images or video frames by carefully removing the noise from the image using AMF. Then the blur is removed from the image by calculating the PSF , to make the image more suitable for recognition task. The image obtained is normalized for Illumination and Pose using DCT and GLR. The virtual frontal view generated for the non-frontal face image is now more suitable for recognition task. In this method we are able recognize the face with good recognition rate of 87.5% for the pose variation of *(22° to 40°)* with a speed of 0.18 seconds on our local dataset.

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