Face Recognition with Real-world Images Acquired from an Outdoor Surveillance Camera, by Compensating Degradation

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***Abstract*—Face images obtained by an outdoor panoramic surveillance camera, are often confronted with severe degradations (e.g., low-resolution, low-contrast, blur and noise). This significantly limits the performance of face recognition (FR) systems used for binding "security with surveillance" applications. This paper presents a framework to overcome the degradation due to poor resolution and blur in the images obtained by an outdoor surveillance camera, to improve the performance of FR. Due to the unavailability of any benchmark face database, acquired from a surveillance system, with gallery (indoor) and probe (long distance outdoor shots) images, we have build our own database and conducted experiments on a realistic surveillance face database that we name as IITM SURV[1]. Super-resolution techniques fail to provide satisfactory performance, due to large difference in the resolutions and poor quality of face templates available as probe samples. We hence propose a combination of partial restoration (using super-resolution) of probe samples and degradation of gallery, to provide superior performance in FR. Based on the difference in entropies of the gallery (large resolution, good quality samples) and probe (with very low resolution, poor contrast and blur) images, the blur parameter is estimated for degradation. A comparative study of the performance of PCA (Principal component analysis) and FLDA (Fisher Linear Discriminant Analysis), as baseline FR classifiers, have been shown using ROC and CMS curves. In our proposed method of compensating the degradation in surveillance data, PCA consistently outperforms FLDA, although both show an enhancement of the face classification accuracy[2].**

I. Introduction

For face recognition (FR) in a surveillance scenario, images used for training are usually available beforehand from sources which are taken under a well controlled environment in an indoor setup (laboratory, control room). Whereas, the images used as test probes are available when a subject comes under a surveillance scene. Images obtained by security and surveillance cameras are generally confronted with severe degradations (e.g., low-resolution, low-contrast, blur and noise) due to environmental conditions (distance of the sensor from the subject, low illumination), interface circuitry (IP, analog camera) or camera's hardware/software limitations. Recognition accuracy of current intensity-based face recognition (FR) systems significantly drop off, if facial images are of low quality (degraded). Most face recognition systems [3][21][4][18], have been shown to perform well in controlled environments, where both training as well as testing samples are acquired in similar controlled illumination conditions in indoor environments.

With ever increasing demands to combine "security with surveillance" in an integrated and automated framework, it is necessary to analyze samples of face images of subjects acquired by a surveillance camera from a long distance (≥ 50 yards). Hence the face must be recognized from a low resolution, blurred and degraded image as obtained from the surveillance camera. The training set of a subject is assumed to be available from clear, good quality near-frontal face bitmaps. We work under the following assumptions: (i) near-frontal pose of the face, (ii) no occlusion, (iii) no change in emotion or aging effect on the face.

In published literature, one barely finds any FR method that has been designed using a real-world surveillance system. Most of the benchmark databases used for performance analysis of FR methods, were obtained in controlled environments (for both training and testing). The only known face database that contains data acquired from both indoor and outdoor sequences is **UTK-LRHM** [20]. This database has been acquired with the help of a sophisticated imaging system with high magnification which introduces blocking artifacts and non-uniform blur. Images obtained from an outdoor surveillance (PTZ) camera are often available with low contrast and rarely contain any useful color information. Thus the scope of using color based face recognition [5] for degraded face images is limited. To deal with the problem of low resolution, a method of simultaneous super-resolution and feature extraction for face recognition has been proposed in [11] and [9]. Gunturk et al. [9] discuss the use of super-resolution in the eigenface domain. In the work by Hennings-Yeomans et al. [11], Tikhonov regularization is used as the baseline super-resolution algorithm. However, they do not model the degradation due to blur. Experiment results are obtained on Multi-PIE, FERET and FRGC face databases using eigen-domain based classifier. Ahonen et al. [1] aimed to derive blur invariant features from the original face images using the phase information in frequency domain, using Local Phase Quantization (LPQ). Very recently, Nishiyama et al. [13] showed further improvement in accuracy by combining their method with

[1]**Samples from this database can be downloaded from http://www.cse.iitm.ac.in/ sdas/vplab/downloads.html**

[2]**This work is supported by the Ministry of C&IT, Government of India, New Delhi.**

LPQ. They proposed to use the learned point-spread function (**PSF**) parameter to deblur the test image, whereas, in our method we simulate the degradation on the training images to solve a deterministic problem. Solving an ill-posed problem of image enhancement and super-resolution involving high degree of degradation and difference in resolution is difficult. In [13], results have been obtained on artificially degraded samples from the FERET and FRGC 1.0 face databases, in which target images were also synthetically blurred. Thus, we find that in all of these methods published in literature, the results are obtained after simulating the degradation (using software tools) on some standard face databases, to create test probes which are far from that available in real-world surveillance data. We have used a more challenging real-world surveillance dataset, where blur is accompanied by other types of degradations (low-resolution, low-contrast and noise) on the test probes.

Our approach fills the gap between good quality training samples from gallery and poor quality test samples available as probes, in a real-world data obtained in true surveillance conditions, by estimating the degradation parameter for a **PSF** (blur) function. We have adapted an indirect fusion of two approaches:- (1) Use the estimated blur parameter to simulate the degradation on good quality (i.e. training) images as well as (2) Enrich the probe samples by a contrast enhancement process. To deal with the problem of mismatch in resolution of training and testing samples, two approaches are adopted: (1) Use super-resolution (or interpolation) with restoration to reconstruct higher resolution, better quality test images as a preprocessing step; and (2) Downsample and degrade the training images with a **PSF** (blur) function. A combination of these methods produce both the training and testing samples at identical resolution, with similar quality and appearance of the face bitmaps. Results are obtained using ROC and CMS measures to analyze the performance.

The rest of the paper is organized as follows: The method of data acquisition using surveillance camera is discussed in Section 2. The proposed framework is presented in Section 3. In Section 4, we present experimental details and performance results using baseline classifier namely **PCA** and **FLDA** [3][6] for different experimental cases. Finally, conclusions are presented in Section 5.

II. Data Acquisition from a Surveillance Scenario

Gallery samples are obtained in a controlled (indoor) environment for different subjects, whereas probe images are the face image samples obtained from video frames using a surveillance camera for the same set of subjects in an uncontrolled (outdoor) environment. The outdoor images are captured from a distance of 50-100m, placing the camera at around 20-25m of elevation. The face regions were extracted from the video frames using the popular Viola-Jones face detector (**VJFD**) [16]. Figure 1 shows typical examples of indoor and outdoor scenes, with the identified face templates. In Fig. 2, we present some samples of gallery and probe images for the same set of subjects. Both set of frames are displayed at the same scale i.e. dots per inch (dpi), to

Fig. 1. Samples of a subject from an indoor shot and outdoor scene, with the rectangular template around the face indicating the spatial extent of the face, as detected using **VJFD** [16]: (a) Frame from indoor gallery, (b) Frame from an outdoor video of the same subject.

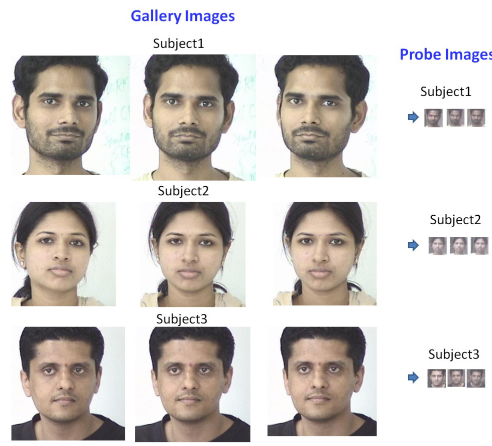

Fig. 2. Samples of (a) gallery images (average resolution ‘250x250’) and (b) probe images (average resolution ‘45x45’) for 3 subjects, displayed at the same scale (dpi).

illustrate the difference in the resolution. The complexity of the problem is evident from the degradation (large change in resolution and contrast) of the outdoor (probe) with respect to that in indoor (gallery) shots (see Fig. 2). This unique database has been acquired using Sony 3CCD Color Video Cameras (Model EVI-D70P). Data acquisition has been done for a typical surveillance system and no special equipments (optical or digital hardware) have been used to magnify or enhance the outdoor images. Thus this database is an useful resource to the research community. Database has been build for 51 subjects, with 50 samples per subject in both gallery and probe. We have obtained these samples using **VJFD** on frames from indoor and outdoor scenes. We have manually identified 20 near-frontal faces per subject from the **VJFD** output, for use in gallery (training) and probe (testing) sets of the database.

III. The Proposed Framework

The proposed framework has three stages. In the first stage, we estimate the degradation parameter of a **PSF** function and in the second stage we perform degradation of gallery and restoration of probe samples. In the third stage, face recognition is performed using an eigen-domain approach using degraded gallery and enriched probes. Figure 3 shows the proposed framework, where videos obtained from the cameras (indoor for gallery and outdoor for probes) are fed to the **VJFD**. A set of gallery and probe images are used to estimate the degradation parameter. Using this estimate, the gallery images are degraded with a **PSF** function to produce (simulated) degraded images. This degraded images are downsampled to a low resolution and used for training the FR system in the third stage. We also attempt to solve the ill-posed problem of image enhancement and restoration for probe images. In that direction, we have used super-resolution (or interpolation) along with Wiener filtering [7] to partially enhance and restore the probe images.

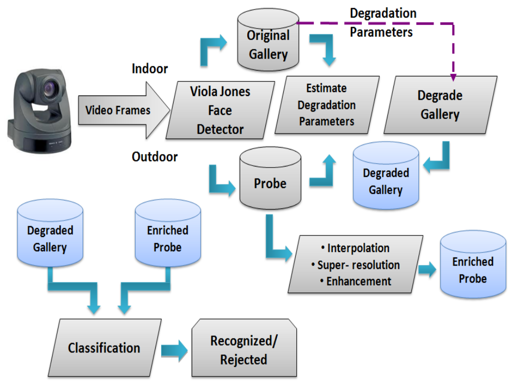

Fig. 3. The proposed framework for compensating degradation, for Face Recognition from a surveillance video.

A. Simulating the Degradation

To estimate the degradation, we define a measure that is simple, intuitive and is based on gray level intensity value of images. In this work, we have consider image degradation only due to blurring by a **PSF**. A typical formulation of the degraded image $p(x, y)$ in the spatial domain and its relation with the ideal image $g(x, y)$ is given by the following [7]:

$$p(x, y) = h(x, y) * g(x, y) + n(x, y) \tag{1}$$

where, $h(x, y)$ is the **PSF**, '*' denotes the 2D convolution and $n(x, y)$ is the additive noise. Our objective is to obtain an estimate of $h(x, y)$ and then use them for improving the accuracy of face recognition. For this, we use an empirical method to estimate the degradation parameter for a blur **PSF**, in the presence of other kind of degradations such as low resolution and contrast. Later, this estimated parameter is used to degrade the acquired gallery images so that they appear qualitatively close to the corresponding probe images. In this way, we obtain a set of (synthetically) degraded gallery images at low resolution that are later used for training the face recognition module. In our experiment, we have assumed that the nature of blur kernel is Gaussian.

We start with downsampling the gallery images. This step is required in order to compensate for the difference in the resolution of gallery and probe faces. On an average, resolution of probe images lie in the range [40-50], while that of gallery images is [220-280]. Next, the intensity range of blurred images are normalized with respect to probe samples. Qualitatively a histogram reflects the difference in global illumination of an image which is used for the formulation of the process used in estimating the degradation parameter σ_{blur} (for blur **PSF**).

B. Blur parameter estimation

Difference of Histogram Entropy (**DoHE**), is defined as a measure based on the intensity histograms of the normalized, blurred, downsampled gallery images and Wiener filtered probe images, as

$$\mathbf{DoHE}_k = \frac{1}{(M.N)} \sum_{j=1}^{M} \sum_{i=1}^{N} |ED_i^{\sigma,k} - EP_j^k| \tag{2}$$

where, $ED_i^{\sigma,k}$ and EP_j^k are the Entropies of gallery and probe samples, computed as:

$$ED_i^{\sigma,k} = Entropy(Hist(Norm(g_i^{\sigma,k}(x, y)|p_j^k(x, y)))) \tag{3}$$

$$EP_j^k = Entropy(Hist(p_j^k(x, y))) \tag{4}$$

where, $g_i^{\sigma,k}(x, y)$ is the degraded gallery image of the i^{th} sample, for k^{th} subject, obtained by convolution with a Gaussian function with standard deviation σ. $p_j^k(x, y)$ is j^{th} probe image of k^{th} subject. Also, $Hist()$ computes the histogram and $Norm()$ denotes a Normalization operation [12]. The normalization operation is necessary, as the dynamic range of gray levels in the gallery do not match that in the probe. M denotes the number of probe images and N is the number of gallery images for subject, used for estimating the degradation. We observe this measure with increasing values of σ. Initially (for $\sigma \cong 0$) the gallery has a better contrast and quality with respect to the probe samples. With increasing σ, the **PSF** causes a greater amount of degradation of the gallery samples, making it appear qualitatively similar to that of the probes. Hence this measure saturates to a small value for larger values of σ.

The plot for $\mathbf{DoHE}_k$ averaged over 51 subjects is shown in Fig. 4. We observe that the measure **DoHE** saturates after some value of σ. This happens when the two images (degraded gallery and probe) appear to have qualitatively similar contrast and illumination range. To find an optimal value of σ, we use the following condition;

$$\sigma_{blur} = \{\sigma : |\frac{d(\mathbf{DoHE})}{d\sigma}| < Th_{DoHE}\} \tag{5}$$

where, **DoHE** is obtained by averaging $\mathbf{DoHE}_k$ over 51 subjects. The measure in Egn. (2) is computed for all different

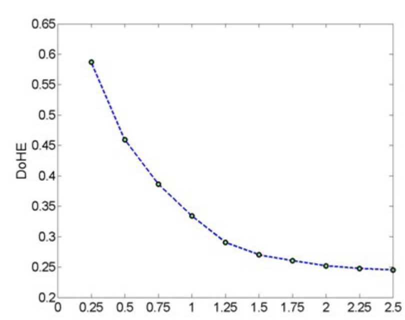

Fig. 4. Plot of the measure **DoHE**, averaged for 51 subjects.

combinations of available gallery and probe images for a particular subject, e.g. 10 gallery images and 10 probe images for a subject produce 100 combinations. This process is then repeated for all the subjects. Note here, that although in each combination we have used gallery and probe images for the same subject, this is not used as class-label information of probe (testing) images in the FR module. At this stage, we are estimating the degradation parameter for the surveillance system with the help of acquired data (both gallery and probe samples for a few subjects). Once the degradation parameter is obtained we can use it to simulate degradation for data of any other (new) subject. We also attempted the same without information of class labels. The result obtained to estimate σ is similar.

With these estimated parameters, we first blur the gallery images. Empirical observation over 51 subjects, produced an optimal value of the parameter, as: $\sigma_{blur} = 2$. Value of Th_{DoHE} is obtained as 0.125 using empirical observations. In this way, we obtain the (simulated) degraded gallery images, which appear identical to the low quality probe images. Figure 5 presents the results of degradation using the estimated **PSF**. The first row in Fig. 5 shows a few downsampled gallery images. Second row contains the (synthetically) degraded gallery images for the corresponding (column wise) subjects and the last row contains the probe images. One can visually observe the closeness in quality between the samples in second and the third rows. This process of blur parameter estimation and degradation of the gallery (see Fig. 3) must be done for any surveillance system installed, as the parameters are sensor dependent.

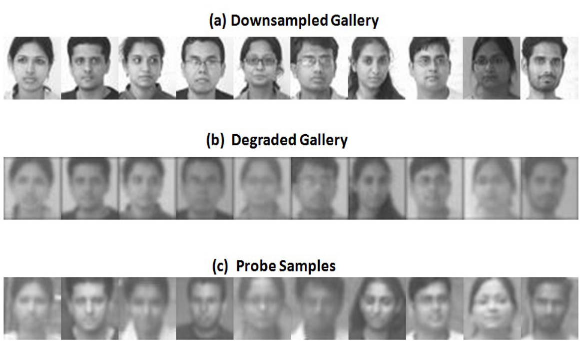

Fig. 5. Example images of: (a) Down-sampled gallery; (b) Degraded gallery from (a); and (c) Acquired probe samples.

C. Interpolation and Super-resolution of probe samples

Downsampling the gallery images is one approach to compensate the gap in resolution between galley and probe images. The other way is, “Interpolation” or “Super-resolution” of probe samples, which is generally an ill-posed problem. Since the resolution of gallery face templates is too high (compared to that of the probe samples), we choose an intermediate resolution of 90x90 (which we term as “medium resolution”). We have also observed that too high a resolution (> 200) of face bitmaps contains redundant information and do not contribute to any improvement in FR performance. For a certain range of resolution (100-200), the FR methods typically do not show any sensitivity in performance. Below this range, the performance of most FR methods start to degrade. For very low resolutions (< 50) the performance of FR methods drop significantly to unacceptable qualities. The probe images are up-sampled using interpolation or super-resolution, whereas the gallery samples are first downsampled to match the same resolution and then degraded using the **PSF** to obtain the degraded version of gallery at this “medium resolution”.

Bicubic interpolation algorithm gives the best performance with our surveillance database. A frequency domain approach for registration of images has been used for super-resolution, as proposed by Vandewalle in [15]. It also works for images of low-resolution with aliasing artifacts. Use of super-resolution in an automated way (without human intervention) on the free form face images (**VJFD** output) is difficult. Successive frames of a video are either not available from outdoor data, due to acquisition conditions of outdoor data capture and camera properties, or the **VJFD** fails due to poor lighting and low resolution. We thus hand-picked a few cases, where super-resolution of the probe samples was possible using face samples from successive video frames. Hence the test cases available for the super-resolved probes were fewer than the case of simple interpolation.

Degraded gallery images are used to train the classifier for face recognition. When a probe is detected, it’s face template is first extracted, enhanced (deblurred using inverse Wiener filter), interpolated (or super-resolved) and then projected into classifier space, for recognition (in the testing phase) using nearest neighbor (NN) criteria. Training with the acquired gallery images produce an unsatisfactory performance with low accuracy values of face recognition, because of the large difference in the quality of gallery and probe images. Next, we show how degradation of gallery improves the classification accuracy.

IV. Experimental Results

A real-world surveillance database as used by us, would be the most preferable for the purpose of rigorous testing and verification. Many face databases are available to the research community, but still they are far from real-world surveillance conditions. The proposed database is very challenging because of the large variations between the training and testing samples. We used (hand-picked) 20 samples in gallery as well as in probes per subject, which are all near-frontal faces without any occlusion.

To describe the different experimental cases, we introduce a set of abbreviations for the training and testing samples. These and the corresponding sample details are presented in Table I. Figure 6 shows the samples for each type of face data as labeled in Table I. Different experimental cases used to verify performance of the proposed framework, are listed in Table II.

We have obtained the Receiver operating characteristics (ROC) for verification and Cumulative match score (CMS) for face recognition, as shown in Fig. 7 and Fig. 8 respectively, with training and testing cases as given in Table II for experiments. The efficiency of the estimated degradation parameters is presented with the help of two baseline FR methods: PCA

TABLE I
LIST OF ACRONYMS OF FACE DATA SAMPLES AT DIFFERENT RESOLUTIONS AND INTERMEDIATE STAGES OF PROCESSING, USED FOR FACE RECOGNITION EXPERIMENTS

Data	***Abbre-viation***	***Sample description***	***Resolution***
Gallery	AG	Acquired gallery	250x250
Downsampled Gallery	LRG	Low resolution gallery	45x45
	LRDG	Low resolution degraded gallery	
	MRG	Medium resolution gallery	90x90
	MRDG	Medium resolution degraded gallery	
Probe	AP	Acquired probe	45x45
Up-Sampled Probe	INTP	Interpolated probe	90x90
	SRP	Super-resolved probe	
	REP	Restored and Enhanced probe	

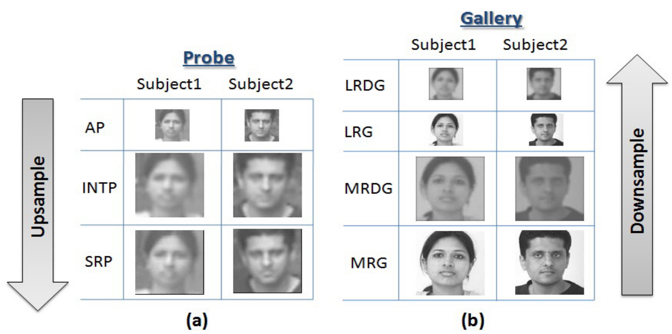

Fig. 6. Some samples for the face data of two subjects at different resolutions, used for experimentation (for details see Table I): (a) Probe (b) Gallery.

and FLDA [3]. The performance of the GREEN (LRG-AP combination) curve shows the worst performance, as this does not involve any processing on the face samples (probe (test) and downsampled gallery (training)) before they are fed to the classifier. The BLUE (LRDG-AP), CYAN (MRDG-INTP), MAGENTA (MRDG-SRP) and RED (MRDG-REP) curves show the performances obtained using the proposed methods, where, either the training gallery has been degraded with the estimated blur parameter (Eqn. 5), and/or the probe has been enhanced.

We see from Fig. 8 that training with degraded gallery images provides a much improved performance compared to training with downsampled gallery without degradation (see GREEN curves). This improvement is significant given the complexity of face samples as probes in our database. We have obtained these performances by taking a 100-fold study of the classifier output. In each fold, 10 training samples per subject were selected randomly from the set of 20 from gallery. Similarly, for testing 10 training samples per subject were selected randomly from the set of 20 probes in each fold. Total number of subjects used for our study is 51. Figure 8 shows that PCA performs better than the FLDA in this scenario, because PCA features are expected to perform better in case

TABLE II
TRAINING AND TESTING DATA PAIRS FOR THE DIFFERENT EXPERIMENTS DONE WITH THE PROPOSED FRAMEWORK, OF FACE RECOGNITION IN SURVEILLANCE SCENARIO

Experiment	***Training***	***Testing***
#1	LRG	AP
#2	LRDG	AP
#3	MRDG	INTP
#4	MRDG	SRP
#5	MRDG	REP

Fig. 9. Samples from gallery and probe after using an elliptical mask, at resolution 45x45.

of noise and degradation.

For all the above experiments we have used an elliptical mask [2] around the face for both, gallery and probe samples. We have used the elliptical mask to crop the significant elliptical part of the face, such that the effect of hairstyle, background and clothing are eliminated. This is done using a 3 point normalization [8] of face images which involve manual annotation of 2 eye points (left and right eye centres) and 1 chin point (chin tip). Figure. 9 shows some samples from gallery and probe at resolution 45x45, after using the elliptical mask. In our earlier work presented in [14], face templates obtained from **VJFD** were used directly (without using the elliptical mask to remove hair and neck portions) to observe the performance of FR. Results presented in this paper provide a significant improvement with respect to that in [14]. The recognition accuracy significantly improves in this case- when the probes are restored and the gallery downsampled to a medium resolution and degraded before matching. Super-resolution fails to provide improved performance compared to interpolation, due to lack of enough support and features in the probe data from successive frames in a video shot.

V. CONCLUSION

The work proposed in this paper concerns a face recognition application under surveillance conditions. It focused on estimating degradation due to out-of-focus blur, low contrast and low resolution. We define a measure- DoHE, which is quite intuitive, simple, fast (for online application) and easy to implement. From this measure, we obtain σ_{blur} as an out-of-focus parameter for the blur function. Next, we simulate the degradation on the gallery images. Probes are enhanced and upsampled to a moderately high resolution. Finally, we trained

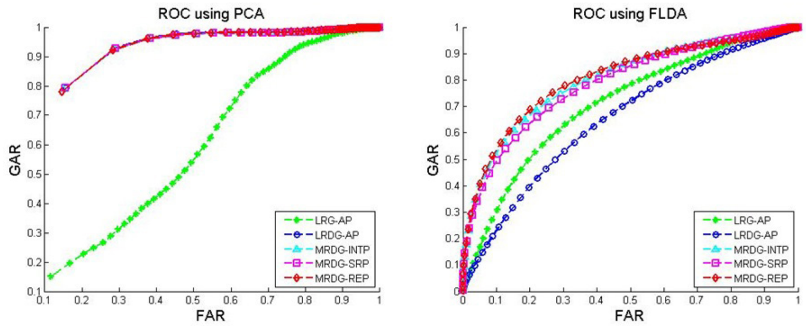

Fig. 7. ROC curves for comparing the performance of the system, when experimented with different training-testing pairs for gallery and probe combinations after using elliptical mask, using PCA and FLDA. Refer Table II for details.

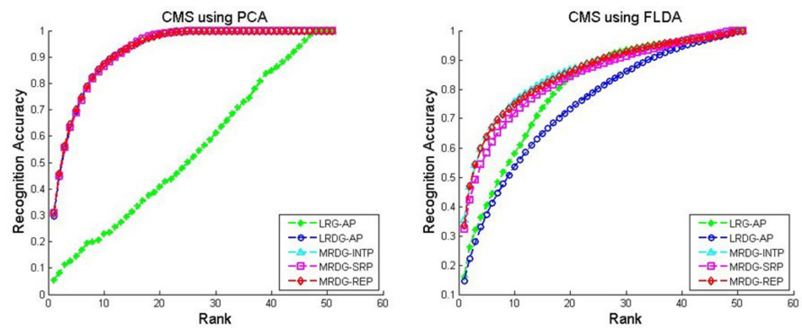

Fig. 8. CMS curves for comparing the performance of the system, when experimented with different training-testing pairs for gallery and probe combinations after using elliptical mask, using PCA and FLDA. Refer Table II for details.

the classifier with degraded gallery instead of acquired gallery to obtain significantly improved recognition accuracy. Results are shown using data acquired from a surveillance video.

A combination of partial restoration and enhancement of probe samples, using adaptive non-linear filters or stochastic optimization based restoration for implementation of a robust super-resolution technique, along with partial simulation of degradation on gallery may be explored for better results. Application engineers may use state of the art methods - K-PCA, K-LDA [19], dual-space [17] and SVM [10] based face recognizer with our proposed method, to improve the classification accuracy further.

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