A Performance Study of SIFT, SIFT-PCA and SIFT-LDA for Face Recognition

Sanket Panda, Shaurya Nigam, Rohit Kumar, Mamatha HR

Abstract*—Humans possess an innate cognitive ability to recognize faces and identify persons in an instantaneous and effortless manner. Face Recognition (FR) aims to emulate this capability using automated mechanisms and has been at the crux of research efforts in the domain of computer vision for the past two decades. Even though this process of emulation is arduous, it holds considerable promise in terms of its potential applicability, and hence, FR has steadily received consistent mainstream attention. The human cognition system generally stores and recollects images instantly based on necessity and similarly, machine vision replicates this process by storing images in a database and accordingly requires to be competently trained in order to accurately recognize faces. In this regard, many diverse algorithms have been proposed over the years with varying effectiveness. Therefore in this paper, we meticulously compare the conventional SIFT features method with its Weighted PCA and LDA variants in order to investigate as to which approach is more potent.

Keywords*—Eigenfaces; Fisherfaces; Face Recognition; SIFT; PCA; LDA.

I. INTRODUCTION

Face Recognition (FR) [12] technology has witnessed monumental advances in the past two decades, and has been ubiquitously incorporated, not only in security [8], law enforcement [9] and other closely-related fields but also in the field of commerce. One of the principal reasons behind the its mainstream presence is its widespread applicability and ease of access of facial images [7] in the form of a variety of standard credentials such as Driving license, Badges, Identity cards / Smart cards and so on, which proffer a legacy of images that can serve in a number of FR purposes. FR proffers a myriad of innovative applications such as the recent employment of driving license pictures to ascertain identity in order to curb identity theft or debit card fraud [9] and other novel biometric applications such as FastAccessAnywhere and FaceCrypt which provide smartphone access authentication. In addition, social networking sites such as Facebook, employ it in their Photo Tagging feature. Due to its widespread, innovative and cross-domain applicability, FR has become an integral part of the *SMART* technological revolution and witnesses novel advancements on a daily basis.

The algorithms that have been proposed to carry out FR range diversely from open-source approaches to proprietary methods. Although FR systems have been extensively employed over the past few years, Their performance is significantly impeded by the presence of extreme variations in terms of factors such as illumination, expression, pose, occlusion, resolution and scale. Therefore, it is a formidable task to conclusively declare certainty in matches, but instead the probability of a match can be established. In order to tackle the challenges posed by the aforementioned parameters, many diverse and robust FR algorithms have been proposed over the years. These algorithms consist of the following two basic aspects [14]: (1) Holistic approaches, which consist of techniques such as PCA (Principal Component Analysis [11]) and LDA (Linear Discriminant Analysis [15][16]) and (2) Feature-based approaches, like Gabor [19] and Scale Invariant Feature Transform-based (SIFT-based) techniques [14]. The Holistic approaches incorporate the entire face region to carry out feature extraction and thus circumvent the issues that are encountered while detecting specific facial landmarks.

Conversely, Feature-based approaches perform extraction of the local features from specific feature points of the face. Typically, holistic approaches yield superior results on images that are acquisitioned under controlled conditions and consequently, the feature-based methods are considerably robust with respect to variations in terms of expressions or variations in pose. The Scale Invariant Feature Transform (SIFT) feature extractor, pioneered by David Lowe [1] is the recent inclusion to the gamut of feature-based face recognition techniques (see [10] for an in-depth survey of the evolution of facial extraction approaches). The SIFT approach has a myriad of distinct properties that makes it a feasible candidate for matching different images (in the presence of strong scale and rotation variations). Yan Ke [6] in their PCA-SIFT approach further enhanced the local image descriptor utilized by SIFT and similar to SIFT, their PCA-SIFT descriptors are capable of robustly carrying out the encoding of the salient aspects of the image gradient in the neighborhood of the feature points [6]. Rather than utilizing the smoothed weighted histograms of SIFT, they apply Principal Components Analysis (PCA) to the normalized gradient patch. LDA is also closely related to PCA in that they both look for linear combinations of variables which best explain the data. LDA explicitly attempts to model the difference between the classes of data. In this direction, our proposed work performs an in-depth comparative study of SIFT, PCA-SIFT and LDA-SIFT techniques to determine as to which technique is more efficient.

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II. SCALE INVARIANT FEATURE TRANSFORM (SIFT)

SIFT (Scale Invariant Feature Transform) [1] is a popular technique that is robustly invariant to the presence of significant variations in terms of rotation, scaling and is also partially invariant with respect to variations in illumination and 3D camera viewpoints. SIFT consists of the following four components [13][17]: (1) Scale-space extrema detection, (2) key-point localization, (3) orientation

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assignment, and (4) computation of the key-point descriptors.

Each of these components operate in the following manner:

A. *Scale-space extrema detection*

The first computational stage [1] involves the scanning of all the scale and image locations, by implementing the Difference-of-Gaussian (DoG) function. DoG identifies potential interest points [13] (which are invariant with respect to scale and orientation).

$$G(x,y,\sigma)=\frac{1}{2\pi\sigma^2}e^{x^2+y^2/2\sigma^2} \qquad (1)$$

It is carried out by convolving the image with Gaussian filters at different scales. Subsequently, the computation of the difference of the successive Gaussian-blurred images is performed, followed by the extraction of key-points as maxima/minima of the difference of Gaussians at multiple scales. A DoG image is represented as follows:

$$L(x,y,\sigma)=G(x,y,\sigma)*I(x,y) \qquad (2)$$

where $L(x,y,\sigma)$ denotes the convolution of the original image:

$$D(x,y,\sigma)=(G(x,y,k\sigma)-G(x,y,\sigma))*I(x,y)=L(x,y,k\sigma)-L(x,y,\sigma)$$
(3)

This operation is illustrated in Fig.1. Essentially, the process of scale-space extrema detection with the SIFT algorithm involves the convolution of the image with Gaussian-blurs at different scales and subsequently, the difference-of-Gaussian images are acquired from the adjacent Gaussian-blurred images based on a per octave basis.

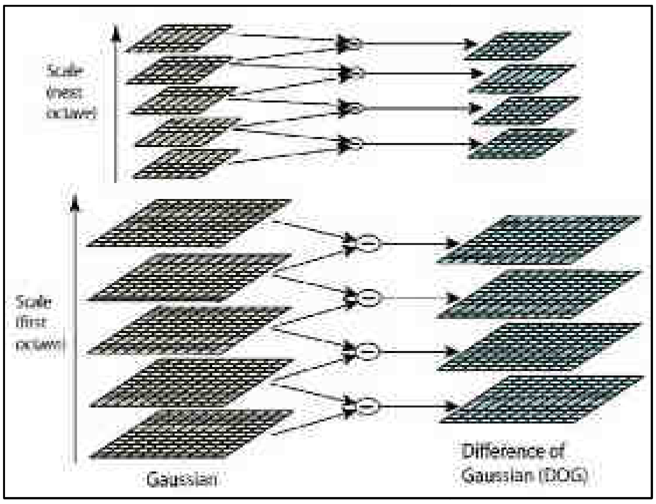

Fig.1: Blurred images at different scales and the computation of the Difference-of-Gaussian (DoG) images [1] 13]

SIFT performs the comparison (in the discrete case) with the nearest 26 neighbors (represented in green) in the discretized scale-space volume, as elucidated in Fig 2.

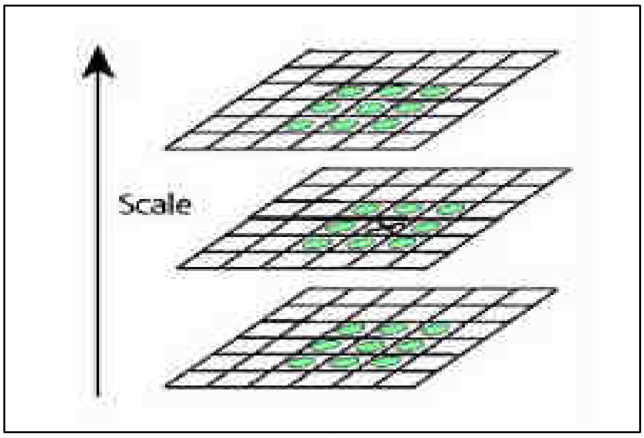

Fig.2: Local Extrema Detection, the pixel marked x is compared against its 26 neighbors in a 3*3*3 neighborhood that spans adjacent DoG images [1][13]

B. *Keypoint localization*

The successive component in the application of the SIFT algorithm is *key-point localization* [1][13]. In order to compute the location and scale information, a model is fitted for each key-point candidate location. These key-points are chosen on the basis of the measurement of their stability and the interpolation process is carried out by utilizing the quadratic Taylor expansion of the Difference-of-Gaussian scale-space function [13]. The Taylor's expansion is represented as follows [1]:

$$D(X)=D+\frac{\partial D^T}{\partial X}X+\frac{1}{2}X^T\frac{\partial D^T}{\partial X}X`$$
(4)

Where x= (x, y) denotes the offset from this point.

C. *Orientation assignment*

The orientation(s) are assigned to every key-point location on the basis of the local image gradient directions and every subsequent operation is carried out on the image data [1][13] (after it has undergone transformation, relative to the assigned orientation scale and location for every such feature), thereby rendering the transformations invariant with respect to the aforementioned parameters. Initially, the Gaussian-smoothed image $L(x,y,\sigma)$ at key-point's scale σ is considered in order to ensure that all the computations are conducted in a scale-invariant fashion. Consider that for a given sample image $L(x,y)$, at a scale σ, the gradient magnitude is represented by $m(x,y)$, and the orientation is denoted by $\theta(x,y)$ (all of which are pre-computed by utilizing the pixel differences). Then $\theta(x,y)$ and $m(x,y)$ can be represented in the following manner [1][13]:

$$m(x,y)=\sqrt{((L(x+1,y)-L(x-1,y))^2+(L(x,y+1)-L(x,y-1)^2)^2} \qquad (5)$$

$$\theta(x,y)=\arctan\frac{L(x+1,y)-L(x-1,y)}{L(x,y-1)-L(x,y-1)} \qquad (6)$$

D. *Keypoint descriptor*

This phase consists of computing the key-point descriptors, which is carried out by measuring the local

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image gradients at the selected scale in the proximity of the region around each key-point [1] [13]. These local image gradients are transformed into a representation that permits significant levels of local shape distortion and illumination changes [13]. This process is depicted in Fig.3.

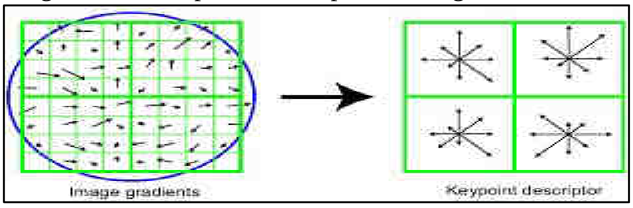

Fig.3.Sift Feature Descriptor

SIFT also performs the computation of vectors that can sufficiently characterize the local image appearance around the location of particular features. The SIFT descriptor utilizes image gradients, instead of intensity values because the image derivatives do not vary if an addition of a constant value is performed on each pixel's intensity. Essentially, SIFT considers the direction of the gradient, instead of their raw magnitude because the gradient directions are highly invariant to changes with respect to brightness and contrast. SIFT operates by considering the local image gradient directions and computes their histogram by creating 4 × 4 histogram grid around a selected feature point [13] (each such histogram consists of eight bins for gradient directions, yielding a 4 × 4 × 8 = 128 dimensional descriptor. Hence, a feature f contains a 2D location (f_x , f_y) along with a descriptor vector f_d [1][13].

E. Matching

In the usage of the SIFT algorithm, the individual key-point descriptors that are extracted from the query (or test) images are independently matched with the database of descriptors that are extracted from all the training images. The best match for each descriptor can be found by identifying its nearest neighbour (closest descriptor) in the database of key-point descriptors from the training images. Furthermore, suppose if the distance ratio between the closest and the second-closest neighbor (the closest neighbor that is established to have stemmed from any object excluding the first) is lower than some pre-defined threshold, the match is considered. Consequently, if it is not within the threshold, it is discarded and the key-point is removed. The face in the database that corresponds with the largest number of matching points is considered as the matched face and is subsequently utilized for the classification of the face in the test image.

III. PRINCIPLE COMPONENT ANALYSIS - SIFT (PCA-SIFT)

Principal Component Analysis (PCA) [11] is a widely adopted technique for dimensionality reduction and de-noising. It has been successfully applied to a broad class of computer vision problems such as object recognition and face recognition [12]. Although PCA has a number of shortcomings [6], like its implicit assumption of Gaussian distributions and its restriction to orthogonal linear combinations, it has steadily retained its prominence due to its relative simplicity and ease of application. The process of applying PCA to image patches was first demonstrated in [18] and its effectiveness with SIFT has been demonstrated extensively in [6].

Yan Ke et. al [6] proposed an algorithm intended for local descriptors called *PCA-SIFT*, which is an extension of the conventional SIFT descriptor and has several of its characteristics such as scale, sub-pixel location and dominant key-point orientations. In this step, a 41x41 patch is extracted at the given scale which is centered over the chosen key point and is subsequently rotated in order to adequately align its dominant orientation to a canonical direction. PCA-SIFT involves the following sequence of steps:

A. Patch Eigenspace Computation

In order to build the eigen-space, [6] demonstrates the implementation of the first three stages of SIFT on a distinct collection of images by collecting 21,000 patches. Each such patch undergoes processing in a manner described by [6] in order to create a 3042-element vector and subsequently, the application of PCA is performed on the covariance matrix of these vectors. The matrix that contains the top n eigenvectors is stored and utilized as the projection matrix for PCA-SIFT. This process is utilized in our study as it produced favorable results in [6].

B. Feature representation

In the process of searching for the feature vector for a given image patch, we build its 3042-element normalized image gradient vector and subsequently perform its projection onto the feature space by utilizing the stored eigenspace. An ideal value for the dimensionality of the feature space (n) has been shown to be 20 [6][20]. The conventional SIFT representation utilizes 128-element vectors and consequently, by employing PCA-SIFT, significant reduction is yielded in the amount of space required (owing to dimensionality reduction).

C. Matching

The Euclidean distance classifier is used to compute the distance between the two feature vectors in order to ascertain whether they belong to the same key-point in the different face images. The process of *Thresholding* this distance [6] yields a binary decision, and accordingly, adjusting the threshold value, facilitates the selection of the appropriate trade-off between false positives and false negatives.

IV. LINEAR DISCRIMINANT ANALYSIS - SIFT (LDA-SIFT)

Linear Discriminant Analysis, previously known as Fisher Discriminant Analysis, easily handles the case where the within-class frequencies are unequal and their performances have been examined on randomly generated test data. The prime difference between LDA and PCA is that PCA does more of feature classification and LDA does data classification. This method also helps to better understand the distribution of feature data [26]. The goal is to maximize the between-class measure while minimizing the within-class measure [28]. Following are the steps to follow to find the Fisher discriminants for a set of images:

A. Fisher face computation

The images (faces) in the database are read and divided into two sets, one for training and the other for testing. The

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training set is created and the average of each class each person's training images is calculated. The average of the training images in the database is determined. LDA is applied to find the within-scatter matrix and between scatter matrix. The eigenvectors are found using the between scatter matrix and within scatter matrix. The test images are transformed and all the faces in the database are fed into the face space created in the previous step. Using Euclidean distance method, the identity of the test image is found.

V. EVALUATION

The various evaluation metrics that are employed to quantify our results along with the particulars of the experimental setup are outlined in *this* section.

A. Evaluation Metrics:

The efficacy of the proposed technique is demonstrated in terms of metrics such as: FAR, FRR, Sensitivity, Specificity, and Accuracy.

The two metrics: False Acceptance Rate (FAR) and False Rejection Rate (FRR) have been used extensively for comparison of biometrics verification performances [22] as they are single index measures and simple and direct in terms of interpretation as compared to the ROC. FAR is the measure of the likelihood that the given biometric system will incorrectly accept a given image and is typically stated as the ratio of the number of false acceptances divided by the number of identification attempts. Similarly, FRR is the measure of the likelihood that the biometric system will incorrectly reject a given image and is stated as the ratio of the number of false rejections divided by the number of identification attempts [23]. Therefore for a proficient system, FRR and FRR should generally show a decreasing trend. Sensitivity (also called True Positive Rate) measures the proportion of actual positives that are correctly identified and is commonly considered with Specificity (True Negative Rate), which measures the proportion of negatives that are correctly identified. An ideal predictor would thus need to be highly sensitive and highly specific. The procedural details regarding the application and computation of these metrics have been extensively elaborated in [24].

B. Experimental Setup

We primarily conducted two types of experiments to demonstrate the robustness of our technique over the state-of-the-art methodologies: Firstly, a scale variance experiment, where we compared the techniques on two images that varied in their scale i.e. resolution. We took the probe image to be of smaller scale than the gallery image and considered the number of key-point matches and subsequently the effect the scale change rendered on the recognition performance (in terms of key-point matches). These scale variant comparison experiments were kept limited to SIFT, as its superiority to SIFT-PCA and SIFT-LDA based methods, in terms of handling scale variances has been demonstrated extensively [1][6]. The second set of experiments was conducted on various databases with a wide gamut of variations in terms of illumination, expression, pose, occlusion and background (with particular focus on affine, when available). We compared the SIFT, SIFT-PCA and SIFT-LDA by performing two sets of tests, one where the probe and gallery images belong to the same face, and another in which they do not i.e. matched and unmatched image.

VI. EXPERIMENTAL RESULTS

The simulations were carried out on the four benchmark databases: AT&T [2], Grimace [3] and Faces95 [5] and Faces96 [21].

A. AT&T Database

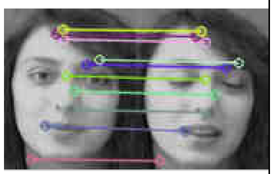
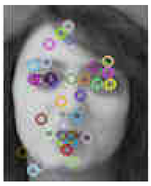
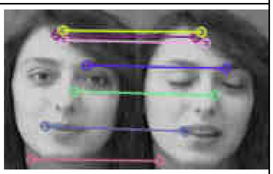
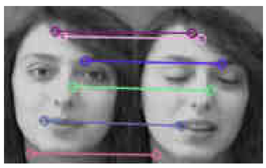
Fig.4: Sample Face Images of three individuals from the AT&T dataset

The AT&T database [2] consists of 400 facial images with 10 images per individual. The resolution of each of the 8 bit images is 112 x 92 pixels, with 256 grey levels per pixel. For some subjects, the images were taken at different times, varying the smiling) and facial details (glasses / no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement yielding affine distortion).

Table 1: Scale Experimentation on the AT&T database

Algorithm	Original Image	Test with Original Images	Scale Test
SIFT		 77 keypoint matches	 13 Keypoint matches

Table 2: General Experimentation on the AT&T database

Algorithm	Key-point Detection	Descriptor Matching
SIFT		 10 Good Matches
SIFT-PCA		 7 Good Matches
SIFT-LDA		 6 Good Matches

For the scale experimentations, as illustrated in Table 1, we considered a test in terms of scale (resolution) variation

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where the probe image is of smaller resolution (92 x112 pixels) and the gallery image is larger (640 x 779). As clearly evidenced by the results, the SIFT method is robust to scale variances in terms of both probe and gallery images and can conclusively perform a match with significantly fewer key-points (13 good matches)

Table 3: Performance Evaluation on the AT&T database

Method	Sensitivity	Specificity	FAR	FRR	Accuracy
SIFT	97.184	66.667	0.334	0.0282	93.75
SIFT-PCA	97.260	71.429	0.286	0.0274	95
SIFT-LDA	98.631	71.4286	0.286	0.0137	96.25

The general experimentations on the AT&T database, as illustrated in Table 2, demonstrate that SIFT can match the faces with 10 keypoints and SIFT-PCA and SIFT-LDA methods can conclusively match the given faces with significantly fewer key-points (7 and 6 respectively).

We can infer from the performance evaluation depicted in Table 3 that the SIFT-PCA and SIFT-LDA outperformed SIFT by 1.33% and 2.667% on the AT&T database.

B. Grimace Database

Fig.5 Sample Face Images of three individuals from the

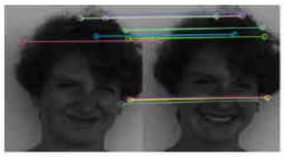
Grimace dataset

The Grimace database [3] consists of face images of 18 individuals with a sequence of 20 images per individual acquired using a fixed camera. During the sequence, the subject moves his/her head and makes grimaces, which get more extreme towards the end of the sequence. There is a gap of about 0.5 seconds between successive frames in the sequence. The resolution of the images is 180x200 pixels (portrait format) and contains both male and female subjects. The conditions of image acquisition include a plain background with small head scale variations along with considerable head turn, tilt, slant and some translation in the position of the face in the image. The image lighting variations are minor, but the dataset contains major expression variations.

Table 5: Performance Evaluation on Grimace

Method	Sensitivity	Specificity	FAR	FRR	Accuracy
SIFT	91.379	35.714	0.642	0.086	80.556
SIFT-PCA	93.548	40	0.6	0.064	86.112
SIFT-LDA	92.187	50	0.5	0.078	87.5

Table 4: General Experimentation on Grimace

Algorithm	Key-point Detection	Descriptor Matching
SIFT		 10 Good Matches
SIFT-PCA		 7 Good Matches
SIFT-LDA		 6 Good Matches

The general experimentations on the Grimace database, as illustrated in Table 4 demonstrate that SIFT can match the faces with 10 keypoints and SIFT-PCA and SIFT-LDA methods can conclusively match the given faces with significantly fewer key-points (7 and 6 respectively).

We can infer from the performance evaluation depicted in Table 5 that the SIFT-PCA and SIFT-LDA outperformed SIFT by 6.451% and 7.936% on the Grimace dataset.

C. *Faces95 Database*

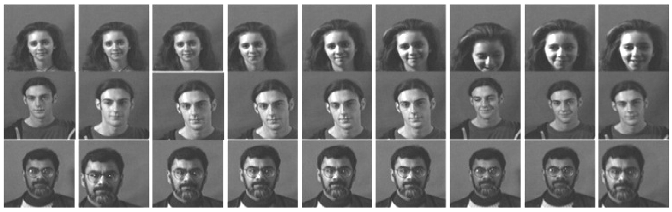


Fig 6: Sample Face Images of three individuals from the Face95 dataset

The Faces95 database [5] consists of a total of 1440 images from 72 individuals with a sequence of 20 images per individual. During the acquisition process, there was a gap of about 0.5 seconds between successive frames in the sequence and the subject was made one step forward towards the camera and this movement was used to introduce significant head (scale) variations between different images of same individual. The resolution of the image is 180 x 200 in portrait format and the background consists of a red curtain with background variation caused by shadows as the subject moves forward. There is minor variation in Head Turn, Tilt and Slant with large variations in Head Scale with some translation in the position of the face in the image. There is some amount of expression variation along with considerable image lighting variation due to the subject moving forward and significant lighting change occurring on the faces due to artificial lighting arrangement.

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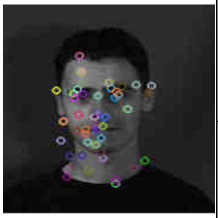
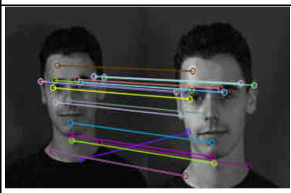
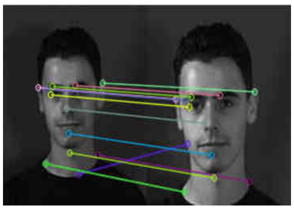
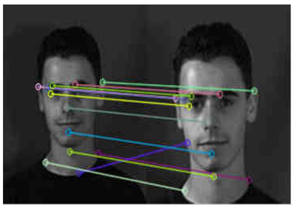
Table 7: Performance Evaluation on Faces95

Method	Sensitivity	Specificity	FAR	FRR	Accuracy
SIFT	97.647	60	0.4	0.023	93.684
SIFT-PCA	97.647	70	0.3	0.023	94.736
SIFT-LDA	97.674	77.777	0.222	0.023	95.789

The general experimentations on the Faces95 database, as illustrated in Table 6 demonstrate that SIFT can match the faces with 17 keypoints and SIFT-PCA and SIFT-LDA methods can conclusively match the given faces with significantly fewer key-points (12 and 12 respectively).

We can infer from the performance evaluation depicted in Table 7 that the SIFT-PCA and SIFT-LDA outperformed SIFT by 1.111% and 2.197% on the Faces95 dataset.

Table 6: General Experimentation on Faces95

Algorithm	Key-point Detection	Descriptor Matching
SIFT		 17 Good Matches
SIFT-PCA		 12 Good Matches
SIFT-LDA		 12 Good Matches

D. *Faces96 Database*

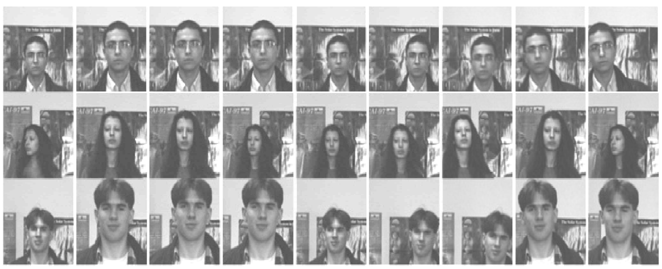
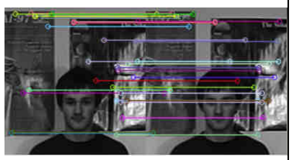
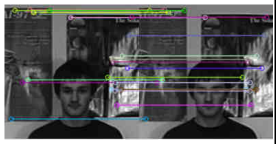
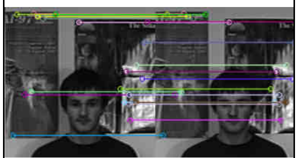


Fig 7: Sample Face Images of three individuals from the Faces96 dataset

The Faces96 database [21] consists of a total of 3040 images from 152 individuals with a sequence of 20 images per individual acquired using a fixed camera. Similar to Faces95, there is a gap of about 0.5 seconds between successive frames in the sequence and during the sequence, the subject was made to take one step forward and the movement was used to introduce significant head variations between the images of same individual. The resolution of the images is 196 x 196 in square format and has a complex background due to the presence of glossy posters and there are minor variations with respect to head Turn, tilt and slant, along with large head scale variations and a minor amount of expression variation. Furthermore, there is some translation in the position of the face in the image along with image lighting variations due to the forward movement of the subject.

Table 8: General Experimentation on Faces96

Algorithm	Key-point Detection	Descriptor Matching
SIFT		 10 Good Matches
SIFT-PCA		 7 Good Matches
SIFT-LDA		 6 Good Matches

The general experimentations on the Faces96 database, as illustrated in Table8 demonstrate that SIFT can match the faces with 10 keypoints and SIFT-PCA and SIFT-LDA methods can conclusively match the given faces with significantly fewer key-points (7 and 6 respectively).

We can infer from the performance evaluation depicted in Table 9 that the SIFT-PCA and SIFT-LDA outperformed SIFT by2.409% and 0.881% on the Face96 dataset.

Table 9: Performance evaluation over Faces96

Method	Sensitivity	Specificity	FAR	FRR	Accuracy
SIFT	88.571	76	0.24	0.114	85.263
SIFT-PCA	90	80	0.2	0.1	87.368
SIFT-LDA	89.855	75	0.25	0.101	86.021

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VII. PERFORMANCE COMPARISON

The accuracy comparison of the SIFT, SIFT-PCA and SIFT-LDA methods over the benchmarks databases is depicted in Table 10 and Fig.8. Cumulatively, SIFT-PCA outperformed SIFT by 2.819% and SIFT-LDA outperformed SIFT by3.483%.

Table 10: Accuracy Comparison over Benchmark Datasets

TECHNIQUE	AT&T	GRIMACE	FACES95	FACES96
SIFT	93.75	80.556	93.684	85.264
SIFT-PCA	95	86.111	94.736	87.369
SIFT-LDA	96.25	87.5	95.789	86.022

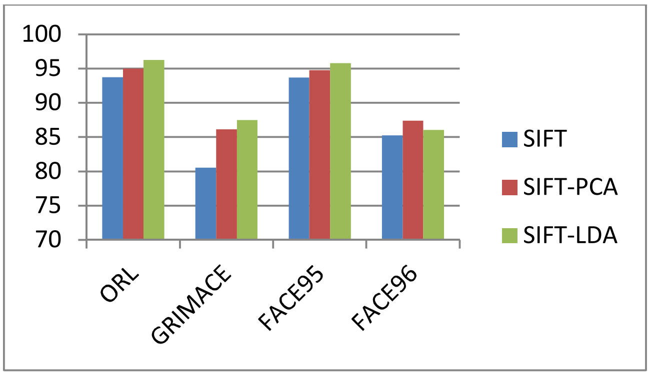

Fig. 8 Accuracy Comparison over Benchmark Datasets

VI. CONCLUSION AND FUTURE WORK

We performed a comprehensive comparison of the SIFT, SIFT-PCA and SIFT-LDA methodologies on the publicly available AT&T, GRIMACE, Faces95 and Faces96 datasets. Our results demonstrated that based on the experimental setup and the type of image, SIFT-PCA and SIFT-LDA were more effective than classical SIFT. The superiority of SIFT-PCA and SIFT-LDA methods can be attributed to its effectiveness in recognizing key-points in a more distinct manner and were also capable of slightly cutting down the redundancy. For general FR tasks, SIFT-PCA and SIFT-LDA are both viable choices. Future Work is also being steered towards conducting a similar study using 2-Dimensional Dimensionality Reduction techniques [25] in order to investigate as to which technique is more effective.

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