Face recognition with Gabor features, PCA, LDA, and cosine distance classifier

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1. Introduction

Eigenspace based face recognition systems have been most widely used flourishing approach in computer vision in recognition of faces from digital images. Numerous different eigenspace based approaches has been proposed up to now starting with the Eigenface algorithm due to its simplicity less and computational cost. In any face recognition system usually the face images to be identified are different from those stored in the database which causes the differences in the feature set too. However any victorious face recognition method depends mainly upon the selection of important features utilized by classifier [1]. Feature selection within face recognition engross the derivation of most important features from raw input data so as to decrease the quantity of data used for classification and concurrently provide enhanced discriminatory capability. The most widely used and popular approaches for choosing the subset of features is Principle component analysis (PCA) and linear discriminant analysis (LDA) [2].

Sirovich and Kirby [3] employed PCA so as to obtain a condensed representation of face images. Turk and Pentland [4] after those latter used PCA projections as feature vectors to resolve the difficulty of face recognition and used the Euclidean distance for classification. This approach, afterward known as Eigenfaces, became the first eigenspace-based face recognition approach from then onwards, many eigenspace-based systems has been anticipated using diverse projection methods and resemblance functions [5].LDA has been a further powerful means used in data reduction along with feature extraction in appearance-based methods. LDA causes entire projected samples to form maximum between-class scatter and minimum within-class scatter concurrently in a projective feature space. Thus its normally supposed that, when it arrives to solving problems of pattern classification, LDA based approach outperform PCA-based approach, since the previous optimizes low-dimensional representation of subjects with focus on mainly discriminant feature extraction whereas the later achieves merely object reconstruction [6]. Though the classifier performance of conventional LDA is generally deteriorated due to their separability criterion is not straightforwardly related with their classification accuracy in output space. The main drawback for employing LDA is small sample size problem.

However, due to the difficulties such as lighting, expression and pose variations, these systems, individually or in combination does not present acceptable accuracies under additional realistic operating conditions. So we propose here a new method of feature extraction which consists of Sampled Gabor Features followed by PCA for dimension decrease and LDA for feature discrimination. Finally for classification purpose we suggest Cosine distance classifier.

The process of sampled Gabor feature extraction, PCA and LDA techniques are explained in brief in the next sections along with merits and drawback of each individual technique.

2. Feature extraction algorithms:

Numerous feature extraction approaches, amongst them mainly appearance based approaches, contain complexity extracting stable features from face images captured in changing illumination circumstances and, thus, perform poorly when positioned in unconstrained surroundings. Gabor features based face representation proposed by Liu and Wechsler [7] doesn't signify an illumination invariant face representation, however somewhat exhibits robustness to illumination variations because of the properties of the positioned Gabor filter bank. The Gabor magnitude features which comprise the improved Gabor features is generally local in nature, that yet once more put in to illumination insensitiveness of calculated Gabor face representation. Offered Gabor based methods are amongst a majority of successful approaches in face recognition, these yet exhibit a little inadequacy that, which properly solved, can result in an enhanced recognition performance [8]. Thus we use propose the use of Sampled Gabor features followed by PCA for dimensionality lessening and then the use of LDA for discriminant feature extraction. A brief review of these methods is given in the following sections.

2.1 Sampled Gabor Feature Extraction:

The Gabor filter is the linear filter that has impulse reaction defined by the harmonic function that is multiplied with the Gaussian function. Since due to the multiplication-convolution property, a Fourier transform of a Gabor filter's impulse reaction is a convolution of the Fourier transform of a harmonic function and a Fourier transform of a Gaussian function. Gabor filters are straightly related to Gabor wavelets, since these are designed for several numbers of rotation and dilation. Conversely, extension isn't applied for Gabor wavelets, because this needs computation of biorthogonal wavelets that can be much lengthy in time. Hence, typically, the filter bank consisting of Gabor filters having different rotations and scales is created. These filters are convolved by a signal (face image), that results in the Gabor space. This concept is intimately correlated to progression in a primary visual cortex. Gabor space is awfully helpful e.g., in image processing applications like iris matching and fingerprint matching. Relations among activations of the particular spatial location are much distinguishing amongst objects within an image [9]. In addition, significant activations may be extracted from a Gabor space for creating the sparse object representation.

The Gabor Filters has acknowledged substantial consideration due to characteristics of certain cells in the visual cortex of several mammals may be approximated with such filters. Additionally these filters has illustrated for containing optimal localization properties within the both spatial and frequency domain and thereby is better suitable in texture segmentation problems. Gabor filters has been utilized for many applications, such as target detections, textures segmentation, images coding, image representations, fractal dimensions management, edge detection, documents analysis, and retinal recognition. A Gabor filter may be analyzed as the sinusoidal plane of specific orientation and frequency that is modulated with a Gaussian envelope [8].

2.2 Gabor Filter Bank:

As revealed before, the characteristics of a Gabor filters, particularly for orientation and frequency representations, can be equivalent to like human visual system and these are predominantly suitable for texture representation and discrimination. With Gabor filter features, straightly extracted from gray level images, are extensively and successfully utilized to diverse pattern recognition tasks [10]. Within a spatial domain, the 2-dimentional Gabor filter is the Gaussian kernel function that is modulated with a sinusoidal plane wave, which may be represented as follows:

$$\boldsymbol{\Psi_{\omega,\theta}(x,y) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{y' + y'^{2\prime}}{2\sigma}\right)\exp(j\omega x')\ (2.2.1)}$$

$$\boldsymbol{x' = xcos\theta + ysin\theta, \quad y' = -xsin\theta + ycos\theta}$$

Here(x, y)represents pixel position within a spatial domain, (ω)represents central angular frequency of a sinusoidal plane wave, (θ)represents anti-clockwise rotation of a Gaussian function, and $(\sigma)$is the sharpness of a Gaussian function along the directions $(x)$and (y). Generally set (σ) *is set to* $(\sigma \approx \pi / \omega)$which defines the relationships between σ and ω. A Gabor filters having the diverse frequencies and orientations that forms a Gabor filter bank, has been utilized to derive most expressive important features of face images. A Gabor filter bank with 5 frequencies and 8 orientations is utilized in most applications [8]. Fig. 2.2.1 represents the real parts of Gabor filter bank employing five dissimilar scales and eight dissimilar orientations, depicted in equation below:

$$\boldsymbol{\omega_m = \frac{\pi}{2} \mathrm{X} \sqrt{2}^{-(m-1)} \ , \theta_n = \frac{\pi}{8}(n-1)} \qquad \boldsymbol{(2.2.2)}$$

Where (m = 1, 2… 5) and (n = 1, 2… 8)

Gabor Feature Extraction:

For extracting Gabor features the given input grey image $I(x, y)$ is convolved with a Gabor filter $\Psi\omega,\ \theta(x, y)$that obtains Gabor features depiction as:

$$\boldsymbol{G_{m,n}(x,y) = I(x,y) * \psi_{\omega_m,\theta_n}\ (x,y)} \qquad \boldsymbol{(2.2.3)}$$

In the above expression, $G_{m,n}(x, y)$is the complex convolution that can be decomposed into real and imaginary (even or odd) parts by with:

$$\boldsymbol{E_{m,n}(x,y) = Re\left[G_{m,n}(x,y)\right] and O_{m,n}(x,y) = Im\left[G_{m,n}(x,y)\right]} \qquad \boldsymbol{(2.2.4)}$$

Depending upon these outputs, the phase $(\phi_{m,n}(x, y))$ and magnitude responses $(A_{m,n}(x, y))$ both are derived, i.e.:

$$\boldsymbol{A_{m,n}(x,y) = \sqrt{E^2{}_{m,n}(x,y) + O^2{}_{m,n}(x,y)}}$$

$$\boldsymbol{\phi_{m,n}(x,y) = \frac{\arctan\left(O_{m,n}(x,y)\right)}{E_{m,n}(x,y)}} \qquad \boldsymbol{(2.2.5)}$$

An example of the magnitude information from a Gabor face representation resulting from a testing face image is shown in Fig. 2.2.2.

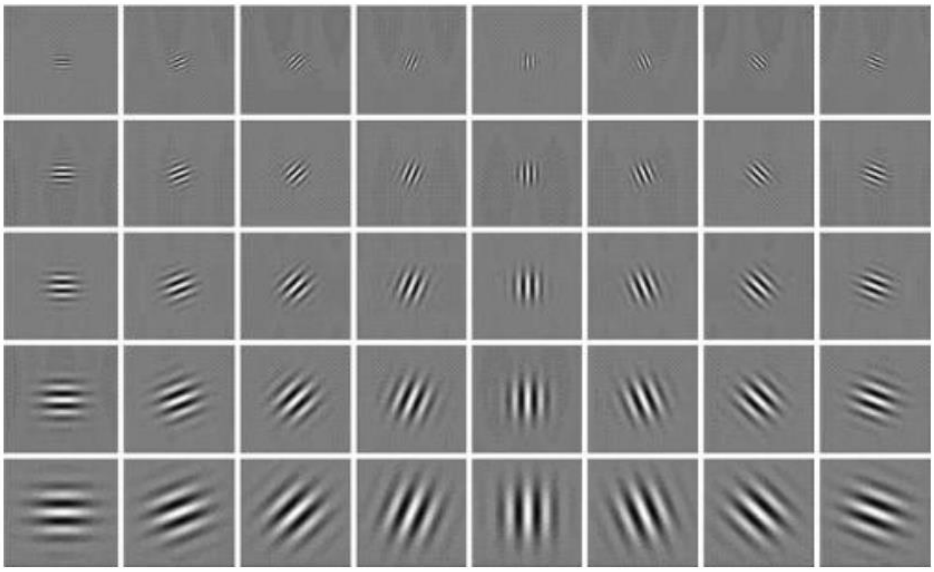

Figure 2.2.1: Real parts of a Gabor filter with 5 x 8 scales and orientations.

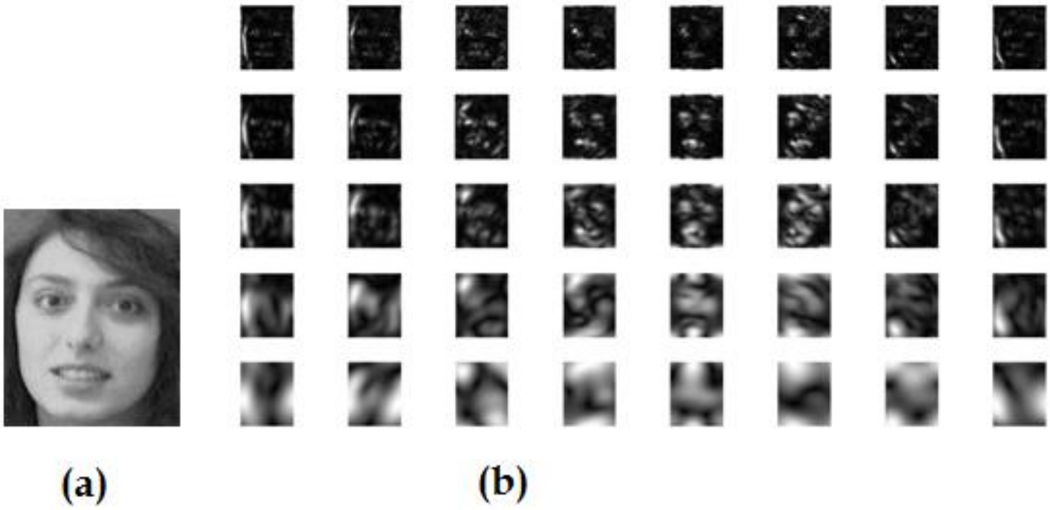

Figure 2.2.2: An example of the Gabor magnitude output: a sample image from ORL database (a) and the magnitude output of the filtering operation with the entire Gabor filter bank of 40 Gabor filters (b).

However, even for a small image of say 128 X 128 pixels, a magnitude response of a filter output contain a feature vector with 655360 elements that is extreme in proficient storage space and processing. To defeat this predicament, we use a sampling strategy. The sampling techniques condense dimensionality of magnitude responses, regrettably usually with the cost of potentially helpful discriminatory information. However the results reveal that there is negligible effect on overall performance of the system but there is much enhancement in the computational cost.

2.3 Principle component analysis (PCA)

PCA is one among foremost attractive techniques that are employed in image compression and recognition. It is the statistical approach belonging to factor analysis. Its aim of is to minimize great dimensionality of feature space to slighter inherent dimensionality of feature space which is required to represent data efficiently. This is possible when there is well-built correlation among observed variables. Functions which PCA can perform are feature extraction, data compression, redundancy removal, prediction, etc. since PCA is the classical technique that operates in a linear domain, and utilization with linear models are appropriate, like signal processing, system and control theory, image processing, communications, etc. Essential thought behind PCA, which when applied to the face recognition problem, can find vectors from high image space that better describes deviation between the provided set of face images. These vectors describe subspace within which face features are usually clustered. These vectors are merely the eigenvectors of a eigensystem of a covariance matrix of a provided set of face images that may be obtained using singular value decomposition [11, 12]. The eigenvectors are later arranged in descending order for associated eigenvalues and the few numbers of which having lowest eigenvalues are ignored, because it is supposed that these vectors have a tendency to encode noise. The face images of recognized persons are later projected onto preserved eigenvectors that forms the face class vectors. The face input image which is to be identified is projected onto preserved eigenvectors and resulted projection vectors are thereafter matched to every face class vectors with the similarity distance classifier to discover closest match.

Limitations of PCA method:

PCA provides projection directions which maximize total scatter across all categories. Thus, PCA also preserves unwanted variations due to illumination and facial expression. Though the PCA projections can be optimal for reconstruction from a small dimensional basis, they may not be most advantageous from a discrimination point of view. A limitation of PCA method is that the scatter that is maximized is not only because the between-class scatter which is useful for classification, but also to the within-class scatter which, for classification purposes, is surplus information. The variation in face images is mostly due to illumination changes. Thus if PCA is applied on illumination variant faces, it retain the variation in the projected feature space also. That means, the projected space will not be well clustered, and the classes may be merged together. It has been suggested that the variation lies mainly in the most significant principal components, i.e. those having larger eigenvalues. Thus ignoring the 3 most significant principal components, variation because of illumination is minimized. But, unlikely that first several principal components correspond to some useful information also; as a consequence, useful information for discrimination may be lost [13]. Even though the face recognition results are acceptable, the system using only eigenfaces won't be appropriate as a real system. It is required to be more robust and must have additional discriminant features.

2.4 Linear discriminant analysis (LDA)

LDA is generally the class-specific approach which intends to construct a linear transformation which expands the differentiation amongst classes whereas minimizes the differentiation within them. The aim is to obtain a subspace which is linearly separable amongst classes. In this context of the face recognition problem, a class refers to a person and samples within the classes' represents face images of that person. In LDA utilizing subsequent approaches like PCA and latter operating in a compacted subspace, search for discriminatory features by considering within and between-class scatter as the relevant information for face recognition. While PCA maximizes for the complete scatter as suitable for signal representation, LDA differentiates among within and between-class scatter as suitable for face recognition. With the application of PCA firstly for dimensionality lessening and then LDA for discriminant analysis [5] developed a technique called Fisherfaces for human face recognition. Using a similar technique, [14] have revealed that the eigenfaces derived using PCA are only the most expressive features (MEF). However MEF are unconnected to actual face recognition, and in order to obtain the most discriminating features (MDF), subsequent LDA projection is necessary. The LDA technique employs the instantaneous diagonalization of the both within and between-class scatter matrices. it can considered stepwise equivalent to 2 operations: 1st whitening the within-class scatter matrix, and 2nd applying PCA on the between class scatter matrix utilizing the transformed feature data. Aim of whitening step is to normalize within-class scatter matrix for consistent gain control. Further 2nd operation increases the between-class scatter for separating dissimilar classes far from one another. The stoutness of the LDA technique is based on whether or not the within-class scatter is able to capture trustworthy variations for a precise class. The aim of LDA is to carry out dimensionality lessening at the same time as preserving maximum of the class discrimination information. LDA tires to find vectors those in the underlying space which greatest differentiate between classes (instead of which greatest express information). Additionally, presented the number of independent features comparative to which the information is described, LDA obtains the linear grouping of those thatgives the maximum mean differences amongst desired classes.

Limitations of LDA method:

For the face recognition the difficulty using LDA is that the within-class scatter matrix $S_w \in R^{\text{mxn}}$is always singular. This arises from the situation that the rank of Sw is at most N - c, and, in general, the number of images in the learning set N is much more insufficient as compared to the number of pixels within an image. Hence this implies that it is possible to choose the matrix W which can make the within-class scatters of the projected samples precisely zero.

The LDA algorithm does not work properly in the following cases:

1. When the probe images are from individuals not within the training set.
2. When distinctly dissimilar images of trained classes are asserted.
3. Images with diverse background are used.

3. Classification Methods

Classification methods based on the similarity distance classifier is an important concept in pattern recognition. It is extensively used to judge whether an image matches a query, and to measure the resemblance of 2 images. Amongst all distance measures which are proposed so far in the literature, some of them have very comparable behaviors in similarity aspects, while others may behave quite in a different way. Considering the relations among distance measures may be useful to select a proper distance classifier for a specific application. Selecting a specific distance measure causes impact on computational overhead and in turn on overall system performance. When extracted feature vectors are huge, some distance measures can consume more computing resources as compared to others. It's also noteworthy to select a similarity measure that is consistent with human ideas of similarity. Nearest neighbor classifiers derives the nearest neighbor 'k' of a query subject 'l' and return the class label of 'k' to predict the class label of 'l'. Apparently, the definition of an appropriate distance function is vital for the efficiency of nearest neighbor classification. A mathematical analysis of Euclidean distance and cosine distance has been done in [15]. It was shown that cosine distance has a special property to favor relatively larger component in a vector.

3.1 Euclidean distance classifier

The Euclidean distance is the straight-line distance connecting two pixels that are calculated using the Euclidean norm. Generally the distance based similarity measures follows the beliefs that the face images that are close together are expected to be extremely analogous. Nevertheless in such cases, all the possible directions are regarded equal. The distance based similarity measures take merely the effect of the distance into consideration, despite of the variations in the directions of the concerned image. In other words, face images with the identical distance to the reference face image are supposed to have the same resemblance. Although the 2 face images that are sharing the same direction, it can be argued that the legitimacy of the high similarity of 2 face images is minimized to little extent when they are much apart in considering calculated distance between them. Even though the Euclidean distance is a much common distance measure for high dimensional feature spaces as like face features, it reveals rigorous drawbacks in respect to similarity measurement. In general, the individual components of the feature vectors that correspond to the dimensions of the feature space are supposed to be independent from one another and no relations of the components such as substitutability and compensability may be observed. This classifier can perform better when the distance amongst the means of face images is huge as that compared with the stretch or arbitrariness of each class in comparison with its mean.

Let's consider the 2 feature vectors say$X_i = y_1^i, \ldots\ldots y_d^i$&$X_j = y_1^j, \ldots\ldots y_d^j$.

The Euclidean distance amongst these 2 feature vectors is then given as in equation 3.3.1.

$$\boldsymbol{Dist}(\boldsymbol{X_i} - \boldsymbol{X_j}) = \sum_{k=1}^{d} ||\, \boldsymbol{y_k^i} - \boldsymbol{y_k^j} || \qquad (\mathbf{3.1})$$

here $||y_k^i - y_k^j||$represents the Euclidean distance amongst the 2 feature vectorsy_k^i and y_k^j .

3.2 Cosine distance classifier

It is type of distance metric that considers the comparative disparity considering that the scale is uniform meaning that the distance from zero is relative. In several cases this may show better performance, mainly when the presented data is abnormally distributed. It is a measure of similarity between 2 vectors by calculating the cosine of the angle between them. The cosine value of zero is one, and is less than one for any another angle; the lowest value of the cosine being minus one. The cosine of the angle between 2 vectors thus decides whether two vectors are pointing roughly in the same direction. Cosine similarity of the 2 vectors can be represented using Euclidean dot product similar to the equation in 3.2,

$$\mathbf{cos\ (\theta)} = \frac{\boldsymbol{A.B}}{||\boldsymbol{A}||\ ||\boldsymbol{B}||} = \frac{\sum_{i=1}^{n} \boldsymbol{A_i} \times \boldsymbol{B_i}}{\sqrt{\sum_{i=1}^{n} (\boldsymbol{A_i})^2} \times \sqrt{\sum_{i=1}^{n} (\boldsymbol{B_i})^2}} \qquad \mathbf{(3.2)}$$

The resulting resemblance ranges from 'minus one' that means exactly opposite, to 'one' indicating exactly the same, with 'zero' generally indicating independence, and the within-range values indicating midway similarity or dissimilarity. Weakness of the cosine measure is that it is not able differentiate images having the same direction, however are far from one another in terms of distance in an image vector space.

3.3 City Block Distance classifier

The city block distance metric measures the path between the pixels based on a four connected neighborhood and pixels whose edges touch are one unit apart and pixels diagonally touching are two units apart. The City block distance between two points, a and b, with k dimensions is calculated as:

$$\boldsymbol{Dist}(\boldsymbol{p}, \boldsymbol{q}) = \sum_{k=1}^{d} |\, \boldsymbol{p_j} - \boldsymbol{q_j}| \qquad (\mathbf{3.3})$$

The City block distance is at all times greater than or equal to **0**. The measurement would be **0** for identical points and high for points that show little similarity. The figure below shows an example of 2 points called p and q. Each point is described by 5 values. The dotted lines in the figure are the distances (p1-q1), (p2-q2), (p3-q3), (p4-q4) and (p5-q5) which are entered in the above mentioned equation.

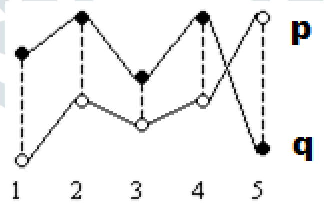

Figure 3.3.1: Calculation of City block distance

Most of times, this distance metric give results similar to the Euclidean distance for the highly correlated data. However, since the distances are not squared with City block distance, the effect of a large difference in a solo dimension is suppressed.

3.4Mahalanobis Distance classifier

Mahalanobis distance between 2 vectors, say p and q, is given by the formula:

$$\boldsymbol{d_M}(\boldsymbol{p}, \boldsymbol{q}) = \sqrt{(\boldsymbol{p} - \boldsymbol{q})^{\boldsymbol{T}} \boldsymbol{S}^{-\mathbf{1}} (\boldsymbol{p} - \boldsymbol{q})} \qquad (\mathbf{3.4})$$

here S denotes the covariance matrix. Mahalanobis distance is used by the probability density function for a multivariate Gaussian distribution instead of the Euclidean distance. The Mahalanobis distance is the measure of a distance between a given point P and its distribution D. It is the multi-dimensional generalization of measuring actual standard deviations of the given point from its mean. This distance is 0 if p is at the mean of D, and tends to grows as p moves farther from the mean along each of the principal components axis. When each of the axis is re-scaled for having the unit variance, under such circumstances then the Mahalanobis distance in the transformed space would correspond exactly to standard Euclidean distance. The Mahalanobis distance is scale-invariant and thus unitless, which only takes into account the correlations of the presented data set.

4. Proposed algorithm:

The proposed algorithm Sampled Gabor features + PCA + LDA is given by the following steps:
• Input: Given input image $I(x,y)$;and Output: The optimal discriminant vector sets of all N input face image vectors.

• Algorithm:
1. Gabor filter $\Psi\omega,\ \theta(x,y)$ to obtain Gabor feature representation as:
$$G_{m,n}(x,y) = I(x,y) * \psi_{\omega_m,\theta_n}\ (x,y)$$
Where $$\Psi_{\omega,\theta}(x,y) = \frac{1}{2\pi\sigma^2} exp\left(-\frac{y'+y'^2{}_{\prime}}{2\sigma}\right) exp(j\omega x')$$

2. Obtain k sampled feature vectors $y_k \in G^{mxn}$
$$y_k = W^T_{xk,}\quad k = 1,2,\dots,N$$
here, $W \in G^{m\times n}$.
3. Calculate the total scatter S_T as,
$$S_T = \sum_{k=1}^{N}(x_k-\mu)(x_k-\mu)^T$$
here, n is the number of sample images and $\mu \in R^{mn}$ denotes the mean image of all face images.
4. Calculate the scatter of transformed feature vectors $\{y_1, y_2, \dots, y_N\}$ as,
$$W^T S_T W$$
5. Calculate within-class scatter S_W and between-class scatter S_B
6. Calculate W_{opt} using,
$$W_{opt} = W^T_{lda} W^T_{pca}$$
where, $W^T_{pca} = argmax_W |\ W^T S_T W\ |$
and,
$$W^T_{lda} = argmax_W \frac{|W^T W^T_{pca} S_B W_{pca} W|}{|W^T W^T_{pca} S_W W_{pca} W|}$$

5. Experimental results:

Extensive experimental results carried on the three publically available face databases viz., ORL, IFD and Yale. Results demonstrate that the proposed "S-Gab+PCA+LDA" approach has error rates those are much inferior than that of the Eigenface (PCA) and LDA technique. Table 5.1 depicts the results obtained with different classifiers. Figures 5.2 to 5.4 show the result of the proposed technique compared with PCA, LDA and Gab+PCA.

Table 5.1: Recognition rates (in %) for different types of distance classifiers

ORL Face Database

No. of Training /Testing Images	**Distance Classifiers (Accuracy in percentage)**			
	Cosine *(Proposed)*	**Euclidean**	**Cityblock**	**Mahalanobis**
2/8	**90.94**	83.75	86.25	89.38
3/7	**93.57**	92.50	92.14	92.50
4/6	98.75	98.75	95.42	99.17
5/5	**99.00**	98.50	98.00	99.00
6/4	**100**	**100**	98.75	**100**
7/3	**99.17**	99.17	99.17	99.17
8/2	**100**	**100**	**100**	**100**
9/1	**100**	**100**	**100**	**100**

Yale Face Database

No. of Training /Testing Images	**Distance Classifiers (Accuracy in percentage)**			
	Cosine *(Proposed)*	**Euclidean**	**Cityblock**	**Mahalanobis**
2/8	**82.57**	63.82	66.78	82.24
3/7	**89.10**	87.22	87.97	88.35
4/6	**89.91**	89.04	88.60	88.60
5/5	88.42	88.42	**89.47**	87.89
6/4	88.16	**89.47**	87.50	88.16
7/3	**94.74**	94.74	93.86	94.74
8/2	**98.68**	98.68	98.68	98.68
9/1	**97.37**	97.37	94.74	97.37

IFD Face Database

No. of Training /Testing Images	**Distance Classifiers (Accuracy in percentage)**			
	Cosine *(Proposed)*	**Euclidean**	**Cityblock**	**Mahalanobis**
2/8	**87.90**	81.05	82.06	86.49
3/7	**92.63**	92.40	91.47	92.17
4/6	**93.55**	91.94	91.40	93.55
5/5	**94.84**	93.87	93.23	94.52
6/4	**95.16**	93.95	94.35	95.16
7/3	**97.31**	96.77	97.31	97.31
8/2	**99.19**	98.39	97.58	99.19
9/1	**100**	98.39	98.39	100

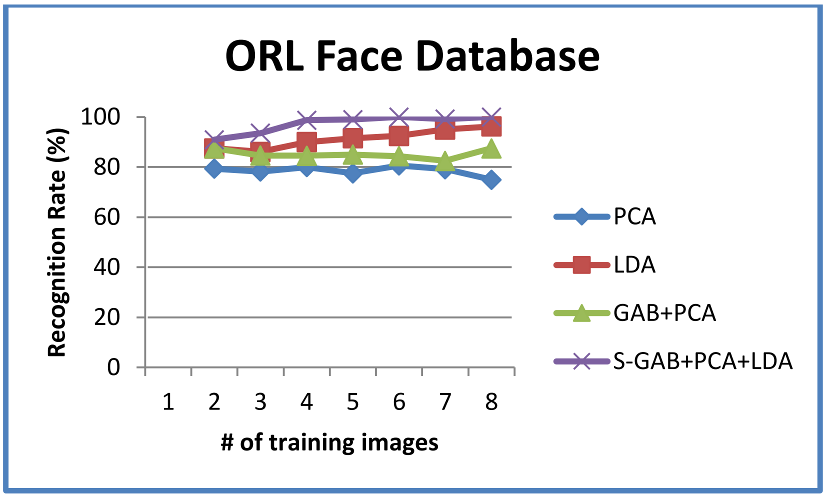

Figure 5.2: Results for ORL Face Database

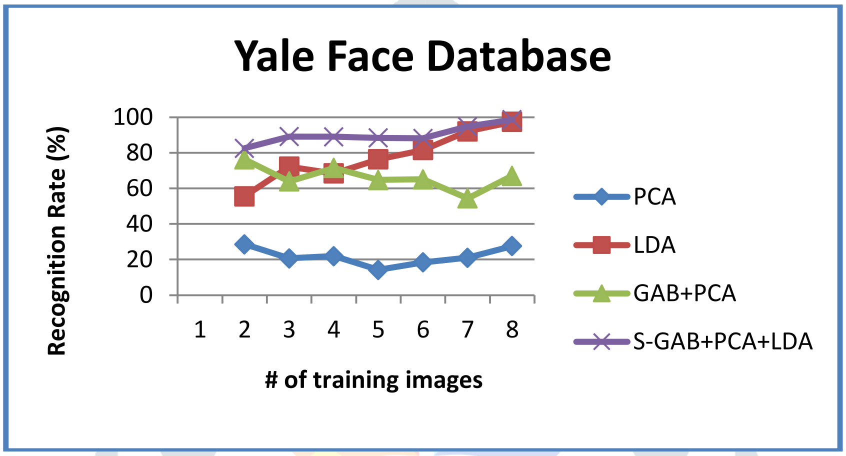

Figure 5.3: Results for Yale Face Database

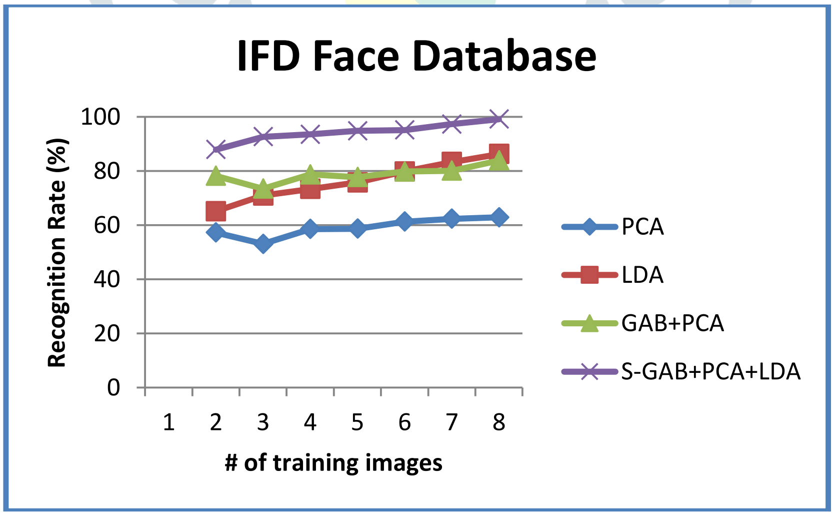

Figure 5.4: Results for IFD Face Database

6. Conclusion:

In this paper, experiments to observe the performance of 3algorithms, i.e., PCA, LDA and the proposed Sampled Gabor features+PCA+LDA technique are presented. The performance of these algorithms in terms of recognition rate in percentage is tested for three different databases with different types of variations viz. Expressions, illumination and pose. This study has identified that the proposed technique of combinations of features perform better than that of the individual methods.

Ideally, features with good discrimination are expected but it is not possible with PCA technique. PCA projection directions maximize the total scatter and it performs well only when samples per class are small. LDA method also has its limitations. We therefore focused our research towards developing a face recognition technique based on combination of PCA and LDA. This technique helps for obtaining a linear projection that maps the input face image X into the face subspace Yand then into a classification space Z. A suitable similarity matching method based on a cosine distance measure is used that calculates the distance between the individuals using the angle to improve the recognition accuracy of existing methods that uses Euclidean distance or other measures. In this research work, we made use of and compared four familiar distance measures, Cityblock distance, Euclidean distance, Mahalanobis distance and Cosine distance on different database like ORL, Yale and IFD consisting of all type of facial variations.

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