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Local Feature Based Face Recognition

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1. Introduction

A reliable automatic face recognition (AFR) system is a need of time because in today's networked world, maintaining the security of private information or physical property is becoming increasingly important and difficult as well. Most of the time criminals have been taking the advantage of fundamental flaws in the conventional access control systems i.e. the systems operating on credit card, ATM etc. do not grant access by "who we are", but by "what we have". The biometric based access control systems have a potential to overcome most of the deficiencies of conventional access control systems and has been gaining the importance in recent years. These systems can be designed with biometric traits such as fingerprint, face, iris, signature, hand geometry etc. But comparison of different biometric traits shows that face is very attractive biometric because of its non-intrusiveness and social acceptability. It provides automated methods of verifying or recognizing the identity of a living person based on its facial characteristics.

In last decade, major advances occurred in face recognition, with many systems capable of achieving recognition rates greater than 90%. However real-world scenarios remain a challenge, because face acquisition process can undergo to a wide range of variations. Hence the AFR can be thought as a very complex object recognition problem, where the object to be recognized is the face. This problem becomes even more difficult because the search is done among objects belonging to the same class and very few images of each class are available to train the system. Moreover different problems arise when images are acquired under uncontrolled conditions such as illumination variations, pose changes, occlusion, person appearance at different ages, expression changes and face deformations. The numbers of approaches has been proposed by various researchers to deal with these problems but still reported results cannot suffice the need of the reliable AFR system in presence of all facial image variations. A recent survey paper (Abate et al., 2007) states that the sensibility of the AFR systems to illumination and pose variations are the main problems researchers have been facing up till.

2. Face recognition methods

The existing face recognition methods can be divided into two categories: holistic matching methods and local matching methods. The holistic matching methods use complete face region as a input to face recognition system and constructs a lower dimensional subspace using principal component analysis (PCA) (Turk & Pentland, 1991), linear discriminant

analysis (LDA) (Belhumeur et al., 1997) , or independent component analysis (ICA) (Bartlett et al., 2002). The query face image is then projected into this subspace and matched with nearest face image on the basis of distance criterion. Recently, local matching methods are gaining more importance for face recognition application (Mandal et al., 2006; Zhang et al., 2005; Ersi & Zelek, 2006; Kisku et al., 2007; Luo et al., 2007) because of the following reasons

1. It represents face image by a set of low dimensional local feature vectors and hence reduces computational cost and storage requirement.
2. The extracted local feature vectors are distinctive and invariant to many kinds of geometric and photometric transformations. Hence good face description can be obtained with few training samples.
3. It recognizes a face based on its parts; hence the common and class-specific features can be easily identified.
4. The use of face specific features increases classifier diversity and hence improves face recognition rate.
5. The problem of imprecise localization can be avoided by using proper feature matching algorithm such as voting based algorithm.

The general idea of local matching methods is to first locate several facial features and then classify the faces by comparing and combining the corresponding local statistics. The comparison of holistic and local matching methods given by (Heisele et al., 2003) shows that local matching methods are superior to holistic matching methods. The detection of local features can be done by local appearance based methods or local feature based methods. The local appearance based methods detects feature points by segmenting the image into sub regions. But since the performance of current image segmentation techniques are still limited, performance of recognition using local appearance based methods is limited too. However, this problem can be solved easily with local feature based methods because it forms the database of local features, each representing a unique object and during recognition, local features for an object are matched with the features stored in the database. Since images of the same object can be taken in different environmental and instrumental conditions, they are probably different but related. A difference between these images occurs due to noise level, change in illumination, scaling, rotation and change in viewing angle. In order to match such images, local features should be invariant to these differences. Thus success of local feature based methods depends largely on correct detection of local features which are highly distinctive and invariant to different imaging conditions.

The comparison of various face recognition methods, given in Table 1, confirms that local matching methods (LGBPHS and Person specific SIFT) outperform holistic matching methods. It is also evident from table that the performance of local appearance based method is better as compared to local feature based methods but the results are reported with certain restrictions and local feature based method have a potential to overcome these restrictions.

The restrictions are as follows:

1. The performance of local appearance based methods depends largely on proper image segmentation. But image segmentation is a very hard problem in itself and requires a high-level understanding of the image content. However, local feature based methods detects most discriminative feature points in the image and operates on them. Hence it does not require image segmentation.
2. The results of local appearance based methods largely depend on proper image registration which is again very difficult in presence of occlusion and geometric and photometric transformations. It is not required in local feature based methods.

3. The dimensionality of feature vector is very less in local feature based methods as compared to local appearance based method because optimum number of feature points required for image representation can be determined.

<div>Variation</div> <div>Distance metric</div>	Expression	Illumination	Session	Time
Holistic matching method (Bartlett et al., 2002)	83.85%	64.95%	42.66%	28.21%
Local appearance based methods (Zhang et al., 2005)	94%	97%	----	68%
Local feature based Methods (Luo et al., 2007)	97%	47%	61%	53%

Table 1. Recognition rates comparison

2.1 Local feature based methods

Three important stages involved in local feature based methods are feature detection, feature description and feature matching.

2.1.1 Feature detector

The objective of this stage is to detect feature points of the image which are highly distinctive and invariant to different imaging conditions. The 2-D image windows, where there is some form of 2-D texture likes corner, are the most distinctive image patches compared with other types of image windows. The (Mikolajczyk & Schmid, 2002), presented evaluation of various feature point detectors and found that the performance of Harris detector is better for variations in scale, rotation, illumination, view point changes and image blur. However the repeatability of Harris detector degrades significantly when the images have large-scale changes. In order to cope with such changes, scale space representation of Harris detector is useful such as relative scale Harris detector or Harris-Laplace detector.

2.1.2 Feature descriptor

The objective of this stage is to describe detected feature points with the help local image statistics. A number of techniques for representing local image patch have been reported in the literatures such as differential descriptors (Mikolajczyk & Schmid, 2002), complex filters (Schaffalitzky & Zisserman, 2002), moment invariants (Van gool at el., 1996) and SIFT (Lowe,2004). The experimental evaluation of these descriptors is given by (Mikolajczyk, 2004) and it shows that SIFT descriptor provide best matching results. However, SIFT descriptor have high dimensionality and is also computationally expensive and can be replaced with Gabor filters. The (Zou at el.,2007) presented comparative study of local matching approach for face recognition and showed that good recognition rate can be obtained with Gabor features. This is possible because Gabor filter can detect changes in object location, scale, and orientation and these properties of Gabor filters make invariant detection of object possible, but in addition, Gabor filters also establish a significant degree

of robustness to photometric disturbances, such as illumination change and image noise, and to natural image variations, such as backgrounds.

2.1.3 Feature descriptor matching

In most face recognition applications, there are many classes, but very few training samples are available per class and it makes difficult to estimate the parameters of sophisticated classifiers. In the view of this difficulty, the simple nearest neighbor classifier is usually adopted. The key to classification then is the similarity or distance function. Many similarity measures for both histogram and vector features have been proposed and studied in (Beveridge et al., 2004; Rubner et al., 2001). But in local matching approaches, faces are partitioned into local components and an unavoidable question is how to combine these local components to reach the final classification. Nearly all of the existing local matching methods choose to concatenate local features into single global feature before classification. An alternative approach for combining local features is to let them act as individual classifiers and then combine these classifiers for final decision. Many classifier combination methods have been studied in the literature, from static combiners, such as majority vote, sum rule, and Borda count to trainable combiners, including logistic regression and AdaBoost (Friedman et al., 2000; Ho et al., 1994; Kittler et al., 1998).

3. Local feature based face recognition algorithms

The three different algorithms are implemented for AFR and each of these algorithm consist of three stages i.e. feature point detector, feature point descriptor and classifier. The each algorithm is developed with different feature point detector and classifier to get reliable face recognition algorithm. The details of these algorithms and their performances in terms of recognition rate achieved for illumination, pose and expression variations as well as average recognition rate are given in sections 3.1 to 3.4.

3.1 Algorithm 1

The algorithm consist of three stages i.e. feature point detection with Harris corner detector, feature extraction with 2-D Gabor filters and feature matching with nearest neighbor classifier. The steps of the proposed algorithm given by (Pardeshi & Talbar, 2006) are

1. Detect important facial feature points by application of Harris corner detector to given face image.
2. Perform segmentation of facial region from non-facial region with skin color based face segmentation algorithm. It is useful to remove the feature points detected on image background, neck, hair etc. and retain face-specific feature points.
3. Group the retained feature points into 14-clusters. The number of clusters used is 14 assuming: 2 clusters for forehead (left side and right side), 2 clusters for ears (left and right ear), 4 clusters for eyes corners (left and right corners of each eye), 2 clusters for nose corners, 2 clusters for mouth corners and 2 clusters for chin corners. After clustering, each cluster center is used as feature point.
4. Extract image local information from these feature points with 2-D Gabor filters. The Gabor filters are designed for 4-scales and 4-orientations and it results in total 16 masks. Each Gabor mask is centered at feature point and convolved with local image patch of size 25×25 . The magnitude value of each convolution is used to construct a feature

- vector. Since each feature point is convolved with 16 Gabor masks, the resulting feature vector has a size of 1×16 .
5. Concatenate the feature vectors extracted from 14 feature points to form single global feature vector of size 1×224 .
 6. In training phase, apply PCA to global feature vectors extracted from all training images and build an eigenspace.
 7. During recognition phase, project the global feature vector extracted from test image, by application of all steps mentioned in 1 to 5, into eigenspace.
 8. Check image similarity in eigenspace with six different distance metrics i.e. city-block distance (L1 norm), Euclidian distance (L2 norm), Cosine distance (COS), Mahalanobis distance (MAH), sum of L1 and MAH distance (L1 + MAH) and sum of L2 and MAH distance (L2 + MAH). The image with shortest distance to test image will be considered as a best match.

3.1.1 Feature point detector

The Harris corner detector analyzes the auto-correlation matrix M of every location in an image that is computed from image derivatives as given in equation (1):

$$M = g(\sigma_I) * \begin{bmatrix} I_x^2(X) & I_x I_y(X) \\ I_x I_y(X) & I_y^2(X) \end{bmatrix} \quad (1)$$

here X is pixel location vector, $I_x(X)$ is x-gradient at location X , $I_y(X)$ is y-gradient at location X and $g(\sigma_I)$ is Gaussian kernel of scale σ_I . A point is located as a corner if

$$R = \text{Det}(M) - K \times \text{Trace}(M)^2 = I_x^2 I_y^2 - (I_x I_y)^2 - K \times (I_x + I_y)^2 \quad (2)$$

here K is an empirical constant ranged from 0.04 to 0.06. The repeated detection of same corner point in local neighborhood of feature point is avoided by setting threshold and ensuring that feature point has maximum value of R in its local neighborhood as

$$R(X) > R(X_w) \forall X_w \in W \wedge R(X) > \text{threshold} \quad (3)$$

here W denotes the 8-neighbors of the point X . The result of application of Harris corner detector to one of the subject of Asian Face database is shown in image displayed as Fig.1.

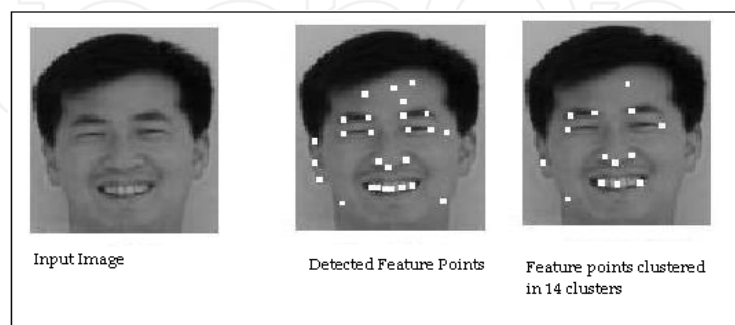


Fig. 1. Feature Point Detector Stage

It shows input image, detected feature points and result of clustering. The all feature points are shown by highlighting its 3×3 neighborhood for the purpose of visibility. It is evident from figure that feature points are detected at eyebrow corners, eye corners, nose corners,

mouth corners and chin i.e. at locations where signal changes in both directions simultaneously. These points carry highly discriminative information and used as feature points.

3.1.2 Feature extraction

The 2-D Gabor filters are used for feature point description. The Gabor filters enhances low level image features such as the peaks, valleys and ridges so that the eyes, the nose and the mouth, as well as the other salient local features like dimples are get enhanced. These key features are important for discrimination of different faces. A family of complex Gabor filters is defined as

$$W(x,y) = \ell \frac{e^{-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}}}{2\sigma^2} \cos\left(2\pi \frac{x'}{\lambda} + \varphi\right) \quad (4)$$

where $x' = x \cos \theta + y \sin \theta$ and $y' = -x \sin \theta + y \cos \theta$

here θ : Orientation, λ : wavelength of cosine wave, φ : phase of sinusoid, σ : radius of the Gaussian and γ : aspect ratio of the Gaussian. The Gabor filter bank is designed for 4-scales (λ) and 4-orientations (θ) and it results in total 16 Gabor filters. The values of λ and θ used are

$$\lambda \in (4, 4\sqrt{2}, 8, 8\sqrt{2}) \text{ and } \theta \in \left(0, \frac{\pi}{4}, \frac{\pi}{2}, \frac{3\pi}{4}\right) \quad (5)$$

To extract a feature vector, each Gabor filter mask of size 25×25 is placed at selected feature point and convolved with local image patch centered at feature point. The magnitude values of these convolutions are used to get feature vector of size 16×1 for each feature point. All these feature vectors extracted from feature points are concatenated to get final global feature vector. Since each image is represented by 14 feature points and each feature point is represented by feature vector of size 16×1 , global feature vector has size of 224×1 as

$$x^i = [x_1^i \dots \dots \dots x_N^i]^T \text{ where } N = 224, i = \text{subject} \quad (6)$$

The Asian face database is used to carry out various experiments. This database consists of true-color face images of 103 people, out of that 53 are men and remaining 50 are women. This dataset is divided into training dataset and test dataset. The images from training dataset are used for training of algorithm while images from test dataset are used for checking the results. For each training image, single global Gabor feature vector is extracted and these vectors are placed, side-by-side, to create a data matrix X of size $N \times P$ (where $N=224 \times 1$ is size of global feature vector and P = number of persons used for training) as

$$X = [x^1 | x^2 | \dots \dots \dots x^p] \quad (7)$$

3.1.3 Feature vector dimensionality reduction

The dimensionality of data matrix X is very high i.e. $224 \times P$ and is reduced further by PCA technique. The PCA is used to obtain the low dimensional representation of the data contained in data matrix while retaining as much information (energy) from the original data matrix as possible. For this mean centered feature vector \bar{x}^i is obtained as

$$\bar{x}^i = x^i - m \text{ where } m = \frac{1}{p} \sum_{i=1}^p x^i \quad (8)$$

The mean centered data matrix \bar{X} is obtained as

$$\bar{X} = [\bar{x}^1 | \bar{x}^2 | \dots | \bar{x}^p] \quad (9)$$

The \bar{X} is multiplied by its transpose to get the covariance matrix as

$$\Omega = \bar{X} \bar{X}^T \quad (10)$$

The eigenvectors and eigenvalues of the covariance matrix Ω are calculated as

$$\Omega V = \Lambda V \quad (11)$$

here v is the set of eigenvectors associated with the eigenvalues Λ . The eigenvectors $v_i \in v$ are ordered according to their corresponding eigenvalues $\lambda_i \in \Lambda$ from high to low because eigenvector associated with largest eigenvalue represent greatest variation in features and eigenvector associated with smallest eigenvalue represent small variation in features. Finally, each mean centered feature vector is projected into eigenspace as

$$\tilde{x}^i = V^T \bar{x}^i \quad (12)$$

3.1.4 Recognition

The face recognition is done by projecting the test image, to be recognized, into eigenspace and then checking its similarity by nearest neighbor classifier. To achieve this, test image is subjected to all steps mentioned in section 3.1 to get global feature vector \mathcal{Y} . It is then subtracted from mean vector of data matrix (m , as calculated in equation 8), referred as $\bar{\mathcal{Y}}$, and projected into same eigenspace defined by v as

$$\tilde{y} = V^T \bar{\mathcal{Y}} \quad (13)$$

The projected test image is compared to every projected training image in eigenspace and the closest training image is selected based on minimum distance criterion

3.1.5 Distance criterion

The distance between training image and test image is calculated with six distance metrics as proposed by (Moon & Phillips, 2001) and given by equations 14 to 19.

1. City-block distance (L1 norm):

$$d(x, y) = |x - y| = \sum_{i=1}^k |x_i - y_i| \quad (14)$$

2. Squared Euclidian distance (L2 norm):

$$d(x, y) = \|x - y\|^2 = \sum_{i=1}^K (x_i - y_i)^2 \quad (15)$$

3. Cosine distance (COS):

$$d(x, y) = -\frac{x \cdot y}{\|x\| \|y\|} = -\frac{\sum_{i=1}^k x_i y_i}{\sqrt{\sum_{i=1}^k x_i^2} \sqrt{\sum_{i=1}^k y_i^2}} \quad (16)$$

4. Mahalanobis distance (MAH):

$$d(x, y) = \sum_{i=1}^k x_i y_i \frac{1}{\sqrt{\lambda_i}} \quad \text{with } \lambda_i = \text{eigenvalues of } i^{\text{th}} \text{ eigenvector} \quad (17)$$

5. Sum of L1 and Mahalanobis distance (L1+MAH):

$$d(x,y)=\sum_{i=1}^k|x_iy_i|\frac{1}{\sqrt{\lambda_i}} \tag{18}$$

6. Sum of L2 and Mahalanobis distance (L2+MAH):

$$d(x,y)=d(x,y)=\sum_{i=1}^k(x_i-y_i)^2\frac{1}{\sqrt{\lambda_i}} \tag{19}$$

3.1.6 Test dataset

A well-designed Korean Face Database (KFDB) is used to check the algorithm performance. The database consists of images of 640 × 480 pixel resolution, 24-bit color depth and is stored in BMP and JPEG formats. It consist images of 56 male subjects and 51 female subjects with 17 variations: one frontal face image with natural expression; 4 illumination variations; 8 pose variations and 4 expression variations. The illumination variations are obtained by changing lighting directions and illumination color. The lighting direction is changed by using circular arrangement of 8-light sources separated by interval of 45^o and illumination color variation is achieved by using fluorescent light and glow light. The pose variations are obtained by capturing the images with 7-different cameras, one camera is placed at center to capture frontal image and remaining 6-cameras are placed with 3-cameras to left side of center camera and 3-cameras to right side of center camera. The cameras on left side and right side are separated by interval of 5^o, 10^o and 15^o with respect to center camera to achieve total variation of 15^o on either side of center camera. The four expression variations are also provided as Happiness, Anger, Blink and Surprise with 2-illumination colors. The experiments are carried out to report recognition rates for three categories of test images i.e. illumination variation, pose variation and expression variation. In addition, average recognition rate is also calculated by taking average of recognition rates obtained for illumination, pose and expression variations. For each variation, one frontal face image and 50% of images of respective variation category are used for training and remaining 50% images of respective variation category are used for testing. It result in gallery and probe dataset with sizes as mentioned in Table 2.

	Probe category		
	Illumination variations	Pose variations	Expression variations
Gallery Size	168	280	168
Probe set size	112	224	112

Table 2. Sizes of gallery dataset and probe dataset for three variations

3.1.7 Experimental results and analysis

The (Moon &Phillips, 2001) carried out various experiments for design of PCA based holistic face recognition system and concluded that

- Illumination normalization as pre-processing step improves recognition rate.
- The good recognition rate can be obtained by using only first 40% eigenvectors or by removing 1st eigenvector from face representation.

- The COS is good distance metric to measure image similarity in eigenspace. However, these results are reported for FERET database with holistic PCA based face recognition system. But, algorithm under consideration is local feature PCA based face recognition and database is also different i.e. Asian face database. Hence it is very much essential to check the applicability of these results to the algorithm under consideration. This is done by conducting similar experiments on Asian face database with proposed algorithm. Total four experiments are conducted to check recognition rates for illumination, pose and expression variations with six different distance metrics.

The first experiment is conducted as per the steps mentioned in section 3.1 and is referred as “baseline algorithm”. The second experiment is performed by using illumination normalization as pre-processing step to baseline algorithm and is referred as “illumination normalization as pre-processing step”. The third experiment is conducted with illumination normalization and by using only first 40% eigenvectors for face representation. It is referred as “first 40% eigenvectors”. The last experiment is carried out with illumination normalization and by removing first eigenvector from face representation. It is referred as “removal of 1st eigenvector”. The comparison of results obtained for illumination variation is shown graphically in Fig.2. It shows that maximum recognition accuracy of 76.25% is obtained by using illumination normalization as pre-processing step with COS distance metric. Thus illumination normalization as pre-processing step is helpful to improve the performance of proposed algorithm but use of first 40% eigenvectors for image representation or removal of 1st eigenvector from image representation actually reduces the performance.

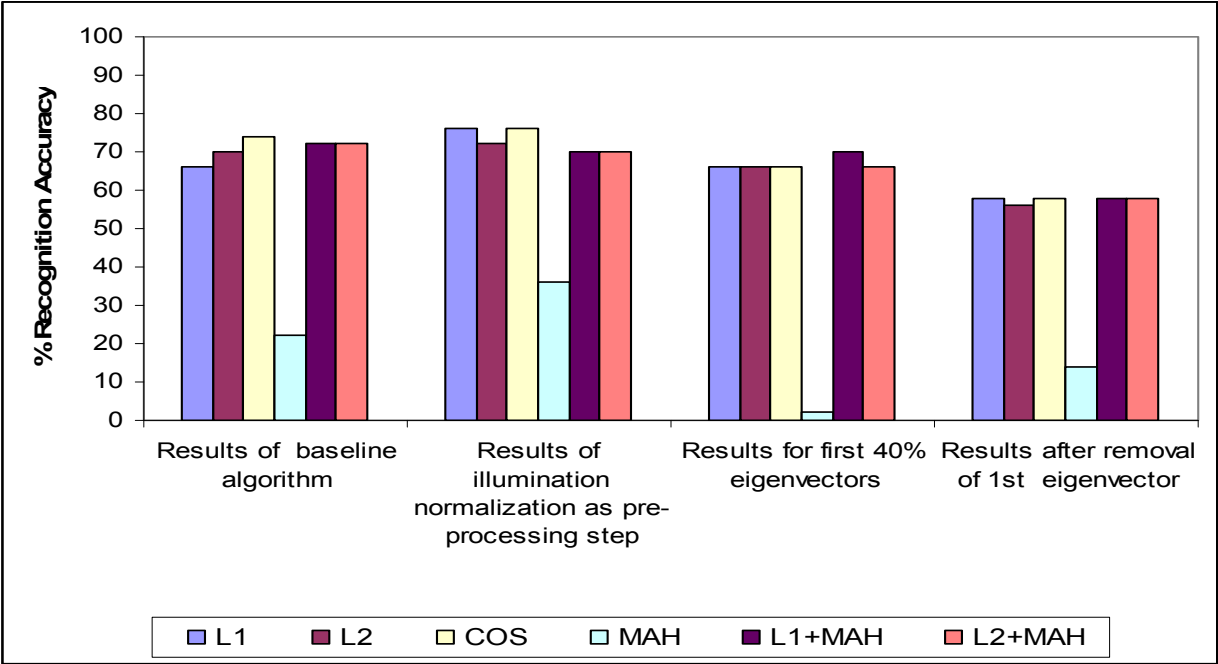


Fig. 2. Comparison of recognition rates obtained for illumination variation: Algorithm 1

The similar comparison for pose variation is shown in Fig. 3 and it shows that recognition rate of 72.5% can be obtained by using illumination normalization as pre-processing step with COS distance metric or by using 40% eigenvectors for image representation with L2 and COS distance metrics or by removing 1st eigenvector with L1 distance metric. Hence selection of proper distance metric it is very difficult.

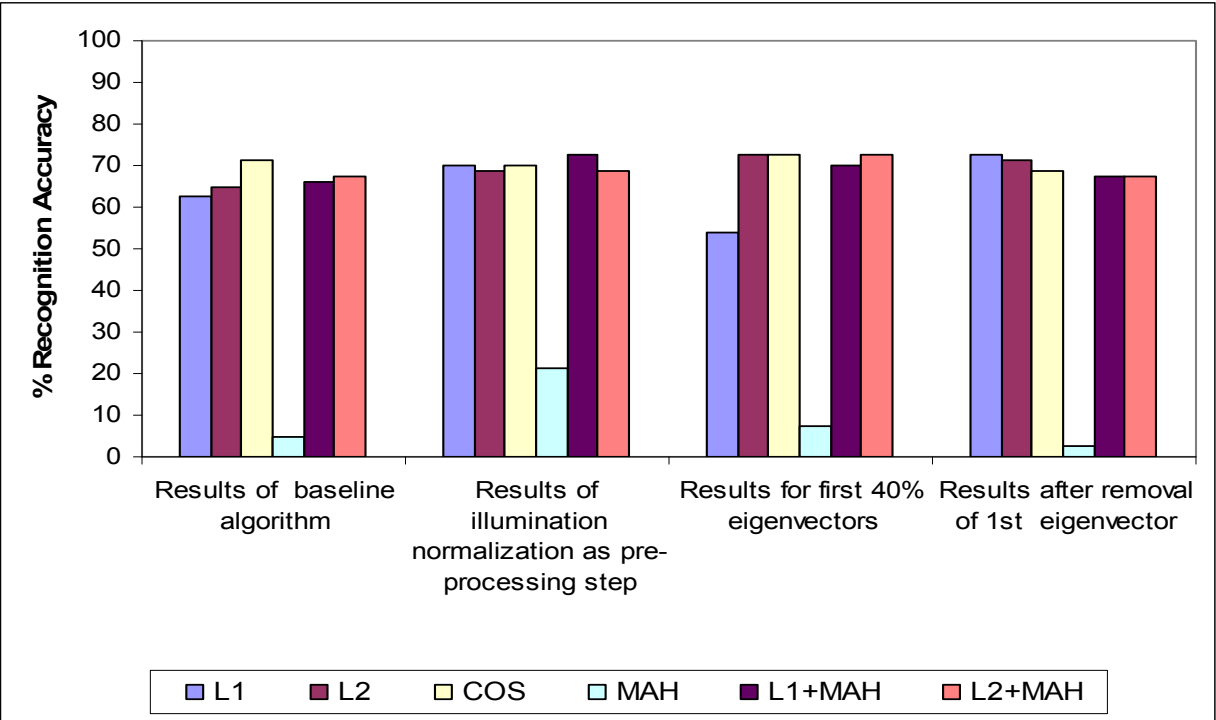


Fig. 3. Comparison of recognition rates obtained for pose variation: Algorithm 1

The graphical representation of comparison for recognition rates obtained for expression variation is shown in Fig 4. The comments of pose variation are also applicable to expression variation and maximum recognition rate achieved is 67.5%.

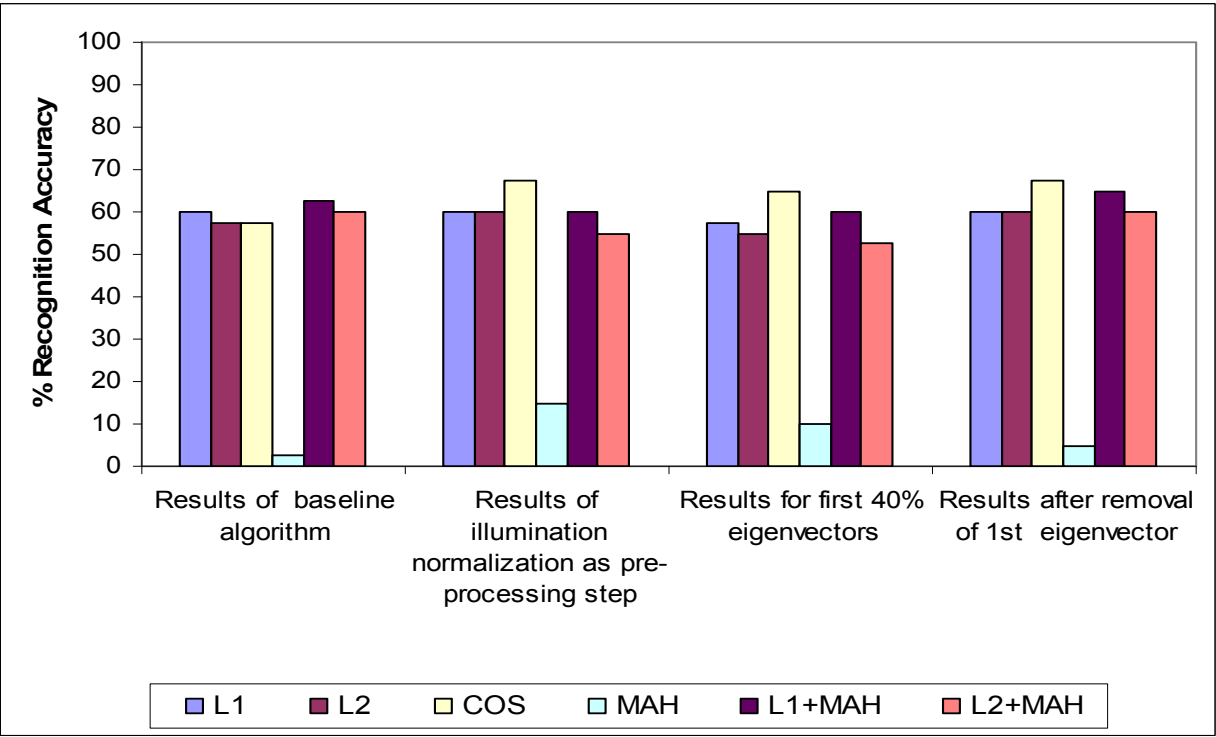


Fig. 4. Comparison of recognition rates obtained for expression variation: Algorithm 1

It is clearly evident from above comparison that it very difficult to select most suitable distance metric which works well in presence of all image variations. This problem is solved by comparing average recognition rates and its comparison is shown graphically in Fig. 5. It is evident from this comparison that maximum recognition rate of 70% can be achieved with proposed algorithm. Further it also shows that use of illumination normalization as pre-processing step is useful to improve the performance of local feature based face recognition algorithm and cosine distance metric is most suitable to measure image similarity in eigenspace.

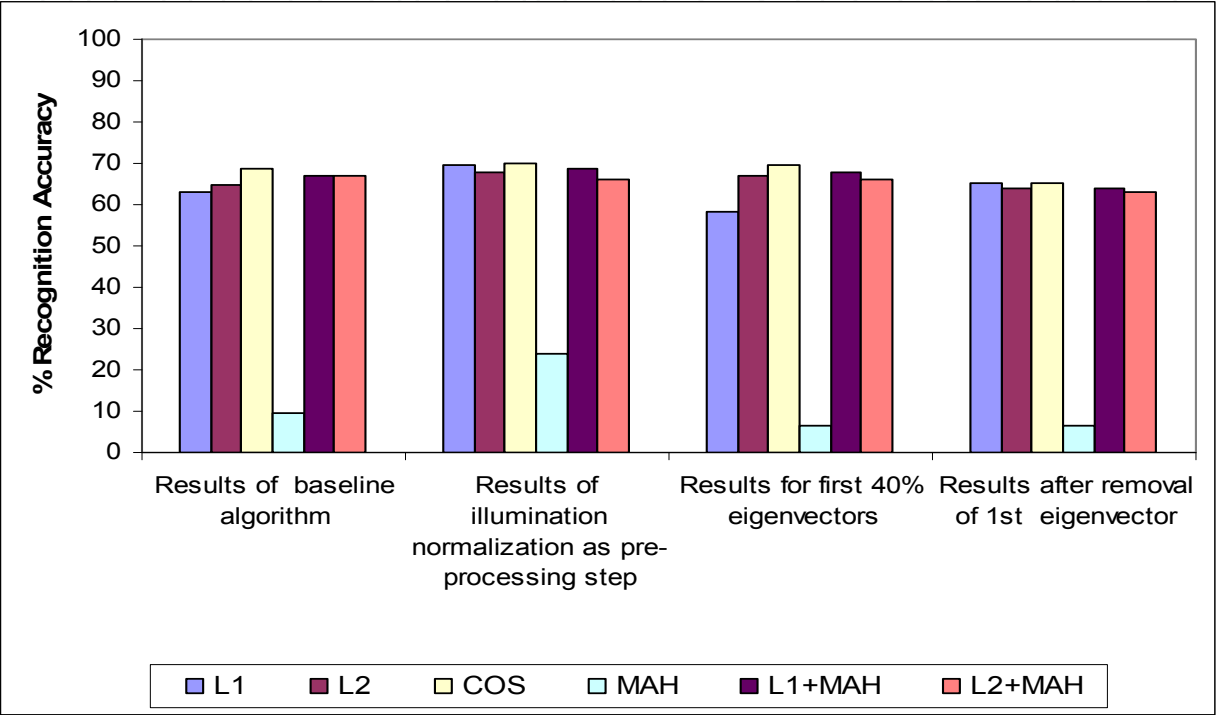


Fig. 5. Comparison of average recognition rates: Algorithm 1

3.1.7 Limitations

The recognition rates achieved with the Algorithm 1 are limited and required to be improved further. The recognition rate for expression and pose variations can be improved by making the process of feature point detection scale invariant. The reason for this is that Harris corner detector detects the feature point invariant to image rotation, scale change, illumination variation, viewpoint changes and imaging system noise but still the range is very limited. In addition, the number of feature points used to represent face image are only 14 and required to be increased further because representing the entire face image by only 14 feature points does not provide enough discrimination power to the classifier.

3.2 Algorithm 2

It is similar to Algorithm 1 except feature point detection is done with relative scale Harris detector. The steps of the proposed algorithm as given by (Pardeshi & Talbar, 2008) are

1. Illumination normalization of gray scale version of the original color face image so that normalized face image have zero mean and unity standard deviation.

2. Detect important facial feature points by application of relative scale Harris detector to given face image.
3. Perform segmentation of facial region from non-facial region with skin color based face segmentation algorithm.
4. Selection of required number of feature points based on their stability and magnitude of Harris corner response.
5. Extract image local information from these feature points with 2-D Gabor filters as mentioned in Algorithm 1.
6. Concatenate the feature vectors extracted from all feature points to form single global feature vector.
7. In training phase, apply PCA to global feature vectors extracted from all training images to build the eigenspace.
8. During recognition phase, project the global feature vector extracted from test image, by application of all steps mentioned in 1 to 6, into eigenspace.
9. Check image similarity in eigenspace with three distance metrics i.e. L1 norm, L2 norm and COS. The image with shortest distance to test image will be considered as a best match.

3.2.1 Feature point detector

The Harris corner detector, used in Algorithm 1, is not invariant to large scale changes and hence hampers correct detection of feature points in presence of pose and expression variations. To make Harris corner detector scale invariant, the scale-space representation of Harris corner detector can be explored. The idea behind this is that real-world objects are composed of different structures at different scales i.e. real-world objects may appear in different ways depending on the scale of observation. Hence to identify and select interesting image components, it is required to observe them at appropriate scale. The scale-space representation of Harris corner detector is given by (Islam et al., 2005). It allows detection of stable feature points in presence of rotation, scale change, intensity scaling, background clutter and partial occlusion. It uses relative scale σ_I as the variance of Gaussian for Harris integration while variance of Gaussian for Harris differentiation is given by $\sigma_D = K\sigma_I$, where K is a constant. The scale normalized auto-correlation matrix of Harris detector at a point $X = (x, y)$ of the image I is given as

$$N(X, \sigma_I) = \sigma_D^2 g(\sigma_I) \otimes \begin{bmatrix} I_x^2(X, \sigma_D) & I_x I_y(X, \sigma_D) \\ I_x I_y(X, \sigma_D) & I_y^2(X, \sigma_D) \end{bmatrix} \quad (20)$$

$g(\sigma_I)$ is the circular Gaussian integration window at the scale σ_I and given by

$$g(\sigma_I) = \frac{1}{2\pi\sigma_I^2} e^{-\frac{x^2+y^2}{2\sigma_I^2}} \quad (21)$$

$I_x(X, \sigma_D)$ and $I_y(X, \sigma_D)$ are given by

$$I_x(X, \sigma_D) = h(\sigma_D) \otimes I(x) \text{ and } I_y(X, \sigma_D) = (h(\sigma_D))^T \otimes I(x) \quad (22)$$

here $h(\sigma_D)$ is the 1-D Gaussian first derivative kernel at the scale of σ_D defined as

$$h(\sigma_D) = -\frac{x}{\sigma_D^3 \sqrt{2\pi}} e^{-\frac{x^2}{2\sigma_D^2}} \quad (23)$$

The measure of corner response at the point X and scale σ_l is

$$R(X, \sigma_l) = \det((N(X, \sigma_l)) - \lambda \text{tr}^2(N(X, \sigma_l)) \quad (24)$$

where λ is a constant. The point is selected as a corner point if

$$R(X, \sigma_l) > 0 \text{ and } R(X, \sigma_l) > R(X_w, \sigma_l) \forall X_w \in W \quad (25)$$

here W is the 3×3 neighborhood of the point X . To build the scale-space representation as mentioned in (20), pre-selected scales are used with $\sigma_n = k^n \sigma_0$; σ_0 is the initial scale factor set to 1; factor k is scale factor between successive scale levels (set to 1.4 as mentioned in (Lowe, 1999), n give number of resolution levels. The matrix $N(X, \sigma_l)$ is computed with $\sigma_l = \sigma_n$ and $\sigma_D = s\sigma_n$, where $S \in [0.7, 0.8, \dots, 1.4]$. The large scale change of 1.4 is used to detect initial interest points i.e. $k=1.4$ and $n=1$ and then small scale changes, specified by s , are used to observe the detected interest points at various scales.

It detects large number of feature points, representing important image contents, at various resolution levels. But as scale changes, the spatial location of feature point changes slightly and it result in detection of same image structure at various resolution levels. To avoid this feature points are selected on the basis of its stability and strength. The feature point is said to be stable if same feature point is detected at every level of the scale while strength of the feature point is judged on the basis of magnitude of its corner response. These feature points are further sorted in descending order of their corner responses because larger corner response represents larger bidirectional signal variation at that point and hence indicate the presence of discriminant information at that point. The experiments are carried out with different number of feature points and recognition rate is checked with the objective to decide optimum number of feature points required to get good recognition rate. The detected feature points based on criterion of stability and out of these selected 30 feature points based on their corner strength are shown in Fig. 6. The feature points are superimposed on original image and 3×3 neighborhood of the feature point is highlighted for proper visibility. The remaining details of this algorithm are similar to Algorithm 1 as mentioned in 3.1.2 to 3.1.6.

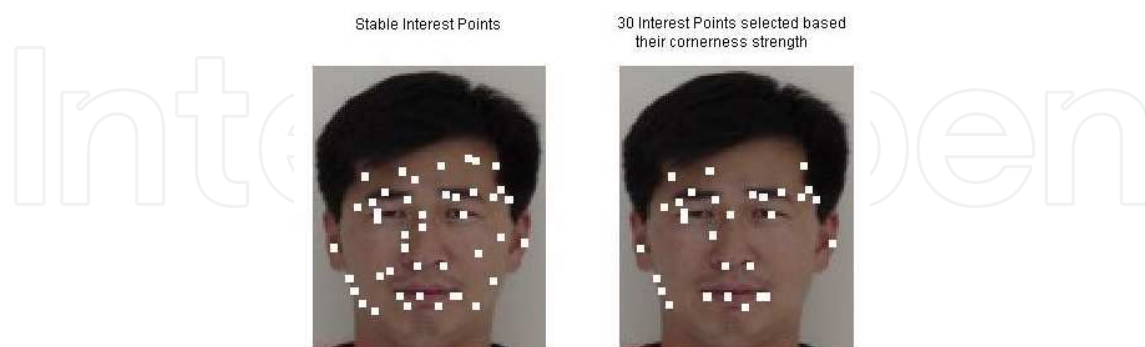


Fig. 6. Feature Point Detector Stage

3.2.2 Experimental results and analysis

The experiments are conducted to determine recognition rates obtained for illumination, pose and expression variations. These experiments are conducted by using 10, 20 and 30 feature points with the intention to determine optimum number of feature points required for face

representation. The maximum number of feature points used for experimentation is only 30 because very few feature points satisfies the criterion of stability. The comparison of results obtained for illumination variation is shown graphically in Fig.7. It shows that maximum recognition accuracy of 72% is obtained by using 30 feature points with L1 and COS distance metrics. It also shows that recognition rate increases with number of feature points.

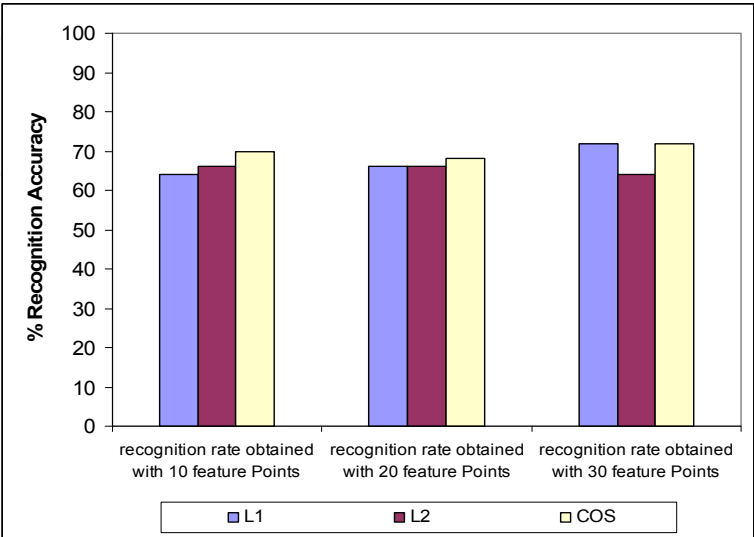


Fig. 7. Comparison of recognition rates obtained for illumination variation: Algorithm 2

The similar comparison for pose variation is shown in Fig. 8. It shows that maximum recognition rate of 72.5% is obtained by using 20 feature points with L2 and COS distance metrics and also by using 30 feature points with all distance metrics. The graphical representation of comparison for recognition rates obtained for expression variation is shown in Fig 9. It is evident that the recognition rate achieved with 30 feature points and L2 distance metric is excellent. These comparisons show that algorithm performance increases with number of feature points. But performances of distance metrics are not consistent.

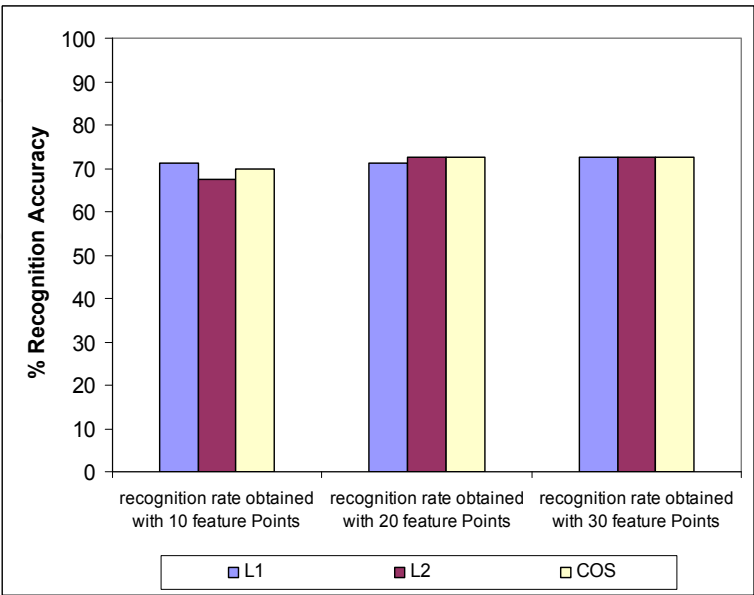


Fig. 8. Comparison of recognition rates obtained for pose variation: Algorithm 2

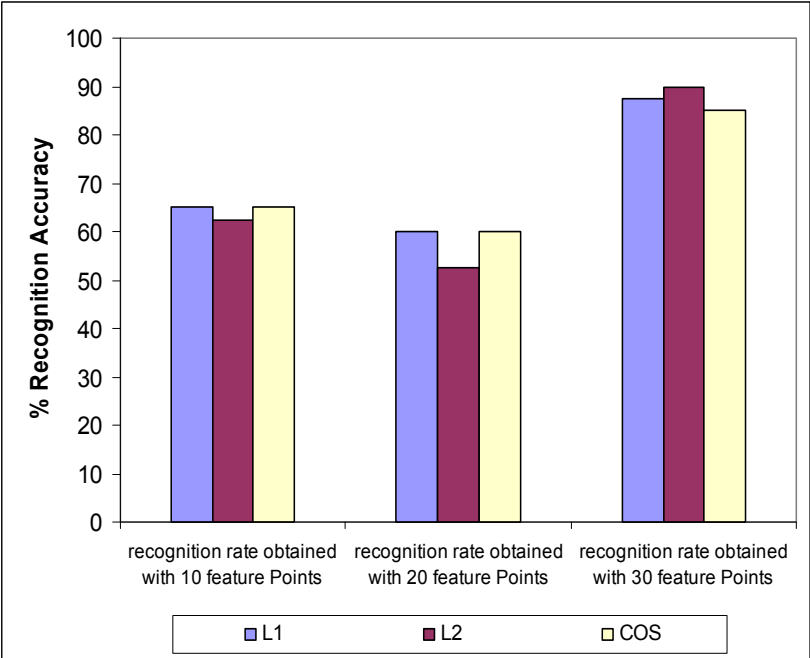


Fig. 9. Comparison of recognition rates obtained for expression variation: Algorithm 2

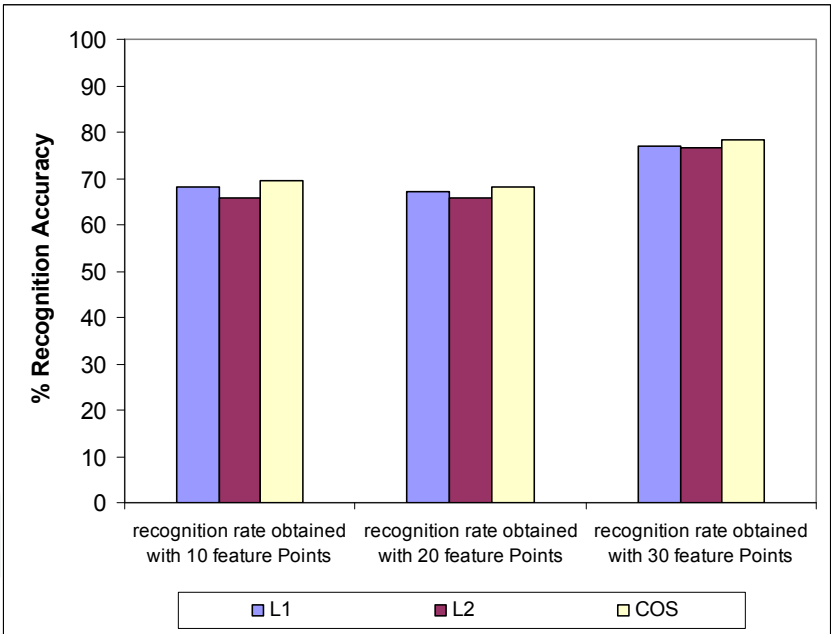


Fig. 10. Comparison of average recognition rates: Algorithm 2

To solve this problem, average recognition rates are compared and shown graphically in Figure 10. It shows that maximum recognition rate of 78.24 % can be achieved by using 30 feature points with COS distance metric.

3.2.3 Limitations

It is observed that the recognition rate increases with number of feature points used for face representation and possibility is there to increase the recognition rate further if more

number of feature points is used for face representation. The limitation of the proposed algorithm is maximum number of feature points available for face representation is only 30 hence it is also difficult to determine optimum number of feature points required for face representation. It is necessary to modify the stability condition so that more number of feature points will be available for face representation. Further, Other limitation is performances of various distance metrics are not consistent and it is very difficult to select most suitable distance metric to measure image similarity.

3.3 Algorithm 3

The algorithm is similar to Algorithm 1 except feature point detection is done with Harris-Laplace detector and classification is achieved with Classifier1 and Classifier2. The Classifier1 is nearest neighbor classifier while Classifier2 is voting based classifier. The steps of the proposed algorithm are

1. Illumination normalization of gray scale version of the original color face image so that normalized face image have zero mean and unity standard deviation.
2. Detect important facial feature points by application of scale invariant Harris detector to given face image.
3. Perform segmentation of facial region from non-facial region with skin color based face segmentation algorithm.
4. Characteristic scale selection of feature points by checking whether it's Laplacian-of-Gaussian (LoG) response is lower for finer and coarser scales than the response at associated scale.
5. Sorting of the selected feature points in descending order of their corner responses.
6. Extract image local information from these feature points with 2-D Gabor filters
7. Concatenate the feature vectors extracted from all feature points to form single global feature vector.
8. Perform classification with Classifier1 and Classifier2
 - a. Classifier 1: (Pardeshi & Talbar, 2008; Pardeshi & Talbar, 2009)
 - i. In training phase, apply PCA to global feature vectors extracted from all training images to build the eigenspace.
 - ii. During recognition phase, project the global feature vector extracted from test image, by application of all steps mentioned in 1 to 7, into eigenspace.
 - iii. Check image similarity in eigenspace with three distance metrics i.e. L1 norm, L2 norm and COS. The image with shortest distance to test image will be considered as a best match.
 - b. Classifier2 (Pardeshi & Talbar, 2009; Pardeshi & Talbar, 2010)
 - i. During training phase, develop reference database by storing each feature vector, obtained by application of steps 1 to 6, in reference database with pointer to model image from which they originates.
 - ii. During recognition phase compare every feature vector, extracted from test image by application of steps 1 to 6, with each feature vector stored in reference database for similarity.
 - iii. Based on similarity, assign the votes to the model image and model image receiving maximum number of votes is considered as best match.

3.3.1 Feature point detector

In Algorithm 2 multi-scale representation of Harris detector is obtained using predefined scales and there is no any guarantee that predefined scales will perfectly reflect the real scale

of the image structure. Other problem associated with multi-scale approach is that in general a local image structure is present in a certain range of scales. It results in detection of the feature point at each scale level within this range. As a consequence, there are many points, which represent the same image structure, but the location and the scale of these points are slightly different. The inclusion of these feature points reduces discrimination ability of the classifier. Similarly, condition used for selection of feature points includes image structures which are prominent at and every level of the scale and ignores image structures which are prominent only at certain scale e.g. The eyebrow corners or eye corners will not be prominent at coarser scales but they will become prominent only at finer scales while eyes will be prominent at coarser as well as finer scales. As per the selection criteria used in Algorithm 2, eyes will be get detected while eyebrow corners or eye corners will get ignored. But it is very much important to include these image structures for face representation because they carry highly discriminative information. This can be done with detection of feature points using multi-scale representation of Harris detector and selection of feature points with LoG. It is referred as Harris-Laplace detector and proposed by (Mikolajczyk,2004). The scale invariant Harris detector allows detection of scale invariant feature points while LoG allows selection of the scale at which each feature point is prominent. Moreover, repeatability and accuracy of detected feature points is also good. The implementation of scale invariant Harris detector is done as described in section 3.2.1 of Algorithm 2. The detected feature points are stored with their spatial locations and associated scales. It is followed with checking that whether scale associated with feature point is characteristic scale. The characteristic scale is the scale at which there is maximum similarity between the feature detection operator and the local image structure and this scale estimate obeys perfect scale invariance under rescaling of the image pattern. It is done with the help of LoG because it finds highest percentage of correct characteristic scale for local image structures such as corners, edges, ridges and multi-junctions. If LoG response attains maximum at its associated scale, feature point is retained else rejected. The LoG response is calculated by

$$|\text{LOG}(X, \sigma_n)| = \sigma_n^2 |L_{xx}(X, \sigma_n) + L_{yy}(X, \sigma_n)| \text{ where } \sigma_n = \text{set of scales} \quad (26)$$

The number of detected feature points is very large. To reduce the number of feature points further, these feature points are sorted in descending order of their corner responses and then experiments are carried out with different number of feature points with objective to determine optimum number of feature points required for face representation. The detected scale invariant feature points and out of that, selected 100 feature points are shown in Fig. 11. The feature points are superimposed on original image and 3×3 neighborhood of the feature point is highlighted for proper visibility.



Fig. 11. Feature Point Detector Stage

After detection of feature points, feature extraction from these feature points is done as described in section 3.1.2 of Algorithm 1 while details of test dataset and gallery dataset are mentioned in section 3.1.6 of Algorithm 1. The training of the algorithm and recognition of test image is done by two classification techniques i.e. Classifier1 and Classifier2.

3.3.2 Classifier 1

The classification technique is similar to technique used in Algorithm 1 and Algorithm 2 and details of the implementation is described in sections 3.1.3 to 3.1.5 of Algorithm 1. The PCA is used for dimensionality reduction of feature vectors followed by measuring image similarity in eigenspace with three different distance metrics. The experiments are conducted with different number of feature points i.e. 50, 75,100,125 and 150 for face representation. The main intention to conduct these experiments is to determine optimum number of feature points required to achieve good recognition rate and to determine how recognition rate varies with number of feature points.

3.3.3 Classifier 1-experimental results and analysis

The experiments are conducted to determine recognition rates obtained for illumination, pose and expression variations. The comparison of results obtained for illumination variation is shown graphically in Fig.12. It shows that maximum recognition rate of 78% is obtained by using 125 feature points with L1 distance metric. The similar comparison for pose variation is shown in Fig. 13. It shows that maximum recognition rate of 82.5% is obtained by using 125 feature points with L1 and L2 distance metrics. Since performance of two distance metrics is similar, it is very difficult to select proper distance metric to measure image similarity in eigenspace. The graphical representation of comparison for recognition rates obtained for expression variation is shown in Fig 14. It shows that maximum recognition rate of 85% is obtained by using 125 feature points with COS distance metric. All these experiments confirm that optimum number of feature points required to get good recognition rate are 125. But performances of distance metrics are not consistent and it is very difficult to select one particular distance metric which works well with all types of image variations. To solve this problem, average recognition rates are compared.

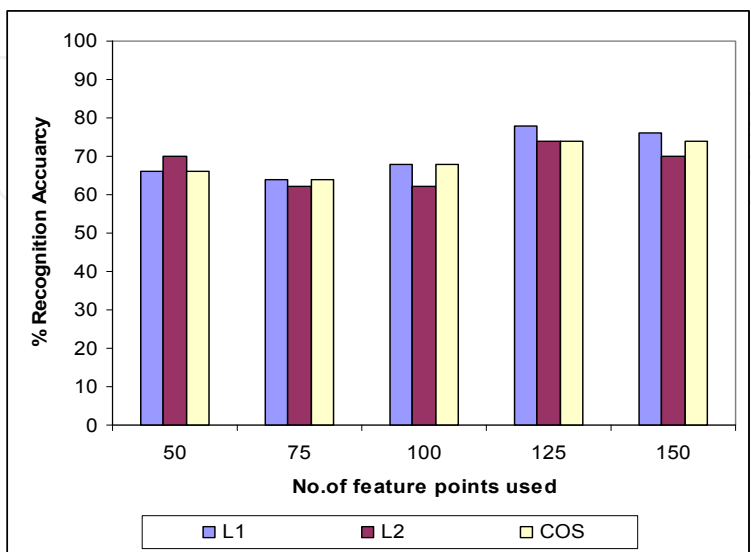


Fig. 12. Recognition rates obtained for illumination variation: Algorithm 3- Classifier1

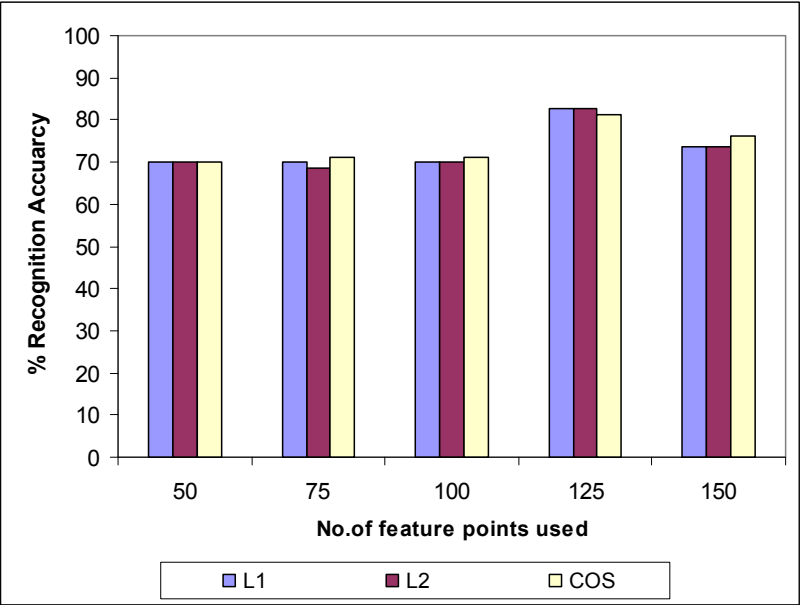


Fig. 13. Recognition rates obtained for pose variation: Algorithm 3- Classifier 1

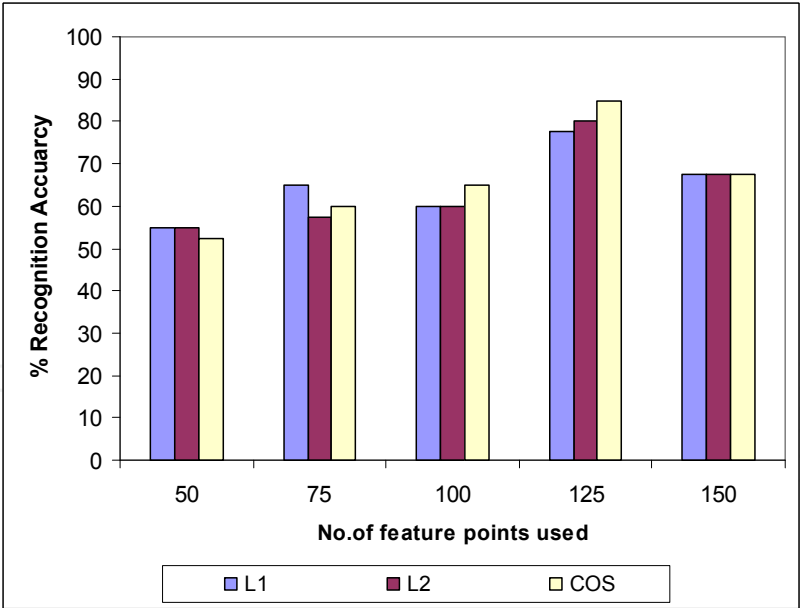


Fig. 14. Recognition rates obtained for expression variation: Algorithm 3- Classifier 1

The comparison of average recognition rates is shown graphically in Figure 15. It shows that recognition accuracy of 80% can be obtained in presence of all image variations by using 125 feature points with L1 and COS distance metric. Thus it is very difficult to select correct distance metric by comparison of average recognition rate also.

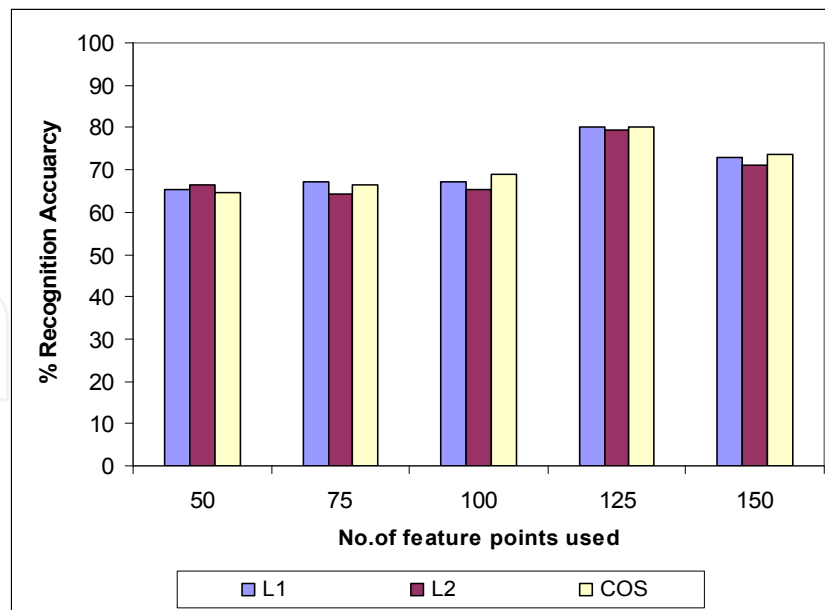


Fig. 15. Comparison of average recognition rates: Algorithm 3- Classifier 1

3.3.4 Classifier 2

The voting based classifier is used to solve the problem of inconsistent performance of various distance metrics. It classifies each feature vector individually and again combines results of individual classifiers, based on voting mechanism, to get final classification result. The reference database is generated by using images from gallery dataset (model images). The extracted feature vectors from each model image are stored in a reference database, along with a pointer to the model image from which they originate i.e. Gabor feature vector extracted from K^{th} feature point of i^{th} reference face is stored as given by (27). Thus Reference database consist a set $\{M_k\}$ of models. Each model M_k is defined by set of Gabor feature vectors $\{V_j\}$ extracted from feature points of model images. During storage process, each V_j is added to the reference database with a link to the model k for which it has been computed. So the reference database is table of couples (V_j, k) .

$$V_{i,k} = \{x_k, y_k, R_{i,j}(x_k, y_k); j = 1, \dots, 16\} \quad (27)$$

Here x_k, y_k = spatial co-ordinates of k^{th} interest point and $R_{i,j}(x_k, y_k)$ is j^{th} Gabor filter response at (x_k, y_k) . To match test image, set of Gabor feature vectors $\{V_l\}$ are extracted from detected feature points on the test image. These vectors are compared with each of the vector V_j in reference database for similarity by using squared Euclidian distance metric given by equation (15). The most similar V_j for each V_l is identified and vote is given to the corresponding model. Then votes received by each model are summed and this sum is stored in the vector $T(k)$. The model received more votes is considered as best match to the test image and is represented by the model $M_{\hat{k}}$ for which $\hat{k} = \text{argmax}_k T(k)$. It works on the assumption that if image similar to test image is stored in reference database, local features on the test image will be matched to the corresponding local features found on similar model images, while non-matching features on test image will be randomly spread over all the database images. As a result, the correct model image corresponding to test image will probably get more votes than the other model images, leading to a correct recognition.

3.3.5 Classifier 2-experimental results and analysis

The experiments are conducted to determine recognition rates obtained for illumination, pose and expression variations and results are represented graphically in Fig. 16. These experiments are performed with different number of feature points i.e. 50, 75 and 100 with the intention to determine optimum number of feature points required to achieve good recognition rate. It shows drastic improvement in performance. The recognition rates are 100% for pose and expression variations while the recognition rate for illumination variation is 78%. Actually recognition rates for pose and expression variations are same for 50, 75 and 100 feature points but comparatively on the basis of recognition rates achieved for illumination variations, recognition rates achieved with 75 feature points are excellent. It confirms that optimum number of feature points required to get good recognition rate with Classifier2 are 75. It also highlights the fact that to get good recognition rate fine tuned combination of feature point detector, feature extractor and classifier is very important.

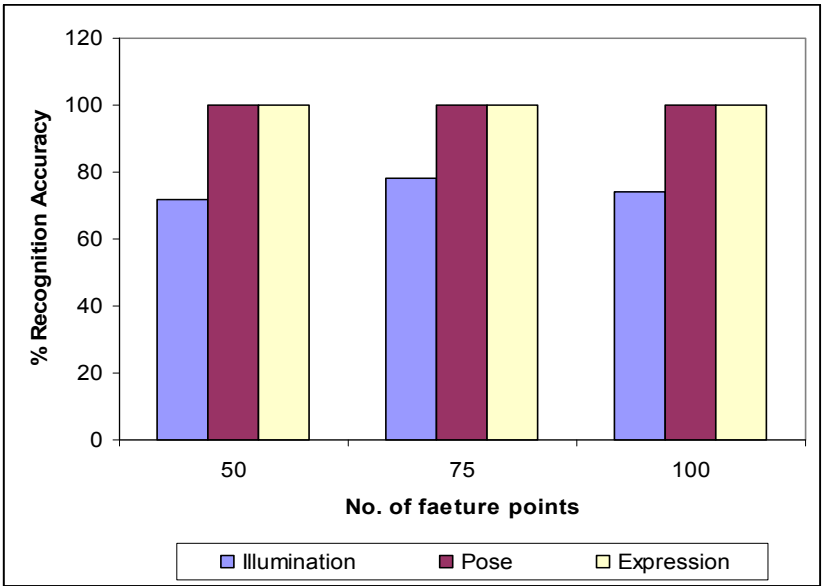


Fig. 16. Recognition rates obtained with Algorithm 3- Classifier 2

4. Performance analysis of proposed algorithms

The comparison of performances of proposed algorithms, as described in sections 3.1 to 3.3, is given in this section. Out of four variations of Algorithm 1, the performance achieved with use of illumination normalization as a pre-processing step to baseline algorithm is better with COS distance metric. This variation is referred as LFPCAIN i.e. local feature based PCA approach with illumination normalization as preprocessing step. The performance of Algorithm 2 was tested by using 10, 20 and 30 feature points with different distance metrics. It is observed that recognition rate obtained with 30 feature points and L1-norm distance metric is best. This variation is referred as LFPCA30 i.e. local feature based PCA approach with 30 feature points. The Algorithm 3 was implemented with Classifier1 and Classifier2. For Classifier1, performance obtained with 125 feature points and COS distance metric is best. This variation is referred as LFPCA125 i.e. local feature based PCA approach with 125 feature points. Similarly in case of Classifier2, recognition rate obtained with 75 feature points is best. This variation is referred as

LFVM75 i.e. local feature based voting mechanism approach with 75 feature points. The comparison of recognition rates achieved with above mentioned methods is carried out to select the most suitable algorithm for face recognition application. Moreover, the recognition rates reported in (Hwang et al., 2004) are also used for comparison because they reported recognition rates on Asian face database using holistic PCA approach for same image variations. The comparison of this approach with proposed algorithms will be helpful to check the effectiveness of the local feature based methods for face recognition application. This approach is referred as HPCA i.e. holistic feature based approach. The Fig. 17, 18, 19 and 20 shows this comparison for variations in illumination, pose, expression and average recognition rate respectively.

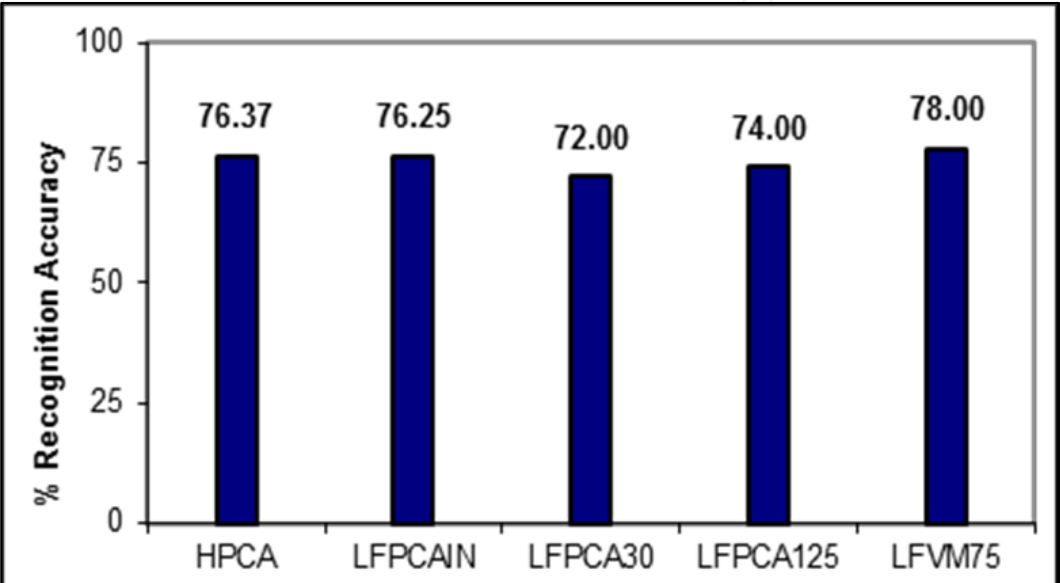


Fig. 17. Recognition rates comparison for illumination variation

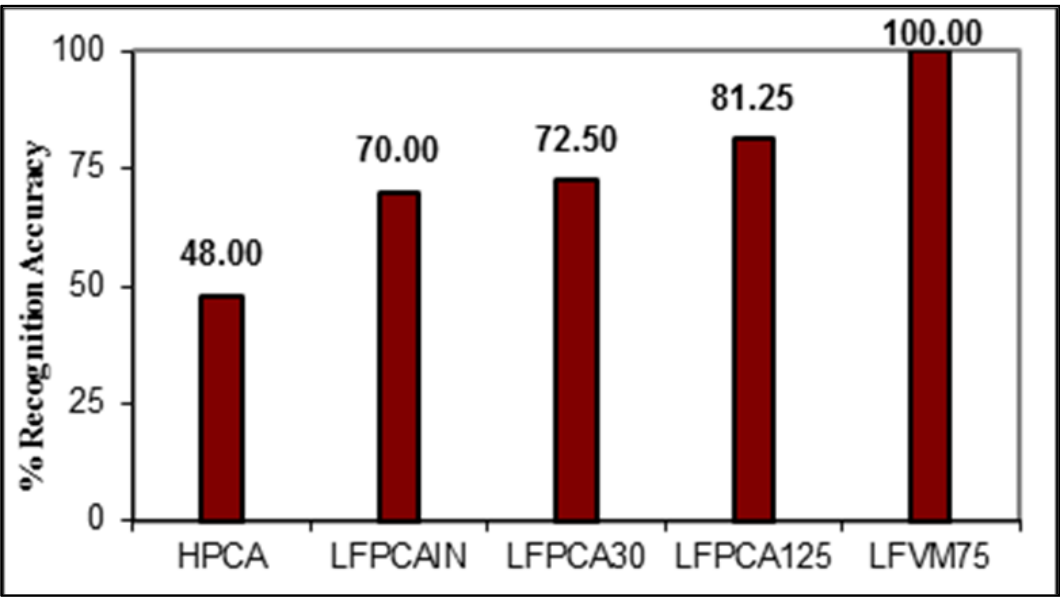


Fig. 18. Recognition rates comparison for pose variation

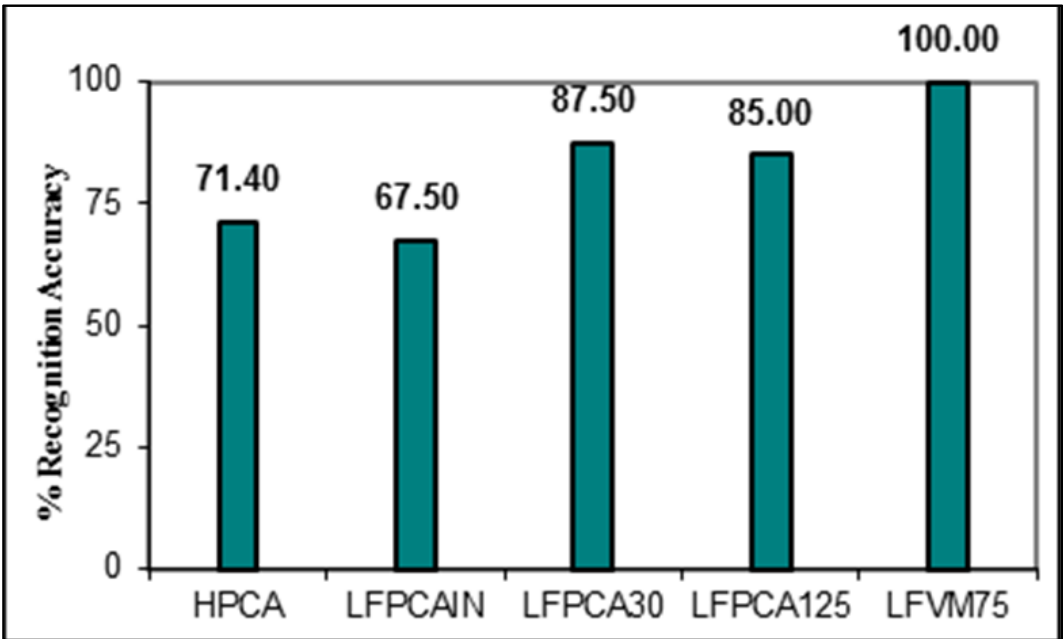


Fig. 19. Recognition rates comparison for expression variation

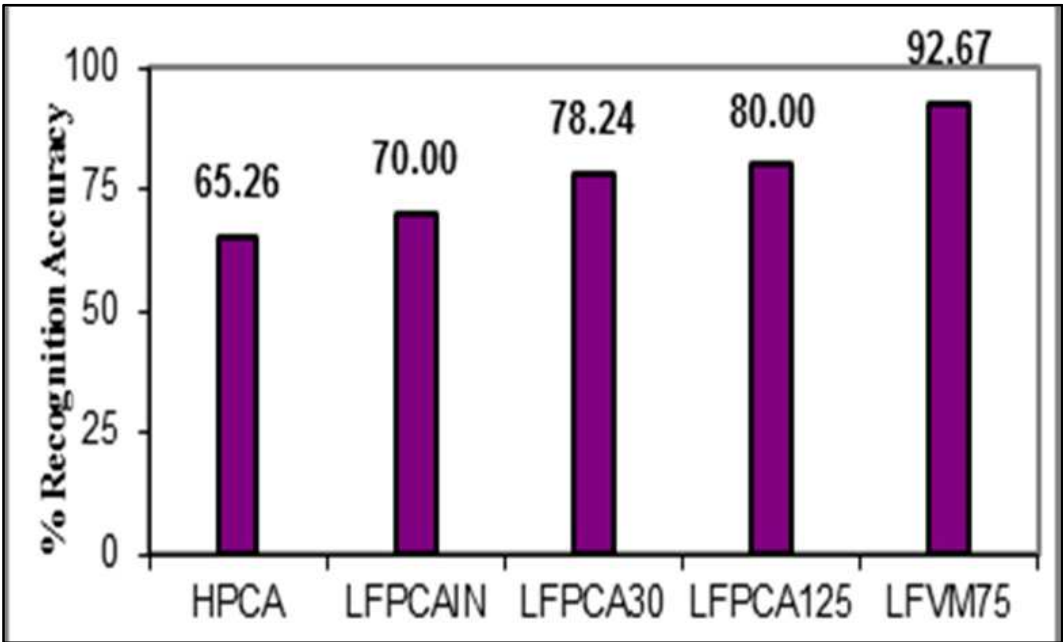


Fig. 20. Comparison of average recognition rates

It confirms that the local feature based algorithms are best suitable for face recognition applications because performances of all proposed local feature based algorithms are better than HPCA approach. Moreover, comparison also shows a continuous rise in recognition rate because each algorithm is proposed with the intention to overcome the limitations of previous algorithm. The maximum average recognition rate of 92.67% is reported by LFVM75 approach, and it reveals the fact that excellent recognition rate can be obtained by using invariant local feature detectors, invariant local feature descriptors and voting based classifier. The LFPCAIN approach uses Harris detector as feature point detector but Harris

detector is not invariant to scale changes, and it results in lower recognition rate for pose and expression variations. This limitation of LFPCAIN approach is overcome by LFPCA30 approach with use of scale invariant feature point detector for detection of feature points. It results in increased recognition accuracy for pose and the expression variations but number of feature points detected is very less. In addition, most of the points represent same image structure and contribution of other important image structures is not taken into consideration while representing face image. It affects the discrimination ability of the classifier and hence recognition rate. These limitations are overcome by LFPCA125 approach. It used Harris-Laplace detector as a feature point detector and is truly invariant detector to most of the image transformations, and it results in increased recognition rate for all image variations. However, use of PCA for dimensionality reduction results in global feature vector and it nullifies the benefits of the local feature based methods. To avoid this, LFVM75 approach does classification of each local feature independently and results of individual classifiers are combined to get a final decision. It is achieved with voting mechanism, and it results in 100% recognition accuracy against pose and expression variations. The recognition accuracy against illumination variations is also increased considerably. The success rate achieved by LFVM75 approach highlights the fact that proper combination of a feature detector, feature descriptor and classifier is very much important to develop the highly efficient automatic face recognition system. The comparison of feature vector dimensionality of proposed local feature based methods with holistic method is given in Table 3. It shows that increased recognition rates are achieved with fewer numbers of feature points so that dimensionality of feature vectors gets drastically reduced. It further reduces the storage requirement, database size and execution time as well.

Approach	HPCA	LFPCAIN	LFPCA30	LFPCA125	LFVM75
Number of feature points	Whole image	14	30	125	75
Feature vector size	10304×1	224×1	480×1	2000×1	1200×1

Table 3. Comparison of feature vector dimensionality

5. Conclusion

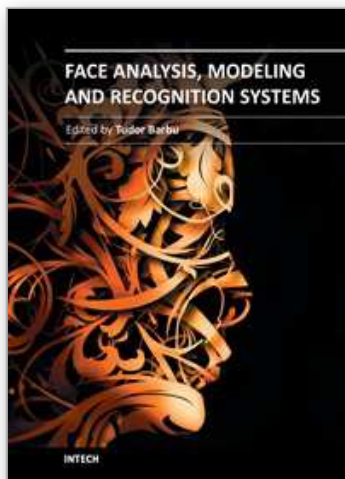
The promising capability of the local feature based method for AFR is presented by taking advantage of recent developments in local feature detection and feature extraction techniques. The important issues addressed by proposed systems are: 1) robustness of the local feature based approach to pose, illumination and expression variations, 2) identification of optimum number of facial feature points required for face description and 3) requirement of fine tuned combination of feature detector, feature descriptor and classifier. The proposed algorithms works on color face images: after having localized the face, it determines and selects important fiducial facial points, and describes them by application of bank of Gabor filters. Finally classification is done with nearest neighbor classifier or voting based classifier. The experiments were carried out on KFDB and the experimental results confirms the superiority of the approach for face recognition. Nevertheless, most interesting point required to be consider is that the reported

performance is obtained at reduced computation cost, storage requirement and computation time. All these advantages are very important for development of a practicable face recognition system.

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Face Analysis, Modeling and Recognition Systems

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The purpose of this book, entitled Face Analysis, Modeling and Recognition Systems is to provide a concise and comprehensive coverage of artificial face recognition domain across four major areas of interest: biometrics, robotics, image databases and cognitive models. Our book aims to provide the reader with current state-of-the-art in these domains. The book is composed of 12 chapters which are grouped in four sections. The chapters in this book describe numerous novel face analysis techniques and approach many unsolved issues. The authors who contributed to this book work as professors and researchers at important institutions across the globe, and are recognized experts in the scientific fields approached here. The topics in this book cover a wide range of issues related to face analysis and here are offered many solutions to open issues. We anticipate that this book will be of special interest to researchers and academics interested in computer vision, biometrics, image processing, pattern recognition and medical diagnosis.

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