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A HYBRID APPROACH FOR FACIAL EXPRESSION DETECTION BASED ON LTP AND PCA SIFT

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Abstract— **The main objective of this paper is recognize the face based on image sets using the co-learned multiview spectral clustering (CMSC). This paper proposed the feature extraction such as LTP and PCA with SIFT. The existing system use the face recognition based on SIFT and LBP features. This project proposed LTP and PCA with SIFT for feature extraction. The LTrP describes the spatial structure of the local texture using the direction of the center gray pixel. Firstly, we find the directions (horizontal and vertical) of the each pixel and then divide the patterns into four parts based on the direction of the centre pixel. After that, calculation of the tetra patterns will be done and separate them into three binary patterns. The next step is to construct the binary patterns and calculate their histogram and finally we construct the feature vector. PCA-SIFT uses PCA to replace the gradient histogram method in SIFT. Its description procedure can be divided into two sub-steps: projection matrix generating and descriptor establishing. It makes a new vector significantly smaller than a standard SIFT vector.**

Keywords— ***Face Recognition, LTP, PCA, CMSC and Gradient Histogram***

I. INTRODUCTION

Face recognition has been an intensely researched field of computer vision for the past couple of decades [1]. Though significant strides have been made in tackling the problem in controlled domains (as in recognition of passport photographs) [1], significant challenges remain in solving it in the unconstrained domain. One such scenario occurs while recognizing faces acquired from distant cameras. The main factors that make this a challenging problem are image degradations due to blur and noise, and variations in appearance due to illumination and pose [2]. In this paper, we specifically address the problem of recognizing faces across blur and illumination. As face recognition applications progress from constrained imaging and cooperative subjects (e.g., identity card deduplication) to unconstrained imaging scenarios with uncooperative subjects (e.g., watch list monitoring), a lack of guidance exists with respect to optimal approaches for integrating face recognition algorithms into large-scale applications of interest. In this work we explore the problem of identifying a person of interest given a variety of information source about the person (face image, surveillance video, face sketch, 3D face model and demographic information) in both closed set and open set identification modes. Identifying a person based on unconstrained face image(s) is an increasingly prevalent task for law enforcement and intelligence agencies.

An obvious approach to recognizing blurred faces would be to deblur the image first and then recognize it using traditional face recognition techniques [3]. However, this approach involves solving the challenging problem of blind image deconvolution [4], [5]. We avoid this unnecessary step and propose a direct approach for face recognition. We show that the set of all images obtained by blurring a given image forms a convex set, and more specifically, we show that this set is the convex hull of shifted versions of the original image. Thus with each gallery image we can associate a corresponding convex set. Based on this set-theoretic characterization, we propose a blur-robust face recognition algorithm. In the basic version of our algorithm, we compute the distance of a given probe image (which we want to recognize) from each of the convex sets, and assign it the identity of the closest gallery image. The distance-computation steps are formulated as convex optimization problems over the space of blur kernels. We do not assume any parametric or symmetric form for the blur kernels; however, if this information is available, it can be easily incorporated into our algorithm, resulting in improved recognition performance. Further, we make our algorithm robust to outliers and small pixel mis-alignments by replacing the Euclidean distance by weighted L_1-norm distance and comparing the images in the LBP (local binary pattern) [6] space. It has been shown in [7] and [8] that all the images of a Lambertian convex object, under all possible illumination conditions, lie on a low-dimensional (approximately ninedimensional) linear subspace. Though faces are not exactly convex or Lambertian, they can be closely approximated by one. Thus each face can be characterized by a low-dimensional subspace, and this characterization has been used for designing illumination robust face recognition algorithms [7], [9]. Based on this illumination model, we show that the set of all images of a face under all blur and illumination variations is a biconvex set. If we fix the blur

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kernel then the set of images obtained by varying the illumination conditions forms a convex set; and if we fix the illumination condition then the set of all blurred images is also convex.

Face recognition from blurred images can be classified into four major approaches. In the first approach, the blurred image is first deblurred and then used for recognition. This is the approach taken in [10] and [3]. The drawback of this approach is that we first need to solve the challenging problem of blind image deconvolution. Though there have been many attempts at solving the blind deconvolution problem [4], [5], [11]–[13], it is an avoidable step for the face recognition problem. Also, in [3] statistical models are learned for each blur kernel type and amount; this step might become infeasible when we try to capture the complete space of blur kernels. In the second approach, blur invariant features are extracted from the blurred image and then used for recognition; [14] and [15] follow this approach. In [14], the local phase quantization (LPQ) [16] method is used to extract blur invariant features. Though this approach works very well for small blurs, it is not very effective for large blurs [3]. In [15], a (blur) subspace is associated with each image and face recognition is performed in this feature space. It has been shown that the (blur) subspace of an image contains all the blurred version of the image. However, this analysis does not take into account the convexity constraint that the blur kernels satisfy, and hence the (blur) subspace will include many other images apart from the blurred images. The third approach is the direct recognition approach. This is the approach taken in [17] and by us. In [17], artificially blurred versions of the gallery images are created and the blurred probe image is matched to them. Again, it is not possible to capture the whole space of blur kernels using this method. We avoid this problem by optimizing over the space of blur kernels. Finally, the fourth approach is to jointly deblur and recognition the face image [18]. However, this involves solving for the original sharp image, blur kernel and identity of the face image, and hence it is a computationally intensive approach. Set theoretic approaches for signal and image restoration have been considered in [19]–[21]. In these approaches the desired signal space is defined as an intersection of closed convex sets in a Hilbert space, with each set representing a signal constraint. Image de-blurring has also been considered in this context [20], where the non-negativity constraint of the images has been used to restrict the solution space. We differ from these approaches as our primary interest lies in recognizing blurred and poorly illuminated faces rather than restoring them. There are mainly two approaches for recognizing faces across illumination variation. One approach is based on the low-dimensional linear subspace model [7], [8]. In this approach, each face is characterized by its corresponding lowdimensional subspace. Given a probe image, its distance is computed from each of the subspaces, and it is then assigned to the face image with the smallest distance [7], [9]. The other approach is based on extracting illumination insensitive features from the face image and using them for matching. Many features have been proposed for this purpose such as selfquotient images [22], correleration filters [23], Eigenphases method [24], image preprocessing algorithms [25], gradient direction [26], [27] and albedo estimates [28].

The remainder of the paper is organized as follows: In Section II, the overview of proposed method is presented. In Section III, the proposed method is specifically depicted, including its design idea and practical implementation approach. In Section IV, the performance of the proposed method is evaluated. Finally, conclusions are made in Section V.

II. FACE RECOGNITION USING LTP AND PCA SIFT

The overall block diagram of the proposed method is shown in Fig.1. This project proposed LTP and PCA with SIFT for feature extraction. The LTrP describes the spatial structure of the local texture using the direction of the center gray pixel. Firstly, we find the directions (horizontal and vertical) of the each pixel and then divide the patterns into four parts based on the direction of the centre pixel. After that, calculation of the tetra patterns will be done and separate them into three binary patterns. The next step is to construct the binary patterns and calculate their histogram and finally

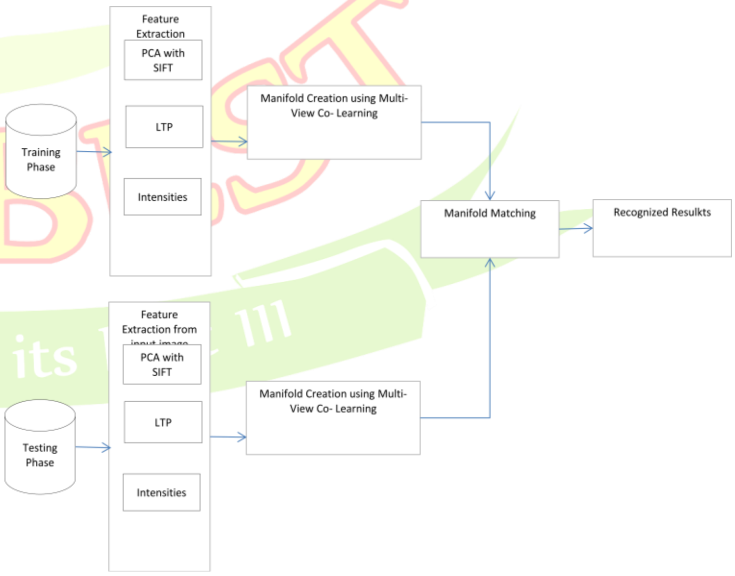

Fig. 1. Overall Block Diagram of Proposed Methods

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we construct the feature vector. PCA-SIFT uses PCA to replace the gradient histogram method in SIFT. The further details of these modules are discussed below:

III. THE PROPOSED FACE RECOGNITION PRCODURE

There are two phase

1. Training phase
2. Testing Phase

- In training phase the following methods are used.

1. Feature extraction
2. Manifold Creation using Multi view co-learning

The testing Phase contains the following methods.

1. Feature extraction
2. Manifold Creation using Multi view co-learning

- To combine both training and testing manifolds and following methods are used.

1. Manifold Matching
2. Recognized Results

In feature Extraction There are 3 features are used.

1. LTP
2. PCA with SIFT
3. Intensity

A. Feature Extraction:

In pattern recognition and in image processing, feature extraction is a special form of dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be very redundant (e.g. the same measurement in both feet and meters, or the repetitiveness of images presented as pixels), then the input data will be transformed into a reduced representation set of features . Transforming the input data into the set of features is called feature extraction. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. First, the input image set is divided into multiple blocks and to extract the PCA with SIFT, LTP and intensities features for the each block.

SIFT Features:

Scale-invariant feature transform (or SIFT) is an algorithm in computer vision to detect and describe local features in images. Applications include object recognition, robotic mapping and navigation, image stitching, 3D modeling, gesture recognition, video tracking, individual identification of wildlife and match moving. SIFT keypoints of objects are first extracted from a set of reference images and stored in a database. An object is recognized in a new image by individually comparing each feature from the new image to this database and finding candidate matching features based on Euclidean distance of their feature vectors. From the full set of matches, subsets of keypoints that agree on the object and its location, scale, and orientation in the new image are identified to filter out good matches. The determination of consistent clusters is performed rapidly by using an efficient hash table implementation of the generalized Hough transform. Each cluster of 3 or more features that agree on an object and its pose is then subject to further detailed model verification and subsequently outliers are discarded. The SIFT features are local and based on the appearance of the object at particular interest points, and are invariant to image scale and rotation. They are also robust to changes in illumination, noise, and minor changes in viewpoint. In addition to these properties, they are highly distinctive, relatively easy to extract and allow for correct object identification with low probability of mismatch.

Algorithm:

PCA-SIFT can be summarized in the following steps:

(1) pre-compute an eigenspace to express the gradient images of local patches;

(2) given a patch, compute its local image gradient;

(3) project the gradient image vector using the eigenspace to derive a compact feature vector.

This feature vector is significantly smaller than the standard SIFT feature vector, and can be used with the same matching algorithms.

The Euclidean distance between two feature vectors is used to determine whether the two vectors correspond to the same keypoint in different images.

LTP Features:

It is one of the content based features. Local tetra pattern is simple and efficient pattern.

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Algorithm:

1. Initialize and load the image, and then convert it into greyscale.

2. In horizontal and vertical axis, apply the first-order derivatives.

3. For each and every pixel, calculate the direction.

4. Based on the direction of the centre pixel, divide the obtained patterns into four parts.

5. After that calculate the tetra patterns and then separate them into three binary patterns.

6. Then histograms of binary patterns will be calculated.

7. Calculate the magnitudes of centre pixels.

8. Calculate their histogram after constructing the binary patterns.

9. Combine the histograms calculated from steps 6 & 8.

10. Construct the feature vector using Gabor Transformation.

11. Do the comparison of the query image with the images stored in the database.

12. Retrieve the images based on the best matches which are similar to the query image.

Intensity:

These features are based only on the absolute value of the intensity measurements in the image. A histogram describes the occurrence relative frequency of the intensity values of the pixels in an image. The intensity features that we will consider are the first four central moments of this histogram: Mean, Standard Deviation, Skewness, Kurtosis. Histogram is a graph showing the number of pixels in an image at each different intensity value found in that image. For an 8-bit gray scale image, there are 256 intensity values are possible. The intensity histogram features are first order statistics. The histogram is plotted from the image and from the histogram a four features are extracted that can discriminate between the two classes of mammogram. Four features such smoothness, uniformity, third moment and entropy is calculated using intensity histogram graph. The histogram graph is constructed by counting the number of pixels at each intensity value.

B. Manifold Creation Using Multi-View Co-Learning:

A manifold is a topological space that resembles Euclidean space near each point. More precisely, each point of an n-dimensional manifold has a neighbourhood that is homeomorphic to the Euclidean space of dimension n. Lines and circles, but not figure eights, are one-dimensional manifolds. Two-dimensional manifolds are also called surfaces. This project using two methods for multi-view spectral clustering are proposed, namely pairwise-based CMSC and centroid- based CMSC.

Pairwise based CMSC:

Assume an image set with m views from the laplacian matrices. Each single view of an image set is sufficient for clustering independently, we attempt to maximize embedding matrix. This enables the representations of the same data point in different views to be assigned to the same cluster. To achieve this goal, we define the between-view correlation as for any two embeddings. To integrate the above objectives, we propose an objective function that aims to seek a collection of embeddings used to maximize both the individual spectral clustering terms and their correlations.

$$\max_{\mathbf{V}\in\mathbf{R}^{(mn)\times k}} tr(\mathbf{V}^T\mathbf{L}\mathbf{V}), \qquad s.t.\ tr(\mathbf{V}^T\mathbf{B}\mathbf{V}) = d,$$

Centroid-Based CMSC

In the pairwise-based CMSC method, we assume that all the embedding matrices tend to each other, which requires computation of the pairwise correlations among the embedding matrices in different views. To defining the between-view correlation as the proposed objective function aims to seek embedding matrices and to maximize the individual spectral clustering terms and their correlations. The objective function is

$$\max_{\mathbf{V}\in\mathbf{R}^{(m+1)n\times k}} tr(\mathbf{V}^T\mathbf{L}\mathbf{V}), \qquad s.t.\ tr(\mathbf{V}^T\mathbf{B}\mathbf{V}) = d,$$

C. Manifold Matching:

To match the two sets as the same class, the most effective solution is to find the common views and measure the similarity of those parts of data. Therefore, we define MMD

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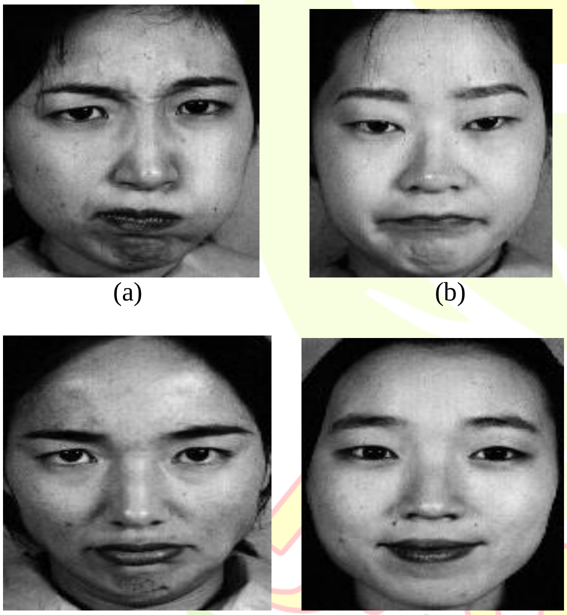
by the closest subspace pair from the two manifolds as follows:

$$d(\mathbf{M}^X, \mathbf{M}^Y) = \min\left\{ \min_i d(\mathbf{m}_i^X, \mathbf{M}^Y), \min_j d(\mathbf{m}_j^Y, \mathbf{M}^X) \right\},$$

IV. PERFORMANCE ANALYSIS

A. *Expirementai Images*

Experiments were conducted on a group of several face images to verify the effectiveness of the proposed scheme. For the experimental purpose several standard face image with different facial expression are taken from JAFEE dataset.



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

Fig. 4. Expirementai Images

B. *Performance Analysis*

To evaluate the performance of the face recognition techniques several performance metrics are available. This project uses the detection accuracy, precision rate, recall rate, Error Rate and F-Measure to analyses the performance.

Detection Accuracy

Detection Accuracy is the measurement system, which measure the degree of closeness of measurement between the original detected face and the detected face by the proposed method.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

Where, TP – True Positive (equivalent with hit)
FN – False Negative (equivalent with miss)
TN – True Negative (equivalent with correct rejection)
FP – False Positive (equivalent with false alarm)

Error Rate

Error Rate is the measurement system, which measure no of falsely detected face form the given input thermal images.

$$\text{Error Rate} = \frac{\text{No of Images of Falsely Detected Face \& } \mathit{Eyes}}{\text{Total No of Images}}$$

Precision Rate

The precision is the fraction of retrieved instances that are relevant to the find.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Where TP = True Positive (Equivalent with Hits)
FP = False Positive (Equivalent with False Alarm)

Recall Rate

The recall is the fraction of relevant instances that are retrieved according to the query.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Where TP = True Positive (Equivalent with Hits)
FP = False Negative (Equivalent with Miss)

F-Measure

F-measure is the ratio of product of precision and recall to the sum of precision and recall. The f-measure can be calculated as,

$$F_m = (1 + \alpha) * \frac{\text{Precision} * \text{Recall}}{\alpha * (\text{Precision} * \text{Recall})}$$

Table 4.1 Detection Accuracy Value Analysis

METHODS	DETECTION ACCURACY VALUE
Template Matching	84%
Feature Invariant Method	86%
Mathematical Morphology	88%
Hough Transform	91%

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Proposed Method	94%

From the table it is shown that the detection accuracy value of the proposed method is higher than the other existing approaches. So the proposed method is best than the existing approaches. The graph of detection accuracy analysis is shown in Fig.4.13.

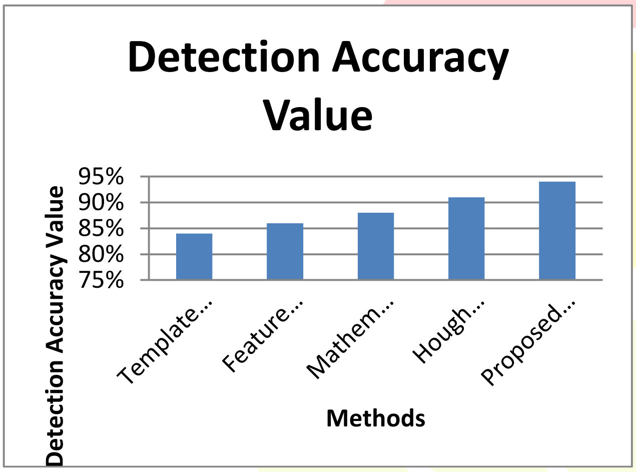

Fig.4.13Detection Accuracy Value Analysis

In table 4.2 shows the error rate value analysis of the proposed and other existing approaches.

METHODS	ERROR RATE
Template Matching	16%
Feature Invariant Method	14%
Mathematical Morphology	12%
Hough Transform	9%
Proposed Method	6%

Table 4.2 Error Rate Value Analysis

From the table it is shown that the error rate value of the proposed method is lower than the other existing approaches. So the proposed method is best than the existing approaches. The graph of error rate analysis is shown in Fig.4.14.

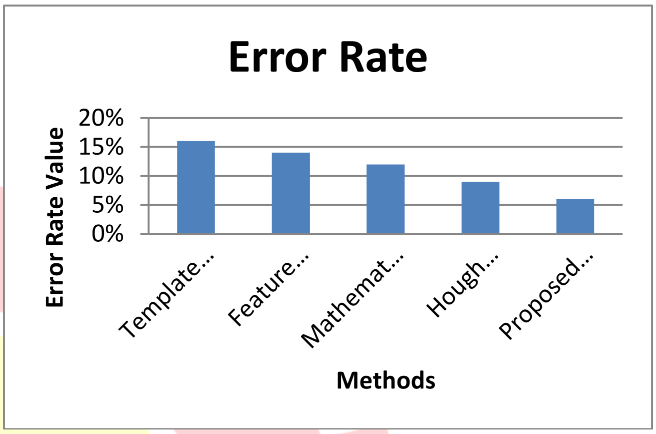

Fig.4.14Error Rate Value Analysis

In table 4.3 shows the precision rate analysis of the proposed and other existing approaches.

Table 4.3 Precision Rate Analysis

METHODS	PRECISION RATE
Template Matching	82%
Feature Invariant Method	84%
Mathematical Morphology	86%
Hough Transform	89%
Proposed Method	92%

From the table it is shown that the precision rate value of the proposed method is higher than the other existing approaches. So the proposed method is best than the existing approaches. The graph of precision rate analysis is shown in Fig.4.15.

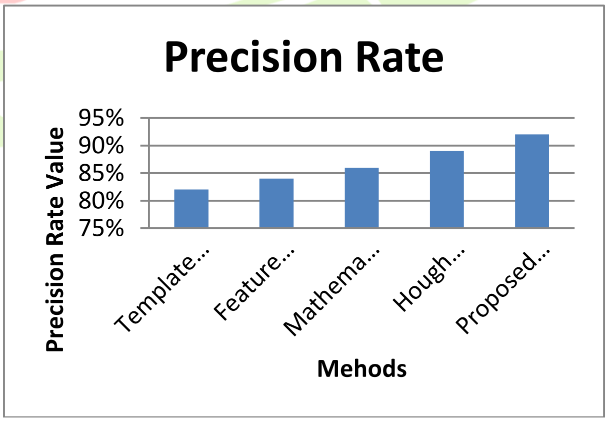

Fig.4.15Precision Rate Analysis

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In table 4.4 shows the recall rate analysis of the proposed and other existing approaches.

Table 4.4 Recall Rate Value Analysis

METHODS	RECALL RATE
Template Matching	80%
Feature Invariant Method	82%
Mathematical Morphology	84%
Hough Transform	86%
Proposed Method	90%

From the table it is shown that the recall rate value of the proposed method is higher than the other existing approaches. So the proposed method is best than the existing approaches. The graph of recall rate analysis is shown in Fig.4.16.

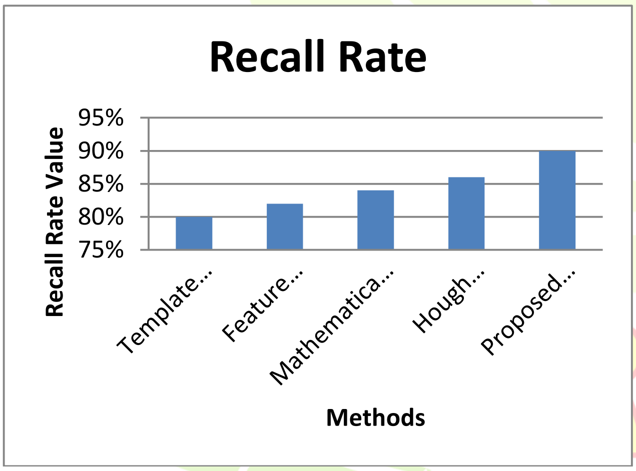

Fig.4.16 Recall Rate Value Analysis

In table 4.5 shows the f-measure rate analysis of the proposed and other existing approaches.

Table 4.5 F-Measure Analysis

METHODS	F-MEASURE
Template Matching	85%
Feature Invariant Method	87%
Mathematical Morphology	88%
Hough Transform	91%
Proposed Method	95%

From the table it is shown that the f-measure value of the proposed method is higher than the other existing approaches. So the proposed method is best than the existing approaches. The graph of f-measure analysis is shown in Fig.4.17.

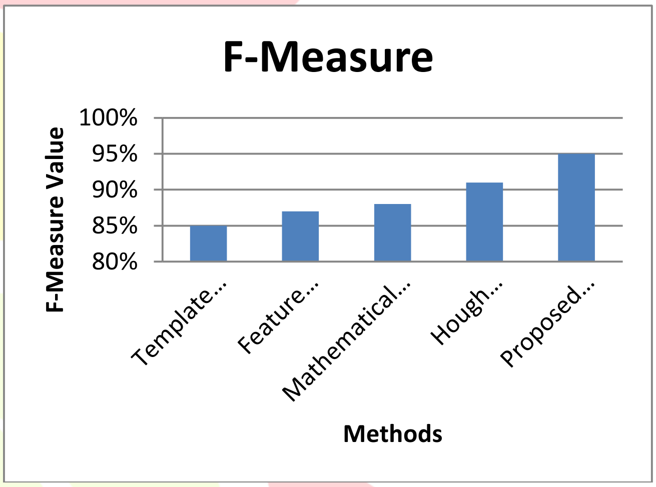

Fig.4.17F-Measure Analysis

V. CONCLUSION

This project proposed image set based face recognition. This project proposed the CMSC method for manifold creation. In CMSC contains two types of manifold creation there are centroid based and pairwise based manifold creation. In feature extraction, LTP, PCA with SIFT and intensity features are extracted. In training and testing phase contain the same process. Finally classification used to combined the features and provides results.

References

[1] W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld, "Face recognition: A literature survey," *ACM Comput. Surv.*, vol. 35, no. 4, pp. 399–458, Dec. 2003.
[2] J. Ni and R. Chellappa, "Evaluation of state-of-the-art algorithms for remote face recognition," in *Proc. IEEE 17th Int. Conf., Image Process.*, Sep. 2010, pp. 1581–1584.
[3] M. Nishiyama, A. Hadid, H. Takeshima, J. Shotton, T. Kozakaya, and O. Yamaguchi, "Facial deblur inference using subspace analysis for recognition of blurred faces," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 4, pp. 838–845, Apr. 2011.
[4] D. Kundur and D. Hatzinakos, "Blind image deconvolution revisited."

ISSN 2395-695X (Print)
ISSN 2395-695X (Online)

International Journal of Advanced Research in Biology Engineering Science and Technology (IJARBEST)
Vol. 2, Issue 6, May 2016

[5] A. Levin, Y. Weiss, F. Durand, and W. T. Freeman, “Understanding blind deconvolution algorithms,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 12, pp. 2354–2367, Apr. 2011.
[6] T. Ojala, M. Pietikäinen, and T. Mäenpää, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 24, no. 7, pp. 971–987, Jul. 2002.
[7] R. Basri and D. W. Jacobs, “Lambertian reflectance and linear subspaces,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 2, pp. 218–233, Feb. 2003.
[8] R. Ramamoorthi and P. Hanrahan, “A signal-processing framework for reflection,” *ACM Trans. Graph.*, vol. 23, no. 4, pp. 1004–1042, 2004.
[9] K.-C. Lee, J. Ho, and D. J. Kriegman, “Acquiring linear subspaces for face recognition under variable lighting,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, no. 5, pp. 684–698, May 2005.
[10] H. Hu and G. De Haan, “Adaptive image restoration based on local robust blur estimation,” in *Proc. Int. Conf. Adv. Concep. Intell. Vis. Syst.*, 2007, pp. 461–472.
[11] W. H. Richardson, “Bayesian-based iterative method of image restoration,” *J. Opt. Soc. Amer.*, vol. 62, no. 1, pp. 55–59, Jan. 1972.
[12] A. Levin, “Blind motion deblurring using image statistics,” in *Proc. Adv. Neural Inform. Process. Syst. Conf.*, 2006, pp. 841–848.
[13] R. Fergus, B. Singh, A. Hertzmann, S. T. Roweis, and W. T. Freeman, “Removing camera shake from a single photograph,” in *Proc. ACM SIGGRAPH Conf.*, 2006, pp. 787–794.
[14] T. Ahonen, E. Rahtu, V. Ojansivu, and J. Heikkilä, “Recognition of blurred faces using local phase quantization,” in *Proc. 19th Int. Conf. Pattern Recognit.*, Dec. 2008, pp. 1–4.
[15] R. Gopalan, S. Taheri, P. K. Turaga, and R. Chellappa, “A blur-robust descriptor with applications to face recognition,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 34, no. 6, pp. 1220–1226, Jun. 2012.
[16] V. Ojansivu and J. Heikkilä, “Blur insensitive texture classification using local phase quantization,” in *Proc. 3rd Int. Conf. Image Signal Process.*, 2008, pp. 236–243.
[17] I. Stainvas and N. Intrator, “Blurred face recognition via a hybrid network architecture,” in *Proc. Int. Conf. Pattern Recogn.*, 2000, pp. 809–812.
[18] H. Zhang, J. Yang, Y. Zhang, N. M. Nasrabadi, and T. S. Huang, “Close the loop: Joint blind image restoration and recognition with sparse representation prior,” in *Proc. IEEE Int. Conf. Comput. Vis.*, Nov. 2011, pp. 770–777.
[19] P. Combettes, “The convex feasibility problem in image recovery,” in *Proc. Adv. Imag. Element. Phys.*, 1996, pp. 155–270.
[20] H. Trussell and M. Civanlar, “The feasible solution in signal restoration,” *IEEE Trans. Acoust., Speech Signal Process.*, vol. 32, no. 2, pp. 201–212, Apr. 1984.
[21] P. Combettes and J. Pesquet, “Image restoration subject to a total variation constraint,” *IEEE Trans. Image Process.*, vol. 13, no. 9, pp. 1213–1222, Sep. 2004.
[22] H. Wang, S. Li, Y. Wang, and J. Zhang, “Self quotient image for face recognition,” in *Proc. Int. Conf. Image Process.*, Oct. 2004, pp. 1397–1400.
[23] B. Kumar, M. Savvides, and C. Xie, “Correlation pattern recognition for face recognition,” *Proc. IEEE*, vol. 94, no. 11, pp. 1963–1976, Nov. 2006.
[24] M. Savvides, B. V. K. V. Kumar, and P. K. Khosla, “Eigenphases vs eigenfaces,” in *Proc. Int. Conf. Pattern Recognit.*, vol. 3. 2004, pp. 810–813.
[25] R. Gross and V. Brajovic, “An image preprocessing algorithm for illumination invariant face recognition,” in *Proc. 4th Int. Conf. Audio- Video-Based Biometr. Person Authent.*, 2003, pp. 10–18.
[26] H. Chen, P. Belhumeur, and D. Jacobs, “In search of illumination invariants,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Sep. 2000, pp. 254–261.
[27] M. Osadchy, D. W. Jacobs, and M. Lindenbaum, “Surface dependent representations for illumination insensitive image comparison,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 1, pp. 98–111, Jan. 2007.
[28] S. Biswas, G. Aggarwal, and R. Chellappa, “Robust estimation of albedo for illumination-invariant matching and shape recovery,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 31, no. 5, pp. 884–899, May. 2009.
[29] R. L. Lagendijk and J. Biemond, “Basic methods for image restoration and identification,” in *Essential Guide to Image Processing*. Ed. A. C. Bovic, Boston: Academic Press, 2009, pp. 323–348.
[30] P. Sinha, B. Balas, Y. Ostrovsky, and R. Russell, “Face recognition by humans: Nineteen results all computer vision researchers should know about,” *Proc. IEEE*, vol. 94, no. 11, pp. 1948–1962, Nov. 2006.
[31] R. Epstein, P. Hallinan, and A. Yuille, “5 plus or minus 2 eigenimages suffice: An empirical investigation of low-dimensional lighting models,” in *Proc. Workshop Phys.-Based Model. Comput. Vis.*, Jun. 1995, p. 108.
[32] V. Blanz and T. Vetter, “Face recognition based on fitting a 3d morphable model,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 9, pp. 1063–1074, Sep. 2003.
[33] W. Smith and E. Hancock, “Estimating the albedo map of a face from a single image,” in *Proc. IEEE Int. Conf. Image Process.*, Sep. 2005, pp. 780–783.
[34] M. H. X. Zou, J. Kittler. and J. R. Tena, “Robust albedo estimation from face image under unknown illumination,” *Proc. SPIE*, vol. 1, no. 8, pp. 1–15, Mar. 2008.
[35] P. J. Phillips, H. Moon, S. A. Rizvi, and P. J. Rauss, “The FERET evaluation methodology for face-recognition algorithms,” *IEEE Trans.Pattern Anal. Mach. Intell.*, vol. 22, no. 11, pp. 1090–1104, Oct. 2000.
[36] T. Sim, S. Baker, and M. Bsat, “The cmu pose, illumination, and expression database,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 12, pp. 1615–1618, Dec. 2003.
[37] R. Chellappa, J. Ni, and V. M. Patel, “Remote identification of faces: Problems, prospects, and progress,” *Pattern Recognit. Lett.*, vol. 33, no. 14, pp. 1849–1859, Oct. 2012.
[38] J. Wright, A. Yang, A. Ganesh, S. Sastry, and Y. Ma, “Robust face recognition via sparse representation,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 31, no. 2, pp. 210–227, Feb. 2009.
[39] T. Ahonen, A. Hadid, and M. Pietikäinen, “Face description with local binary patterns: Application to face recognition,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 12, pp. 2037–2041, Dec. 2006.