IJCTA, 9(10), 2016, pp. 4201-4210

Illumination Invariant Face Recognition using Fisher Linear Discriminant Algorithm (FLDA)

***Ms. P.Malathi *Ms. D.Bharathi and Ms. **Vinodhini.R .E**

Abstract : In image processing domain biometrics is an emerging field, in which matching the face images of optical and infrared is a tough toil. Since the optical and infrared images are captured by two disparate devices there exists a great diversity between one and the other kinds of images. A classy method supported by Feature discriminant analysis[1], which uses fisher linear discriminant algorithm (FLDA) is proposed in this paper. This approach has two steps to minimize this chaos and to maximize the performance of optical-infrared face recognition. In first step, extract all the common discriminant features from heterogeneous (infrared and optical) face images using FLDA. In second step, *k*-Nearest Neighbors (*k*-NN) algorithm is used on the result to conclude whether they match or not. To show that the algorithm works better than the existing ones, experiments are conducted on optical and infrared datasets.
Keywords : Feature Discriminant Analysis, Fisher Linear Discriminant Algorithm (FLDA), *k*-nearest neighbors Algorithm (KNN), optical-infrared face recognition.

1. INTRODUCTION

Automatic face recognition systems use Infrared imaging devices to conflict low illumination at night or indoors. The major task of ARF system is to match infrared images with optical images which is an important application of heterogeneous face recognition[2]. The key idea is to learn an encoding mechanism which will turn the optical and infrared face images into their encoded images to reduce the modality gap between them. It is the most demanding issue for heterogeneous face recognition[2].

Many methods have been proposed to conflict the great modality gap.

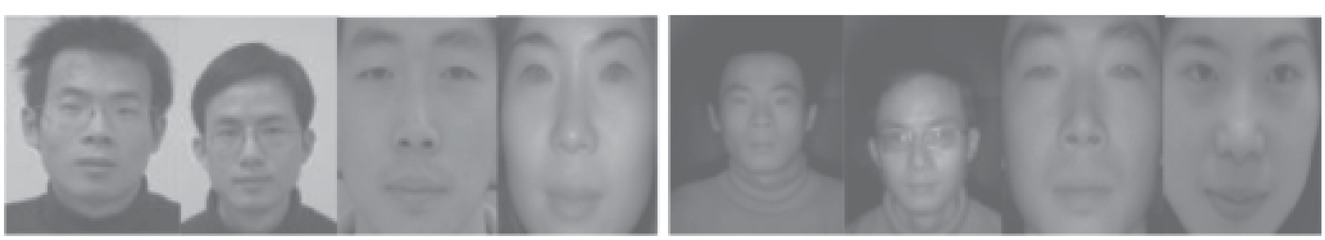


Fig. 1. Samples of optical and its appropriate infrared face images for (*a*) HFB dataset (*b*) CUHK VIS-NIR dataset.

* Assistant Professor,Dept of Computer Science and Engineering, Amrita School of Engineering, Coimbatore, AMRITA VISHWA VIDYAPEETHAM, AmritaUniversity, India. P_malathy@cb.amrita.edu, d_bharathi@ cb.amrita. edu, vinodhinirelangovan @gmail.com

** M Tech Scholar, Dept of Computer Science and Engineering, Amrita School of Engineering, Coimbatore, AMRITA VISHWA VIDYAPEETHAM, Amrita University, India. vinodhinirelangovan @gmail.com

One modality images are converted to another by the following techniques :

- In [3] a mapping technique is applied for the conversion of sketch images from photo image.
- In [7] Xiong et al. integrated VIS (Visible light) face images from NIR (Near Infrared) face images by all of pose rectification.
- Techniques already used to design a model that is unresponsive to the modalities of images are
- In [8] SIFT property descriptors and multi-scale local binary patterns used by Klare et al. for representing sketch and photo images.
- In [9] a classy learning based algorithm approaching by Zhang et al used to catch in the act local face structure discrimination and to verify photo and sketch images.
- In [10] a multi-scale common property descriptor designed by Liu et al. to conflict the large intra-class inequality obtained by the modality variation.

Techniques already usedon common subspaces to compare the heterogeneous images.

- In [17] Lei et al. proposed Heterogeneous face recognition[2] using coupled discriminant analysis.
- In [12] the correlation between the infrared images and optical images can be increased by constructing a common subspace using a technique called Canonical Correlation Analysis (CCA), done by Yi et al.
- In [13] CCA is used for cross-pose faceexpression recognition,done by Li et al.

A new system which uses Fisher Linear Discriminant Analysis and *k*-NN algorithm is proposed to do matching of the features extracted from face images and optical images.The accuracy of the system is calculated by comparing the result of proposed system with those of already existing systems. Sketch to photography and thermal to photography are some of the similar application where the proposed idea can be used.

2. ABBREVIATION AND ACRONYMS

FLDA	Fisher Linear Discriminant Analysis
PCA	Principal Component Analysis
k-NN	k-Nearest Neighbor
HFB	Heterogeneous Face Biometrics
VIS-NIR	Visible Near Infrared
ARF	Automatic Face Recognition
SVD	Singular Value Decomposition
CCA	Canonical Correlation Analysis
LBP	Local Binary Pattern
PLS	Partial Least Squares
SIFT	Scale-Invariant Feature Transform
ANOVA	Analysis of Variance
HMM	Hidden Markov Model
MSL	Multilinear Subspace Learning
EM	Elastic Matching

3. PROPOSED APPROACH

In the proposed system, machine learning and pattern recognition Fisher Linear Discriminant Analysis (FLDA) are used to observe linear combination of features that separates the objects of two or preferably classes. Analysis of variance (ANOVA), principle component analysis (PCA), factor analysis and regression analysis are closely related toFLDA. ANOVA uses categorical independent variable and a continuous dependent variable. Discriminant analysis uses continuous independent variable and a categorical dependent variable. The distinction between the classes of data is modeled by FLDA. Feature combination based on differences is done by Factor analysis. Discriminant analysis is an interdependent technique which is different from factor analysis. Discriminant correspondence analysis is a technique which deals with categorical independent variables. FLDA works when measurements made on independent variable are continuous quantity.

A non parametric method called *k*-NN algorithm is used for classification in which class membership is the output. The object is assigned to that single nearest neighbor class if $k = 1$ and the based on the maximum votes of its neighbor the object is classified. K-NN is a type of lazy learning where until classification the function is locally approximated and all operations are delayed. It is the simplest of all machine learning algorithm.

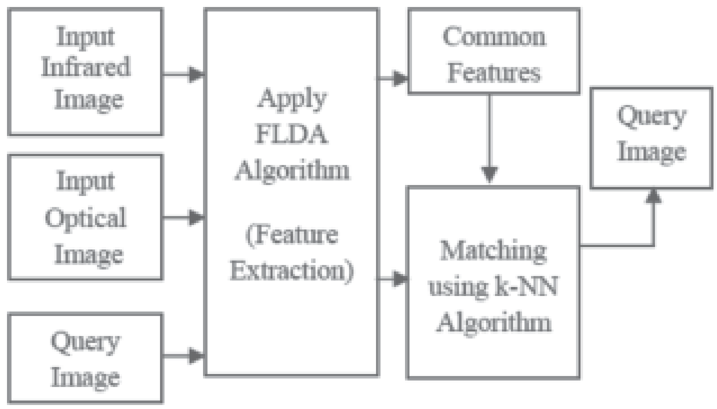


Fig. 2. System Design.

4. OUR FEATURE DESCRIPTOR

A classy idea for optical-infrared face image recognition is proposed. In this approach, Fisher Linear Discriminant Analysis uses an optimal hyperplane to quantize continuous vector space into discrete partitions for common feature extraction and a simple but efficient matching manner classifies the image.

5. VECTOR QUANTIZATION

Vector quantization (VQ) is a firm quantification technique which performs a generalization of scalar to vector quantization.Vector quantization exploits linear and nonlinear dependence that exist among the components of the vector. It is superior to scalar quantization when the components of a random vector are statistically independent to each other. It maps continuous space vectors into discrete code representation which can be used for recognizing objects by creating discrete image representation. Mean shift algorithm [20], *k*-means algorithm, random projection tree [19] and random forest [18] are several algorithms approaching to quantize a continuous space to discrete segments forquantized vector. Here the feature of heterogeneous face images [7] was described by designing a hyper plane based encoding method. Mathematically,

$$B(\vec{y}) = \vec{p}r\,\vec{y} + h \leq 0 \tag{1}$$

Hyper plane divides feature into two parts

- $\vec{Y} \subset R^{E\times 1}$ then it classified into negative part
- Otherwise classifies into positive part

$\vec{P}$ – Unit normal vector

h – Offset

Face images can be expressed as set of vectors

$$I = \{\vec{y}_1, \ldots\ldots \vec{y}_N\}$$

$N = B * P$ – total number of pixels in a image

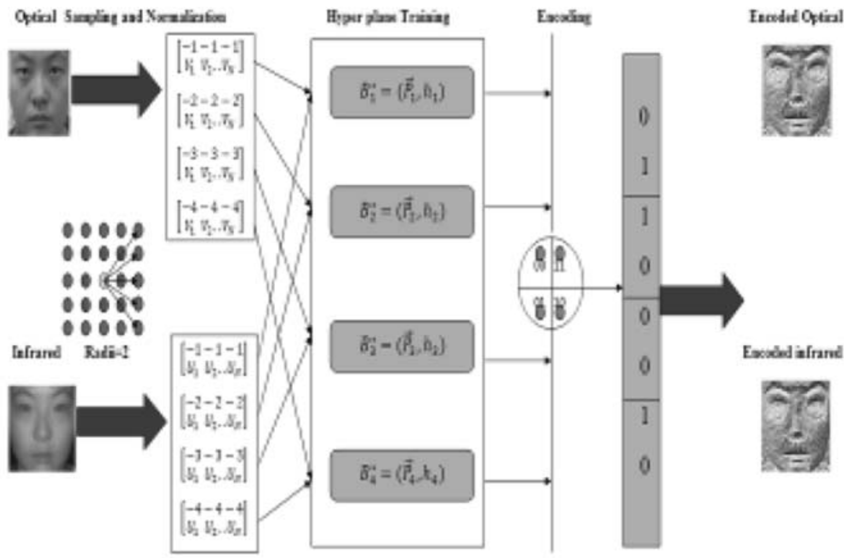


Fig. 3. Fisher Linear Discriminant Analysis.

FLDA is a manner which is used to minimize the dimensionality of the data into one dimension. Take *d*-dimensional $Y \subset R^n$ and by finding $K^T Y$ map that into 1-dimension.

$$K = \begin{pmatrix} K_1 \\ : \\ K_n \end{pmatrix} \text{and}$$

$$Z = K^T Y = (K_1 \ldots \ \ldots K_n) K^T Y \begin{pmatrix} y_1 \\ : \\ y_n \end{pmatrix} = \sum_{j=1}^{n} K_J Y_J \tag{2}$$

Z = 1-dimension used for classification

Consider the two class problem, here the distance between the means of projected class should be maximized and the variance within the class should be minimized.

$$\mu_0 = \frac{1}{d_0} \sum_{i:x_i=0} y_i \ \mu_1 = \frac{1}{d_2} \sum_{i:x_i=1} y_i \tag{3}$$

To maximize the distance between means of projected class is :

$$(K^T \mu_0 - K^T \mu_1)^2 = K^T S_V K \tag{4}$$

S_V- Variance between classes.

To minimize the variance between classes

$$K^T \sum_0 K + K^T \sum_1 K = K^T S_K K \tag{5}$$

S_K- Covariance between classes.

To maximize the distance between means of projected class also to minimize the variance within classes, can be done by maximizing the ratio

$$K^{max} \frac{K^T S_V K}{K^T S_K K}$$

Therefore the direction can be found by fixing the length of W.

$$K^{max} K^T S_V K$$

Subject to the condition $K^T S_K K = 1$

Here the problem is based on constraint optimization so Lagrange multipliers is used to convert it into a non-constraint optimization problem.

$$\Phi(K, \lambda) = K^T S_V K - \lambda (K^T S_K K - 1) \tag{6}$$

By differentiating with respect to W $\frac{\partial \Phi}{\partial K} = 2S_B K - \lambda\, 2S_K K = 0$

$$S_V K = \lambda S_K K$$

the generalized eigenvector problem is

$$S_K^{-1} S_V K = \lambda K \tag{7}$$

λ-Eigen value K-Eigenvector $\mu_0 = \begin{pmatrix} q \\ r \end{pmatrix} \mu_1 = \begin{pmatrix} s \\ t \end{pmatrix}$

$$\mu_0 - \mu_1 = \begin{pmatrix} q-s \\ r-t \end{pmatrix}$$

Then $S_B K = \begin{pmatrix} q-s \\ r-t \end{pmatrix} (q-s r-t) \begin{pmatrix} K_1 \\ K_2 \end{pmatrix}$

The following equation gives the direction,

(8)

6. K-NN ALGORITHM

The *k*-NN classifier is based on non parametric density approximation techniques. Assume density function P(Y) from an example dataset.

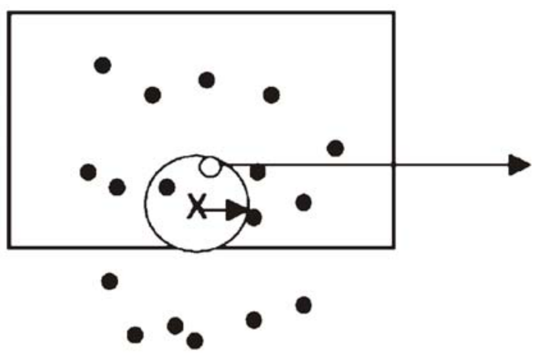


Fig. 4. K Nearest Neighbor classifier.

$$V = \pi R^i$$

$$(Y) \cong \frac{Q}{MV}$$

V – Volume surrounding Y.

M – Total number of examples.

Q – Number of examples inside V.

$$P(Y) \cong \frac{Q}{MV} = \frac{Q}{MV_D\, R_Q^D(Y)} \tag{9}$$

U_D – Volume of the unit sphere in D-dimension.

Unconditional density, $P(Y|\omega_i) = \frac{Q_i}{M_i V_i}$

Priors, $P(\omega_i) = \frac{M_i}{M}$

Posterior Probability, $$P(\omega_i|Y) = \frac{P(Y\,|\,\omega_i)P(\omega_i)}{P(Y)} = \frac{\frac{Q_i}{M_i V_i}\frac{M_i}{M}}{\frac{Q}{MV}} = \frac{Q_i}{Q} \tag{10}$$

Getting discriminant function, $$\theta_1 = \frac{Q_1}{Q} \tag{11}$$

7. IMPLEMENTATION

Implementation of this procedure is carried out using MATLAB. The entire process is given the form of MATLAB code to be worked with. As we have already seen, the complete process can be divided into modules:

- Getting Input
- Hyper plane Encoding
- Feature extraction [FLDA]
- Matching framework [*k*-NN]
- Displaying Output

The optical face image is primarily converted into Grayscale image to make the procedure simple and elegant. Later, using hyper plane encoding the converted image and the equivalent infrared face image are encoded. The encoded images of optical face images and infrared face images will minimize the modality gap between them; this is the key point to get an encoding mechanism.

Now, the encoded face images of both optical and infrared are contained in disc. For performance improvement this manner maximizes the interdependence of the encoded images of the related object.To disclose that the algorithm works outstrip than the current ones, experiments are conducted on optical face images datasets and infrared face image datasets.The suggested new feature description is the arbitrary contribution of this field that is well experienced for matching face images of infrared to optical [1].

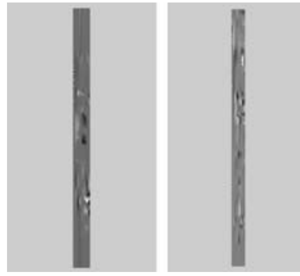
Initially, the optical images for all persons are fed into the database of the system.

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

Fig. 5. (*a*) Input Infrared face image (*b*) Encoded Infrared face image (*c*) Input optical face image and (*d*) Encoded Optical face image.

The inputted images then undergo hyper plane encoding as discussed above. The feature extraction is done by applying Fisher Linear Discriminant Analysis (FLDA) algorithm over the encoded hyper plane images.The features are the pixel values of the optical face images and infrared face images. The discs suppress the extracted features of both the optical face images and infrared Face images. Now, the query image (infrared face image) is subject to as the input data to the system. The same matter of form is then applied for the input infrared query image. (*i.e.*) The query image is also encoded by the hyper plane training, hence FLDA applied in it. Till now, all the procedures are applied to get the feature extraction. As the last step suggests, the matching is being done using k-Nearest neighbor (*k*-NN) algorithm. The encoded infrared query image is compared with the discs available in the databases. Thus, by taking different k-values, the confusion matrix is also plotted. From the confusion matrix, the values of precision and recall can be identified. The query image is now searching for the discs which give the minimum distance and thus matching is done with that discs.

So finally the corresponding optical image is displayed as the output of the system. This matching can be done only when the infrared image is given as input. If the input is given with the optical face images, the system will give the output of the discs which has the minimum distance given by the *k*-Nearest Neighbor algorithm. This system is initially trained with the set of images and then tested by giving infrared input images. Finally, by keeping the testing dataset unchanged and comparatively increasing the count number of training samples to predict the performance of this approach. Thus, the performance of the program is measured.



(*a*) (*b*)

Fig. 6. (*a*) Optical FLDA Encoded image and (*b*) Infrared FLDA Encoded image.

Fig. 7. Matched Output

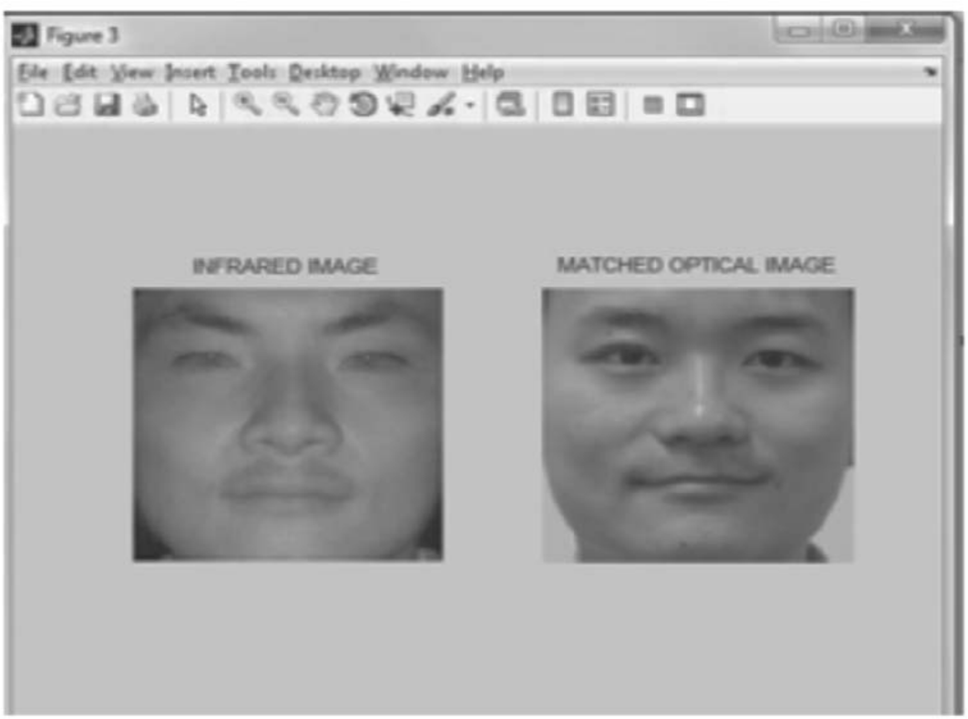


Fig. 8. Unmatched Output

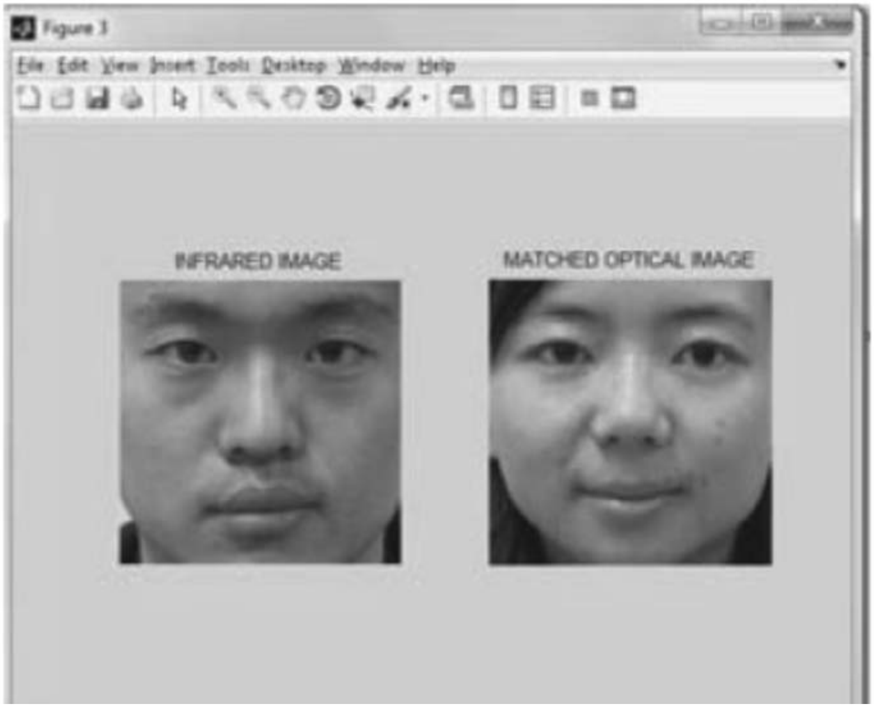


Fig. 9. Output for unspecified image

8. EXPERIMENTS AND RESULTS

Here, with databases from public domain is compared with this method with many new methods that are available in heterogeneous face recognition[2]. The HFB Face Dataset and CUHK Visible light-Near Infrared Face Dataset for matching the infrared to optical face images was used and find out whether they are matching or not. Here the algorithm used 100 images for training, 200 images for testing that are taken from 100 different subjects in HFB Face Dataset. The dataset split arbitrarily and the average over random occurrence is taken as result.

In decision to handle geometry reference, a pixel of an image is encoded with four contradictory directions; this is the masterpiece difference surrounded by this encoding manner and contrasting methods that are available.To show the merit of this encoding method with four different directions we need to design an additional experiment. In CUHK Visible light-Near Infrared Face dataset, the algorithm considers same training and testing data apportion for comparing the images. For this 200 sample face images for training and 400 sample face images for testing that are taken from 200 different subjects. On this two challenging datasets, our approach performs better than other available approaches.

Considering a total of 300 training images and 600 testing images over a huge range of 300 different subjects to calculate the accuracy of this system. We find out that out of the 600 images tested, 421 images turn out to give a correct match. For the remaining 179 images, a wrong match is retrieved. Thus, the accuracy of the system turns out to be 70.167%. This accuracy is outstripped than the contemporary method that is being discussed practically in [1].

9. FUTURE ENHANCEMENT

The project to match infrared face images to optical face images uses *k*-Nearest Neighbors (*k*-NN) Algorithm and to reduce the modality gap, the Fisher Linear Discriminant Analysis(FLDA) was used for extracting the features from the images. To show the substantial improvement of this method over the other method is by extending the experiment on two huge and difficult optical face images and infrared face images dataset. In the upcoming years, this approach can be extended to solve the problems such as matching of sketch-photo [1] images and high resolution to low resolution face [1] images by using general recognition of cross modality face images. Finding missing individuals and knowing criminals by the concept of matching this sketch images with the digital face images is the most challenging task. When the composite sketches was compared with hand drawn sketches, composite sketches will have less effort both in terms of cost and time. Age variation is major challenge as it changes the structural geometry and texture of the space. Technology, cost and speed has to be considered in the rapidly growing plastic surgery field. According to statistics, more and more individuals are expected to undergo facial plastic surgery for cosmetic and medical reasons. Therefore it is imperative for face matching algorithm to be robust for matching face images altered due to plastic surgery. Understanding the effects of plastic surgery in thermal-infrared imagery can be one of the possible future research directions. Preparing large scale databases for different types of plastic surgery procedures in visible as well as thermal-infrared imagery will lead to better understanding of the non-linear variations introduced due to plastic surgery. Substantial attention for video based face recognition, due to limitations of still images in addressing wide intra-personal variations of face in many real world applications. Real world applications require efficient video based face recognition techniques that can identify individuals from videos captured through surveillance cameras. Therefore, developing low resolution face recognition algorithms for videos could be the future research work. Another possible research direction is to combine other modalities such as iris, voice and gait for more robust identification from videos.

10. CONCLUSION

In HFB databases is tested to know the performance of the proposed feature extraction. In order to demonstrate the effectiveness for feature extraction, extensive experiment are carried out using feature vectors. The working of the feature extraction methods in terms of principle is obtained and compared by all of that of some unusual methods.Performance of the applied method presented in the paper has been carried out. The method has been tested using FLDA and k-NN and it has been proven to perform satisfactorily. By the result of the various experiment conducted ,proves that this system is robust and it is capable to detect the different faces of various event. When FLDA method is compared with other existing method, it is more capable to recognize face images with less misclassification compared to the earlier methods. Efficient face Matching and optimal feature extraction can be done by this approach.

11. REFERENCES

1. Li, Zhifeng, et al. *"Common feature discriminant analysis for matching infrared face images to optical face images." Image Processing, IEEE Transactions on* 23.6 (2014): 2436-2445.
2. Li, Stan Z. "Heterogeneous face biometrics." *Encyclopedia of Biometrics* (2015): 873-876.
3. Tang, Xiaoou, and Xiaogang Wang. "Face sketch recognition." *Circuits and Systems for Video Technology, IEEE Transactions on* 14.1 (2004): 50-57.
4. Xiao, Bing, et al. "Photo-sketch synthesis and recognition based on subspace learning." *Neurocomputing* 73.4 (2010): 840-852.
5. Wang, Xiaogang, and Xiaoou Tang. "Face photo-sketch synthesis and recognition." *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 31.11 (2009): 1955-1967.
6. Liu, Qingshan, et al. "A nonlinear approach for face sketch synthesis and recognition." *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on.* Vol. 1. IEEE, 2005.
7. Pengfei, Xiong, Lei Huang, and Changping Liu. "A method for heterogeneous face image synthesis." *Biometrics (ICB), 2012 5th IAPR International Conference on.* IEEE, 2012.
8. Klare, Brendan F., Zhifeng Li, and Anil K. Jain. "Matching forensic sketches to mug shot photos." *Pattern Analysis and Machine Intelligence, IEEE Transactions on* 33.3 (2011): 639-646.
9. Zhang, Wei, Xiaogang Wang, and Xiaoou Tang. "Coupled information-theoretic encoding for face photo-sketch recognition." *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on.* IEEE, 2011.
10. Liu, Sifei, et al. "Heterogeneous face image matching using multi-scale features." *Biometrics (ICB), 2012 5th IAPR International Conference on.* IEEE, 2012.

11. Tenenbaum, Joshua B., and William T. Freeman. "Separating style and content with bilinear models." *Neural computation* 12.6 (2000): 1247-1283.

12. Yi, Dong, et al. "Face matching between near infrared and visible light images." *Advances in Biometrics.* Springer Berlin Heidelberg, 2007. 523-530.

13. Li, Annan, et al. "Maximizing intra-individual correlations for face recognition across pose differences." *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*. IEEE, 2009.

14. Sharma, Abhishek, and David W. Jacobs. "Bypassing synthesis: PLS for face recognition with pose, low-resolution and sketch." *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on.* IEEE, 2011.

15. Yang, Weilong, et al. "2D–3D face matching using CCA." *Automatic Face & Gesture Recognition, 2008. FG'08. 8th IEEE International Conference on*. IEEE, 2008.

16. Liao, Shengcai, et al. "Heterogeneous face recognition from local structures of normalized appearance." *Advances in Biometrics.* Springer Berlin Heidelberg, 2009. 209-218.

17. Lei, Zhen, et al. "Coupled discriminant analysis for heterogeneous face recognition." *Information Forensics and Security, IEEE Transactions on* 7.6 (2012): 1707-1716.

18. Shotton, Jamie, Matthew Johnson, and Roberto Cipolla. "Semantic texton forests for image categorization and segmentation." *Computer vision and pattern recognition, 2008. CVPR 2008. IEEE Conference on.* IEEE, 2008.

19. Cao, Zhimin, et al. "Face recognition with learning-based descriptor." *Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on.* IEEE, 2010.

20. Jurie, Frederic, and Bill Triggs. "Creating efficient codebooks for visual recognition." *Computer Vision, 2005. ICCV 2005. Tenth IEEE International Conference on.* Vol. 1. IEEE, 2005.