IJESRT
INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

HETEROGENEOUS FACE RECOGNITION USING KERNEL LDA METHOD

Ketki Kalamkar*, P. S. Mohod
* Computer Department, G. H. Raisoni Institute of Enginering & Technology for women, India

ABSTRACT

Here we propose the novel method to recognize the heterogeneous face recognition. Initially we remove the noise from the image. To remove the noise present in the image we use median filter. The system involves using a relational feature representation for face images by using kernel similarities between a novel face pattern and a set of prototypes. Initially probe image or test image is normalized, and then it passes for Gaussian filter. Gaussians is a feature enhancement algorithm that involves the blurring of an original image less blurred version of the original. A constant plus a measure of local stimulus contrast. Gaussian filter is windowed filter of linear class by its nature is weighted mean. After this process need to identified the MLBP features. It is an algorithm in computer vision to detect and describe local features in images. For any object in an image, interesting points on the object can be extracted to provide a "feature description" of the object. The similarity between the two pattern images will identify by the kernel similarity. Finally the identified image will be retrieved from the database. The Proposed system introduces the kernel approach with LDA classification method. This has main motivation towards increasing accuracy for HFR (Heterogeneous Face Recognition)..

KEYWORDS: Feature extraction , Gallary Image ,Heterogeneous,HFR(Hetrogeneous Face Recogntion), ,local descriptor,Probe image,

INTRODUCTION

Face is the most common biometric used by humans. Face is that crucial parts of human body that express most of feature which plays vital role in identifying the individual. A lot of techniques have been applied for different applications. Early face recognition produce simple geometric model, but the recognition processes has now matured into a science of sophisticated mathematical representation and matching process. In security systems Robustness and reliability becomes more and more important. In this paper, the technology used is to compare individuals' facial characteristics across different images in order to identify them. The features of the one face i.e. face to be identified is match against the features are of images in an available datasets. If the face in the images is identified that is, the name of the individual is known then, the technology can be used to identify previously anonymous faces in addition to perform matching between two faces. This is the use of facial recognition that potentially raises the most serious privacy concerns because it can identify anonymous individuals in images.

The performance of the recognition can be affected by some external factors such as illumination, expression and posture. Images are classified into VIS (visual light), NIR (near infrared), TIR (thermal infrared) according to the different spectral bands which the images are captured in. These different image types are said to be heterogeneous if they have different image formation characteristics.

In heterogeneous face recognition, we are matching the two face images from alternate imaging modalities, such as an infrared image to a photograph or a sketch to a photograph. While heterogeneous face recognition can involve matching between any two imaging modalities, the majority of scenarios involve a gallery dataset. Probe images can be of any other modality, though the practical scenarios of interest to us are infrared images (NIR and thermal) and hand-drawn facial sketches. The core of the proposed approach involves classification of sampled features using matching of two images on similarities between using a relational feature representation kernel trick. This allows us to generate a high dimensional, nonlinear representation of a face image using compact feature vectors.

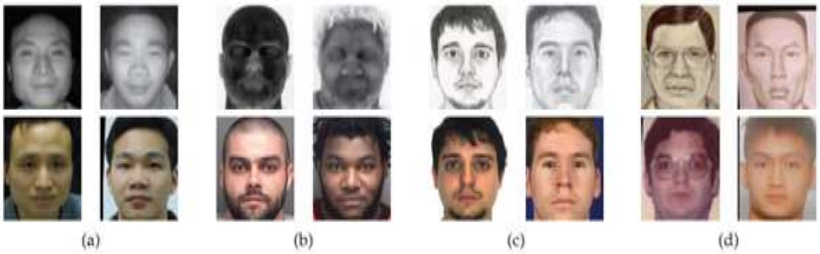

Fig 1: Examples of Images for Heterogeneous Face Scenario

The use of a nonlinear similarities representation is found to best suited for the HFR problem because the set of training image from each modality can be used as the prototype, depending on modality of new image, the image from the each prototype is selected from the corresponding modality. In earlier method they needed a two feature descriptor for two HFR, but the proposed method need descriptors that are effective in each domain.
Nearly all algorithms generally follow same pipeline as listed below.

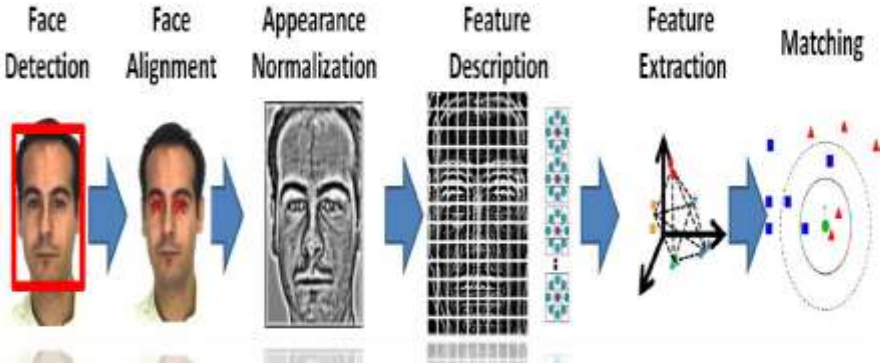

Fig.: 2. General pipeline followed by algorithm

Face recognition research can improve any specific stage above, or can address the entire face recognition pipeline.

Kernel:

The kernel can regards as defining similarities between two data points [9]. During past decades, a major evolution has taken place in pattern recognition technology. The use of convex optimisation and statistical learning theory has been combined with ideas from functional analysis and classical stastics to produce a class of algorithm called kernel methods(KM). Using a kernel function, we project the data in a higher dimensional feature space that can potentially make the data linearly separable. Moreover, one of the kernels' biggest advantages is that one can use several different kernel functions with the same algorithm, and several different algorithms with the same kernel function. We are able to quickly swap them around to run several experiments with little effort. Different kernel functions specify different distance relationships, and implicitly features, between the input vectors, while different algorithms use the distance information from the kernel functions to learn the parameters. In conclusion, kernel methods not only are easy to train and accurate but they are also flexible to use for large complicated learning tasks. Because of their advantages, the research community has heavily explored their use during the last decade.

RELATED WORK

In many different fields such as computer vision, neural networks, image processing and pattern recognition where face recognition is used. [2] This paper addresses many challenges in face recognition process. Face recognition is done by two types of algorithms –appearance-based and model-based [2]. But still challenges of occlusion, pose variation and illumination. Appearance based approaches used to develop illumination-invariant face recognition system. The task of robust face recognition is still difficult, though many face recognition techniques have been proposed and have demonstrated significant promise. Face recognition methods have several problems.
Orientation Problem: Rotation of image may be different with respect to optical axis of camera.
Expression of database: Face expression may influence the appearance of face.
Problem of pose: There may be side view or front view of same face image.
Occlusion: In range camera, then occlusion is areas where do not have any information .It is due to beards or glasses.

Illumination**:** It involves capturing of image in different lighting condition.
The use of effective algorithm can only be solution to above mention problems. The previous research had found that there are two methods for face recognition. First one is model based face recognition and other is appearance based face recognition.[2] paper briefly illustrate about these methods.

Model Based Face Recognition: Information related to face is used for model development. It can sense variation of faces. Typical example featured based matching is used to extract relative position and distance feature.

Appearance Based Face Recognition: in this approach instead use of vector space structure several raw intensity images are used to represents the images. Various statically techniques are used by this approach for analysis and distribution of input image vector in vector space and effective feature space is derived from it. Where feature space is used to project similarity between test image and store prototype. Examples are PCA, LDA.[2]

Appearance based approach has been categorised into holistic and hybrid approaches.[5]also is had been proved that eignfaces and fisher faces are effective with large database. Both holistic and local feature approach is use in hybrid approach. In this concept of Eigen faces and Eigen vector approach are introduce .Eigen feature perform better than Eigen faces for lower order spaces.

The most commonly used algorithms which uses appearance based approach are PCA(principal component analysis) and LDA(Linear discriminant analysis).[11]discuss the PCA and LDA also their compatibility with databases.[11] analysed performance of PCA v/s LDA .Images of n×m pixels is represents by vector in n*m dimensional space. This space is very large in practical to permit robust and fast recognition. The solution of this problem is to use techniques of dimensional reduction. So most popular one technique are PCA and LDA for reduction purpose. Principal component is one sophisticated technique that uses mathematical principals of transformation for conversion of number of correlated variables into smaller number. This process is actually reduction process so the called Principle component analysis.[9]had been discuss about the LDA as another dimensionality reduction algorithm.

The basic difference between PCA and LDA is former deals with the data in its whole for principle component analysis and latter deals with the discrimination between classes [10]. [7]Projection of most descriminent information of face is main aim of LDA.[11][7] found that LDA perform better than PCA for large database.[11]But also surveys that for nonuniformly sample data PCA outperform than LDA .If for high dimensional feature spaces the distribution is complex [9] purposed a kernel approach for LDA i.e. KLDA.The use of KLDA were results more better and feasible to solve pose and illumination problems. The kernel approach has limitations that are selection of parameter of kernel and kernel function .Improper selection may affect KLDA performance.

[10] This paper introduce facial extraction of images using kernel approach in PCA[11][6].In kernel function without explicitly work on feature space ,dot products between pixels is performed in feature space.[10] reduce error rate to 2.5% from experimental results.

[3] In many of application in world face depicted as crucial and most feature use as trusty measure of security. SIFT (scale invariant feature transform) is algorithm use for feature extraction ,extract the most peculiar facial features required for mapping in feature spaces.[1]face recognition become automatic now a day by using may face recognition technique like LDA ,PCA. But they may be problematic due to pose variation, illumination variation. So [1] address the SIFT algorithm which extract more effective feature and are invariant to pose and illumination variation. This feature descriptor diminishes the interpersonal variation while still maintaining sufficient information for interclass discrimination. SIFT detects local feature of descriptive images, are then transform into invariant form by going to some algorithmic steps. SIFT splits into different parts are construction of scale space, Laplacian of Gaussian calculation, finding Key points, Eliminating edges and low contrast region, assigning orientation and SIFT feature generation. Details have been illustrated in [1].

[4]addresses LBP (linear binary patter) algorithm as best descriptor .LBP is more robust and perform well against different pose and illumination variation, occlusion.LBP for high level image analysis proven to be highly distinct with computational efficiency. In LPB the code is measure by comparing each pixel of image by its neighbouring pixels. In LBP it first labels an image by thresholding the 3×3 neighbourhood of each pixel with the centre value and considering the result as a binary string or a decimal number. The histogram of a labels used as texture descriptor.[4]Presents the traditional LBP ,can provide accurate result.[4]also address MLBP(Multiscale local binary pattern) encodes not only microstructure but also macrostructures of image

patterns. Hence Provides more complete image representation than LBP .In some challenging facial datasets has variation in patches, where it require improved facial feature classification for better performance. By combining both sign and magnitude, MLBP has proven to improve the recognition performance.

[6]Now a day's different types of face image dataset are available such as simple photo image, forensic sketches, and view sketches, visible to infrared images. The view sketch and forensic sketch are different from each other. Forensic sketches are images which are drown by police sketch artist as describe by eyewitness.[8]paper proposed a problem in recognition of forensic images. Local feature-based discriminate analysis (LFDA) had been presents to identify the forensic sketches. SIFT and MLBP are more accurate features descriptor [3][4].[6] paper further improved accuracy of these descriptors by using LFDA .In LFA classical subspace analysis is directly apply on feature vector. There are other discriminant method such as direct LDA ,regularised LDA, random sampling LDA are propose to handle SSS(small sample size)problem.[6]purposed LFDA to work with the feature descriptor representation which results in high accuracy. The very first step in LFDA is to divide image into slices of smaller dimensionality. Then discriminant analyses are apply separately on each slices. Slices are concatenation of each feature descriptor vector.

[8]The face recognition system is highly complex and nonlinear under variation of illumination or facial expression. Also small scale size (SSS) problem is prominent in FR (face recognition).The KDDA (Kernel direct discriminant analysis) proposed in [8] is motivation by [5]KPCA, Direct LDA, support vector machines (SVM),GDA (generalised discriminant analysis).The main idea of KDDA is based on GDA and D-LDA ,prior is mapping of classic LDA into feature space instead of input space. Later is to avoid shortcoming in solution to problem of SSS .Also it kept information in null space even it discards .KDDA is implementation of D-LDA in high dimensional using kernel approach. It also solves complex and nonlinear pattern distribution in high dimensional space. KDDA is found to be superior than KPCA or GDA.

PROPOSED METHODOLOGY

KLDA (Kernel LDA) is classification method designing specifically for nonlinear subspace in high dimensional domain. Face recognition of Heterogeneous faces is a challenging task that here deal with. The proposed work deals with the recognition of heterogeneous faces in a large database. Previously most of research was kept on simple single type of face images. So it only applicable on images captured from same source, not deals with images with pose or illumination variation. Heterogeneous faces are the images captured from different camera source also in varying illumination of light, pose variation. Proposed methods address the different HFR(Heterogeneous Face Recognition) scenarios .There efficiency are then compare to find effect one among them.

Preprocessing

Input for designed system is image of variable sizes. A proper and regular system needs an exact and same size of image for operation. So, primarily image is aligned and resize by marking points on face. Also convert every image into grayscale image. Proposed systems consider 200×150 size for image to be process.

Applying Filter on Input Image

Images are often corrupted by random variation in intensity, noise, clutter, illumination or have poor contrast and can't used directly. Solution on this is to use filter which transform pixel intensity value to reveal certain image characteristics such as improves contrast, remove noise and make illumination evenly spread over whole image. Here in proposed work single filter is applied on given input image. It is –

- Gaussian filter

After pre-processing the image of size [200×150] is forward to filtering. Gaussian distribution is given by

$$G(x) = \frac{1}{\sqrt{2}\pi\sigma} e^{\frac{x^2}{2\sigma^2}}$$

$$\boldsymbol{W\square ere, \sigma\ is\ standard\ deviation}$$

The degree of smoothing is determined by the standard deviation of Gaussian. In proposed system the value of standard deviation is selected to be '2'. The Gaussian outputs a 'weighted average' of each pixels neighbourhood, with the average weighted more towards the value of the central pixels.

Feature Extraction using MLBP

Before illustration of MLBP here first illustrate the operation of LBP, later will MLBP. Local Binary Pattern (LBP), a non-parametric method, summarizes the local structures of an image efficiently. The original LBP operator labels the pixels of an image by thresholding the 3×3 neighbourhood of each pixel with the centre value and considering the result as a binary string, of which the corresponding decimal number is used for labelling. An illustration of the basic LBP operator is shown in Figure 3.

ISSN: 2277-9655
(I2OR), Publication Impact Factor: 3.785

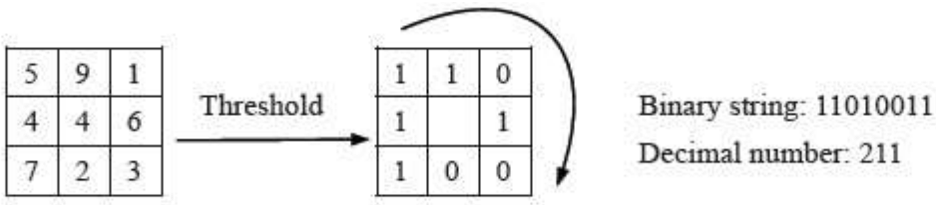

Figure3. An example of the original LBP operator

Here in above example of LBP consider a single radius of central pixel and N=8 i.e. number of neighbouring pixel. Thresholding is carried by comparing each pixel with central value 4, so the value greater or equal to central value is label as 1 otherwise zero. Thus in one orientation binary string computed is11010011. However there are possible 256 orientations that will give more combinations. Such operation not well suited when there are large images and needs more accurate results. So, the proposed system used MLBP algorithm.

MLBP (Multiscale Local Binary Pattern)-

LBP is extended to use a bigger neighbourhood .In this extention a circular neighbourhood is consider which is determined by the radius of ring and the number of samples laying on this ring. LBP proved o to powerful local descriptor but inefficient in case of heterogeneous faces. The proposed system uses this approach in MLBP. Here proposed system chooses step value as 10 and window size as 10 for filtered image of size [200 ×150].In Multisclae LBP texture descriptor are calculate using different radius values such as here system consider R= 1,3,5,7.Also N refers as number of neighbours selected as 8.

Each thresholding value obtains are in decimal form, and then makes total eight orientations using it. In general 256 orientation are possibly made, but here out of 256 eight orientation are calculated that will give expected outputs. Similarly for each radius eight orientation likewise total 32 orientations for each image are calculated. Now, texture descriptors of array size [9600× 256] are obtained. This process is applied to all train and test images.

Figure 4 shows some examples of the extended LBP operators

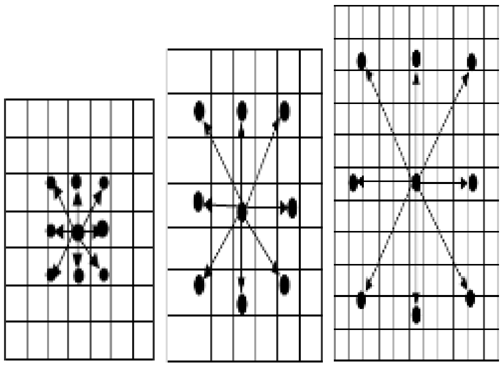

Figure4. Examples of operators: circular (8, 1), (8, 3), and (8, 5)

The Fig.4 shows operator with radius R=1, R=3,R=5 as an example and takes N=8 for all, where N is number of neighbourhood. The general idea for LBP is that a face image can be seen as a composition of micro-patterns which are described by the operator. But the histogram of LBP computed over the whole image encodes only occurrences of the micro-patterns without any indication about their locations. To also consider shape information of faces, t he image can divided into some local regions, from which LBP histograms are extracted and then concatenated into a single global one (containing both local texture and global shape information). So 32 histogram for selected single radius are calculated .Similarly for given image size total histogram are calculated as

Total Histograms =1 window size × 300
=32× 300
=9600

In MLBP size of block indicates scale, yields more robust representation.

Kernel LDA

By using kernel similarities between a novel face pattern and a set of different images are able to exploit the kernel trick, which allows generating a high dimensional, nonlinear representation of a face image using compact feature vectors. The use of nonlinear similarities representation is found to best suited for the HFR problem, depending on modality of new image, the image is selected from the corresponding modality. In earlier

 ISSN: 2277-9655
(I2OR), Publication Impact Factor: 3.785

method they needed a two feature descriptor for two HFR, But the propose method need descriptors that are effective in each domain. Therefore matching process of face recognition for heterogeneous face images will minimum with high accuracy. In the heterogeneous face recognition challenging task is classification or representation of different face images of various modalities. A prototype representation is shown to approximately maintain the desired properties of the high dimensional kernel space in a more efficient representation by using the kernel trick. In this work we emphasize the fact that kernel methods use a training set of images to implicitly estimate the distribution of the nonlinear feature space. The kernel simply takes dot product of two images i.e the descriptor matrix get after feature extraction .The kernel for images are find by equation

$$\mathrm{K} = \frac{x \cdot y^T}{\sum x^2 \cdot \sum y^2}$$

From above equation single kernel value for all training images are obtained .Then mean of kernel is find by

$$Mean\ K = \sum_{n=1}^{n=9600} K$$

The recognition algorithm is very important factor of proposed system. The proposed system used KLDA (Kernel Linear Discreminent Analysis) for feature classification. After calculating the kernels for all training images internal dot product of one to images need to find for classification. In proposed system has 41 images for training .In the training database system has used 7 different classes, each has different set of images. To trains these values to over all groups or classes here, [41×41] matrix is form which denoted as X.Now when any test image is comes, it will then calculate kernel values with train images. So system have [1×41] values of kernel, let's consider it as Y. Then Classification algorithm find best match within given class using X, Y and groups.

Finally output image as result is shows that input image is matching with gallery image or not. This will then decide the accuracy of recognition process.

Systems Flow Diagram

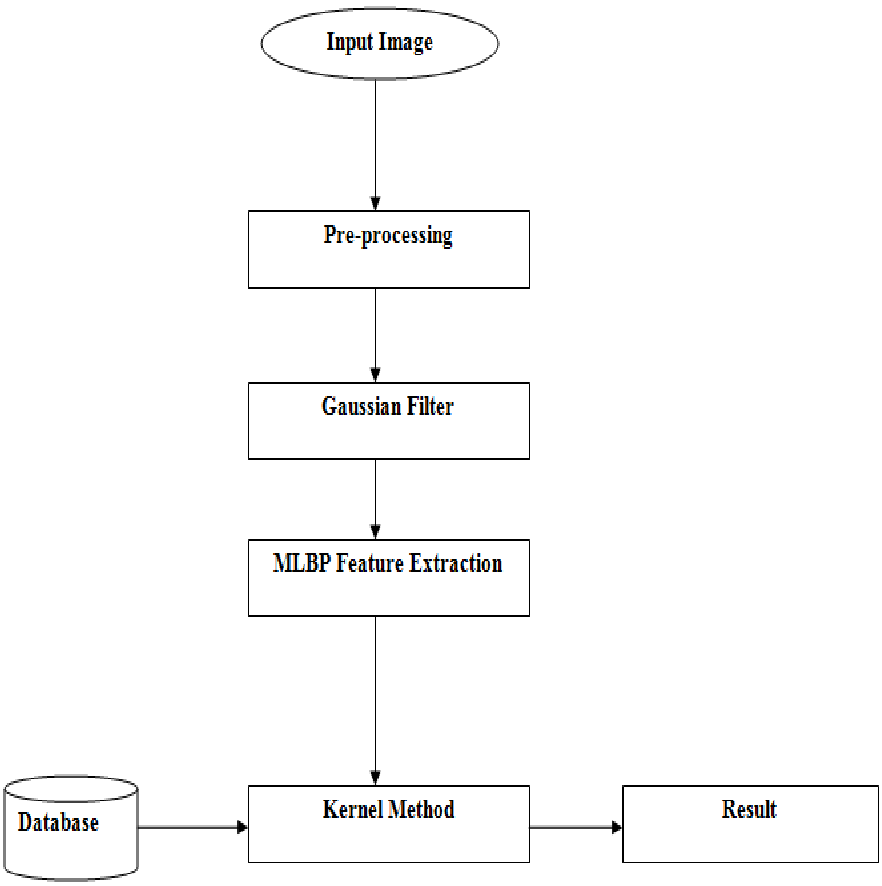

Fig.3.Flow Diagram

The fig6 shows the flow of proposed system. The first step of system is to take input image from test images. Then this image is aligning by taking at some points on face. The Gaussian filter is applied on normalized image to remove the noise and clutter. After filtering image is ready for feature extraction and MLBP is applied for the same. Proposed system has gallery database, which is then used by kernel method for searching equivalent image. Finally at the output results shows corresponding match image.

System Diagram

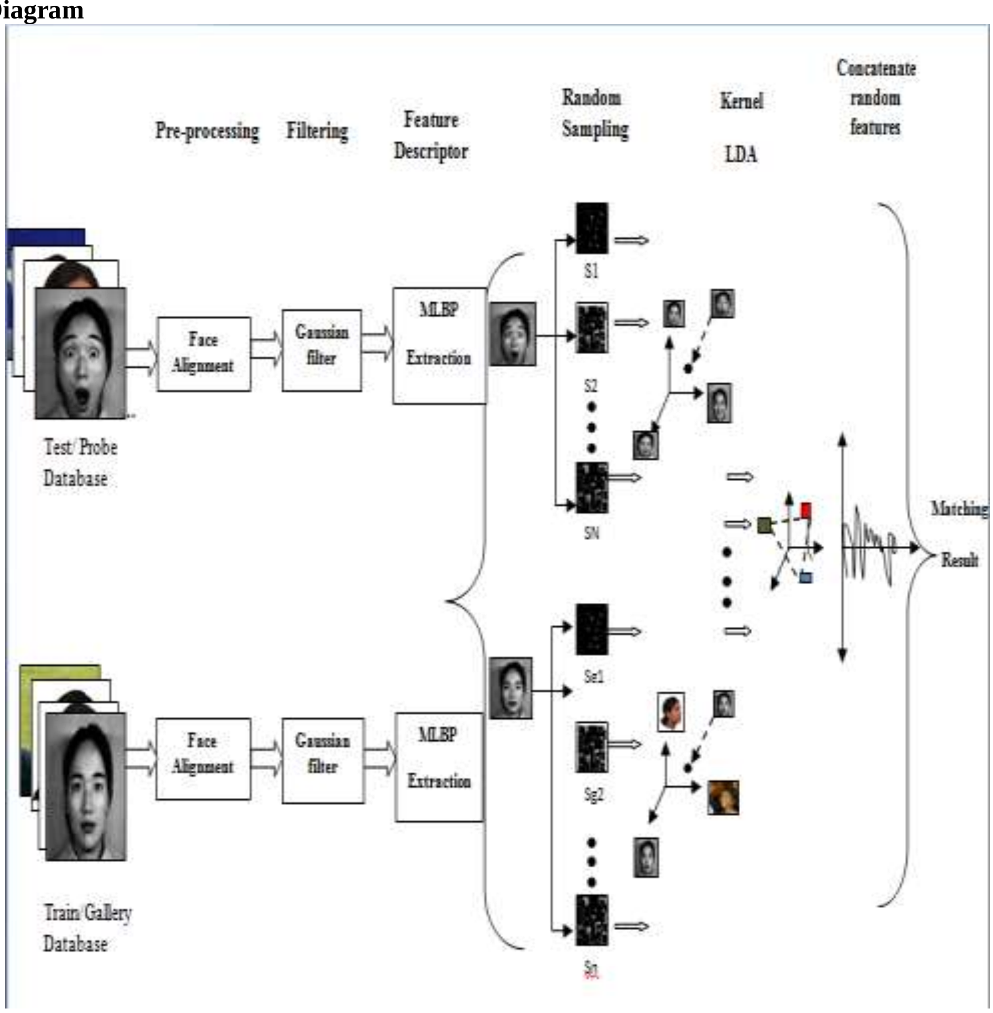

Fig.5. System Diagram

Fig.5 shows the system diagram for propose work. At the input system has train and test database of various types images. At the first each selected test image and images from gallery are pre-process by using face alignment or normalization. Every images are come with lots of external noise added to it has pass through Gaussian filter as shown in Fig.5. Then most accurate MLBP feature extraction method is apply on filtered images. While MLPB divides each pixel in sub regions indicates as scale. In Fig.5 number of descriptors gets by using MLBP algorithm are shown. The process of kernel representation is illustrated in Fig 5. Kernel LDA used for classification of features obtained from MLBP algorithm .In KLDA each set of descriptor are concatenated at last to get single value ,which will then decides proper equivalent match. In this way whole recognition processes is carried out.

DESIGN/IMPLEMENTATION

The flow of design for proposed system is follows flow diagram given in previous section. The implementation of system illustrate by outcomes as below.

Outcomes

The system loaded with database with classes of images. The test or input or probe image is selected and given to system.

Fig. 6Preprocessing of image

The fig6 shows pre-processing of image, in which the face alignment is done. In the fig6 the blue colure cross points are mark on face used for regular only getting face part of object. Image then forwards for filtering.

Fig. 7 Selected Test of Image

After pre-processing the test figure and gallery images looks as shown in fig7.The fig7 has one of test image from test database. It seen from image is cropped where cross points are marked. After this image is forwarded to next section of system.

Fig. 8 Filtered of image

In this section input image is filtered out for removing of excessive noise. It is necessary for further improvement in recognition to smooth image. This is carried by using Gaussian filter in the proposed system.

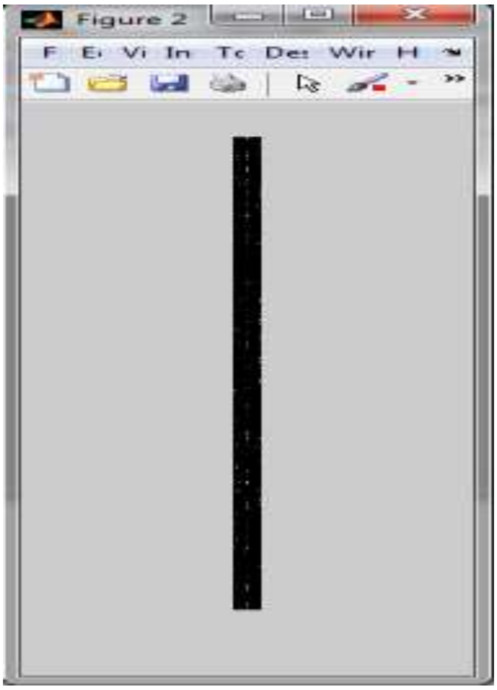

Fig. 9 MLBP Feature Extraction

After filtering the effective points which are required for best matching are extracted rather regrading unwanted features For the selected test image here the fig 9 shows extracted features by using MLBP (Multiscale Linear Binary Pattern) algorithm. This features are then sampled and concatenate for further classification.

Fig. 10 Gallery database of images with different class

The proposed system used the KLDA algorithm for classification of samples features. KLDA then computed kernel matrix values of both test and gallery images to find out accurate match with test image. The fig10 shows gallery database of 41 images from which system search the test image class and further best mach among it. Finally system shows the number of matched image or display equivalent face image at the output.

RESULT AND CONCLUSION

Result

Proposed system has train or gallery image match with test or probe image. The proposed system used a training database of 41 images and test images are 7 or more. Proposed system gives following results KLDA Algorithm.

Fig 11: Final Matching Result with Histogram

The proposed system is tested on various databases such as Asian, expressive, George, Condoleezza Rice, and HalleBarry. The accuracy result in comparison with some earlier recognition methods are shown in Table 1 below.

Previous Recognition Method	**Tested Database**	**Accuracy**
PCA	FRAV	77%
KPCA	FRAV	87%
PCA+LDA+MLBP	CHUNK,VIS,NIR	63.13%
PROPOSED METHOD		
KLDA+MLBP	Asian, Expressive, Gorge, HalleBarry images	98.21%

Table 1: Comparative analysis with Previous Methods

The table 1 shows some earlier recognition methods results tested on various databases. Also proposed method which tested on different database images are shown in table1.Previous methods are referred from different authors works for comparison purpose.

Results.xls

	A VarName1 Number	B VarName2 Number	C VarName3 Number	D VarName4 Number	E VarName5 Number
1	0.5377	0.4724	0.3868	0.1275	0.1375
2	0.4724	0.5436	0.4187	0.1281	0.1392
3	0.3868	0.4187	0.5480	0.1312	0.1450
4	0.1275	0.1281	0.1312	0.4839	0.2592
5	0.1375	0.1392	0.1450	0.2592	0.4996
6	0.1195	0.1188	0.1184	0.3144	0.2614
7	0.1189	0.1191	0.1194	0.1803	0.2373
8	0.1296	0.1294	0.1257	0.1849	0.1961
9	0.1365	0.1337	0.1342	0.1968	0.2227
10	0.1092	0.1077	0.1108	0.1452	0.1387

Fig12: Sample Final Kernel Values of Test Image with All Train Image

Fig16 shows kernel values computed on taking dot product of test image with train image kernel. Proposed system gets [42 ×42] matrix for values of kernel, here in fig16 shows only [10×5] values. Out off these kernel values best match value selects to show final output image. The last 42 row is of test image kernel values that find one to one match with train kernel values.

Conclusion

To further improve the performance of heterogeneous face recognition we have to increase the matching accuracy of face images. The key advantage of this method is that once we transform the images, matching can be performed using existing face recognition algorithm. In the proposed system no direct comparison between face images in probe and gallery modalities is needed. A random subspace framework is employed in conjunction with KLDA subspace analysis to further improve the recognition accuracy. Both filtering and feature extraction (MLBP) methods are help in increasing accuracy of HFR. From result shown earlier it conclude that proposed system give increased recognition accuracy than previous methods.

REFERENCES

1. Issam Dagher, Nour El Sallak and Hani Hazim, "Face Recognition Using The Most Representative SIFT Algorithm", International Journal of Signal Processing, Image Processing and Pattern Recognition Vol.7, No.1 (2014).
2. Uma Shankar Kurmi, Dheeraj Agrawal, R. K. Baghel ,"Study of Different Face Recognition Algorithms and Challenges", International Journal of Engineering Research,Volume No.3, Issue No.2, pp : 112-115 Feb. 2014.
3. Isra'a Abdul-Ameer Abdul-Jabbar, Jieqang Tan, and Zhengfeng Hou, "Adaptive PCA-SIFT Matching Approach for Face Recognition Application", Proceedings of the International MultiConference of Engineers and Computer Scientists 2014 Vol I, IMECS 2014, March 12 - 14, 2014, Hong Kong.
4. Brian O'Connor and Kaushik Roy, "Facial Recognition using Modified Local Binary Pattern and Random Forest", International Journal of Artificial Intelligence & Applications (IJAIA), Vol. 4, No. 6, November 2013.
5. M. Parisa Beham S. Mohamed Mansoor Roomi , " Face Recognition Using Appearance Based Approach: A Literature Survey", International Conference & Workshop on Recent Trends in Technology, (TCET) 2012.
6. Brendan F. Klare, Student Member, IEEE, Zhifeng Li, Member, IEEE, and Anil K. Jain, Fellow, IEEE, "Matching Forensic Sketches to Mug Shot Photos", IEEE Transactions On Pattern Analysis And Machine Intelligence, Vol. 33, No. 3, March 2011.
7. Jian Huang, Pong C. Yuen, Member, IEEE, Wen-Sheng Chen, and Jian Huang Lai, "Choosing Parameters of Kernel Subspace LDA for Recognition of Face Images Under Pose and Illumination Variations", IEEE Transactions On Systems, Man, And Cybernetics—Part B: Cybernetics, VOL. 37, NO. 4, August 2007
8. Juwei Lu, Student Member, IEEE, Konstantinos N. Plataniotis, Member, IEEE, and Anastasios N. Venetsanopoulos, Fellow, IEEE, "Face Recognition Using Kernel Direct Discriminant Analysis Algorithms", IEEE Transactions On Neural Networks, VOL. 14, NO. 1, January 2003.
9. Bernhard scolkopf and Alex Smola, MIT Press, (2002), "Learning With kernel", Australian National University, Canberra.
10. Kwang In Kim, Keechul Jung, and Hang Joon Kim ,"Face Recognition Using Kernel Principal Component Analysis", IEEE Signal Processing Letters, Vol. 9, No. 2, February 2002 .
11. Aleix M. MartõÂnez, Member, IEEE, and Avinash C. Kak, "PCA versus LDA", 228 IEEE Transactions on Pattern Analysis and Machine Intelligence, VOL. 23, NO. 2, February 2001