Research Inventy: International Journal of Engineering And Science
Vol.4, Issue 4 (April 2014), PP 45-52
Issn (e): 2278-4721, Issn (p):2319-6483, www.researchinventy.com

Digital Image Technique using Gabor Filter and SVM in Heterogeneous Face Recognition

M.Janani[#1], K.Nandhini*[2], K.Senthilvadivel*[3],S.Jothilakshmi*[4],
*PG Student[#1,*2*3], Assistant Professor*[4], Dept of CSE[#1,*2,*3,*4]*
*S.V.S College of Engineering[#1,*4], PPG Institute of Technology*[2,*3],*
Coimbatore, Tamilnadu

ABSTRACT— *The main reason for the decrease in changes in appearance of the user is due to the factors such as ageing, beard growth, sun tan. Heterogeneous face recognition involves matching two face images from alternate imaging aesthetic forms, such as an infrared image to a photograph or a sketch to a photograph. A generic HFR framework is proposed in which both probe and gallery images are represented in terms of nonlinear similarities to a collection of prototype face images. The prototype subjects have an image in each modality (probe and gallery), and the similarity between an image and prototype images are measured. The features of this nonlinear prototype are projected into a linear discriminant subspace which increases the accuracy of this nonlinear prototype representation. In HFR framework we introduce Random sampling to control the small sample size problem which arises as a challenge. The excellence of the proposed approach is demonstrated in the experiment result as prototype random subspace. Previous studies have shown that the accuracy of Face Recognition Systems (FRSs) decreases with the time elapsed between enrollments and testing. So we have proposed Gabor filter along with SVM for Feature Extraction and Robustness.*

KEY WORDS— *nonlinear similarity, local descriptors, ambiences, Random subspaces, Mugshot, infrared image, discriminant analysis, sketches, SVM, Gabor Filter.*

I. INTRODUCTION

Face Recognition in recent days involves matching between heterogeneous image ambiences. When different scenarios can provide plausible solutions for difficult scenarios then it is coined as Heterogeneous face recognition. Heterogeneous face recognition involves matching between imaging ambiences like visible light photographs in gallery dataset to Probe images that include NIR, thermal, sketches and mugshot.When only a particular image ambience is available for querying a large database like visible light photographs called Mugshots, the face image captured during night time like infrared imaging cannot be useful to suspect a criminal act. This led to the stimulus behind heterogeneous face recognition. Though there is remarkable development in Face recognition systems, the Commercial off-The Shelf (COTS) face recognition systems were not able to handle HFR Scenarios.

In this paper we propose a collective way to Heterogeneous Face Recognition [1] which,

a) Make recognition in the probe and gallery ambiences using multiple feature descriptors,
b) Attain Accuracy on different HFR Scenarios,
c) Does not demand any feature descriptor to changes in image prototype

II. RELATED WORK

Zhang Wei, Xiaogang Wang, Xiaooua Tang proposed a robust algorithm called 45ultiscale Markov Random Field(MRF) to synthesize a face sketch and face photo taken in different lighting condition and different pose. They achieved robustness to lighting and pose variations in three steps. First, they introduced shape priors to specific facial components to reduce distortions and artifacts created due to variations in pose and lighting. Second, to find candidates to the patches of sketch to a given photo, they produced metrics and patch descriptors that are vivacious to lighting variations. Third, they used gradient compatibility and intensity compatibility which are smoothing term measures to match neighboring sketch patches on the MRF network [2].

Brenden Klare, Zhifeng Li and Anil K Jain have addressed the problem of matching forensic sketch and mugshot images in a gallery. They introduced Local Feature-based Descriminant analysis (LFDA) to solve this problem. Both sketches and photos were represented using 46ultiscale Local Binary Patterns, Histograms and Gradient location in LFDA. The dataset contained 10,159 images of forensic sketches in relation to mugshot gallery images [3].

Brendan F klare and Anil K Jain proposed a novel method of heterogeneous face recognition that uses a common feature based representation for both NIR images as well as VIS images. A robust approach to face recognition with unconstrained illumination is to match near infrared face images to visible light face images. They performed linear discriminant analysis on a collection of random subspaces to learn discriminant projections. They matched NIR and VIS images by (i) using sparse representation classification, (ii) directly using the random subspace projections [4].

Juwei Lu, Konstantinos N Plataniotis, Anastasios N Venetsanopoulos introduced SVM, kernel PCS, GDA for pattern regression and classification tasks. The small sample size problem which was a drawback in most Face recognition system (FRS) was eliminated by the algorithm called Kernel Direct Local Discriminant Analysis (K-D-LDA) [5].

Kathryn Bonnen, Brendan Klare, Anil Jain later introduced Component Based Representation for Face Recognition to obtain accuracy over occluded face images and enhance robust to various facial poses. They first extracted facial landmarks, then they cropped images and obtained feature vector and represented the facial components using Local Binary Pattern [6].

III. PRELIMINARY PROCESS OF AN IMAGE AND ITS REPRESENTATION

Feature based representation is the initial representation of a face image. The human visual processing system uses local feature descriptors for the proposed representation of the face.

A. Normalization of an image geometrically:

Geometric Normalization is the first step to normalize the images of the heterogeneous face using feature descriptors in regard to the location of the eyes. In this step, rotation, scale effectiveness, variations in translations are reduced [1].

We normalized face image geometrically by a) rotating the set of angle between eyes by planar rotation to 0 degrees, b) ascending the distance between the two pupils to 75 pixels of the image, c) cropping the images with eyes placed horizontally centered and vertically placed at row 115 of total height of 250 pixels and width of 200 pixels.

B. Filtering of Image:

We use three different filters to filter the face images. These filters reduce the appearance variations between image realm and intensity variations within an image domain thus enable denoising in the image. The filters are elucidated below:

1) Difference of Gaussian (DoG):

To improve the performance of face recognition for varying illumination we use DoG which is a feature enhancement algorithm. It subtracts blurred image from original less blurred image. It is commonly used in detecting of blob in SIFT. Its main job is to sharp the edges of an image.

Let us consider, ‘a’ to be Gaussian filter image of width $\sigma 1$ and ‘b’ to be Gaussian filter image of width $\sigma 2$ ($\sigma 2>\sigma 1$)

Then DoG = b-a. Here we have taken $\sigma 1=2$ and $\sigma 2=4$.

2) Center Surround Divisive Normalization (CSDN):

The value of each pixel is divided by the mean pixel value. The mean pixel value is taken from s x s neighborhood surrounding the pixel. Here we take s=16.

3) Gaussian:

This is the smoothing filter that removes noise from a high spatial frequency. The width used here was $\sigma=2$.

C. Local Descriptor Representation:

After normalization and filtration, we extract local feature descriptors across the face from uniformly distributed patches. SIFT feature descriptor is widely used in face recognition for effective matching of sketch to VIS and NIR to VIS. LBP features have a successful history in face recognition which is applied to several HFR matching scenarios[1].

SIFT and LBP features can describe the face images and its structures even if there is a minor external variation. An image patch is described in each feature descriptor as a d dimensional vector which is normalized to a sum of one. The face image is divided into a size of 32 x 32 set of N overlapping patches. Each patch overlaps its neighbors both horizontally and vertically by 16 pixels. So a total of 154 total patches are got from a face image of size 200 x 250. Multiscale local binary patterns are used in place of LBP which is a variant of LBP descriptor. MLBP over here has radii r= {1, 3, 5, 7}.

Let us consider, I to be the normalized and filtered face image, $f_{F,D}(I,a)$ as local feature descriptor extracted from image I at patch a, $1 \leq a \leq N$ using image filter F and feature descriptor D, F_d as DoG image filter, F_c as CSDN image filter, F_g as Gaussian image filter, D_m as MLBP descriptors, D_s as SIFT descriptors.

Then we arrive to the result by using,

$$f_{F.D}(I)=[f_{F.D}(I,1)^T,\ldots,f\ F.D(I,N)^T]^T \quad , \qquad (1)$$

which is a combination of all N feature descriptors. Therefore by using three filters and two descriptors, we have six representations for face image I, $f_{Fd},D_m(I)$, $f_{Fc},D_m(I)$, $f_{Fg},D_m(I)$, $f_{Fd},D_s(I)$, $f_{Fc},D_s(I)$, $f_{Fg},D_s(I)$.

IV. ARCHITECTURAL VIEW OF PROPOSED SYSTEM

In this Framework, We obtain a Visible Light Photograph and Thermal Photograph from the Database. There is separate database for Visible light photographs and Thermal photographs which has image of one person taken in different environment. Those images contain noise which has to be preprocessed. Preprocessing is done using Difference of Gaussian (DoG) filter, CSDN, Gaussian filter for better denoised image. The Denoised image uses SIFT (Scale Invariant Feature Transformation) for extracting local Features. SIFT extracts interesting points from the image which provides feature description [1]. From training image SIFT description is extracted to identify the object while trying to locate the object in a test image containing many other objects. For a dependable recognition feature has to be extracted from the training image which has to be detectable even under changes in illuminations, noise, and image scale. Those interesting points usually lie as object edges on high-contrast regions of the image.

We define Local Binary Pattern for each image for differentiating uniform and non-uniform patterns in an image. The idea behind is to calculate LBP-code for every pixel of an image [3]. The incidence of each possible pattern in the image is conserved. The label which is also known as histogram of these patterns forms a feature vector which is a representation for the texture of the image. To measure the similarity between the images, the distance between the histograms is calculated.

After LBP we use Gabor Filter and SVM for feature extraction and Robustness. Gabor filter is used for edge detection which is a linear filter. Frequency and orientation representations of Gabor filters are much as same to those of the recognition of eye of a human, and they have been found to be particularly appropriate for texture representation and discrimination. SVMs can efficiently perform a non-linear classification which maps the inputs in a high dimensional feature spaces called to be kernel trick. The images matched are from probe and gallery dataset and the results are analysed.

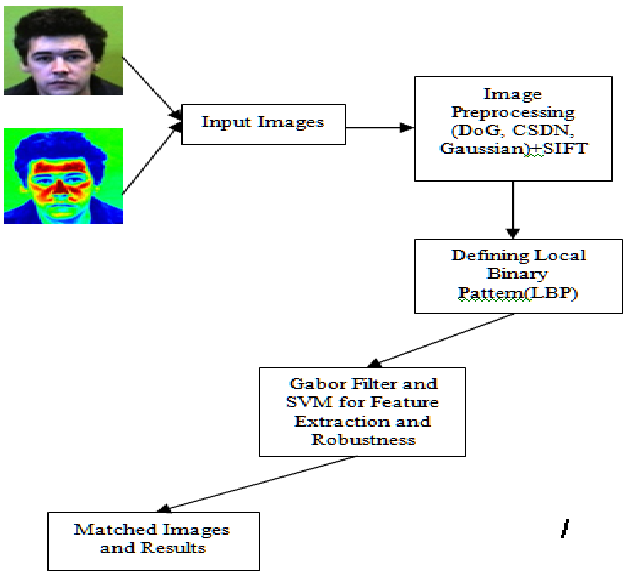

Fig 4.1 Architectural View of Proposed System

V. ALGORITHM USED

A. Gabor Filter:

There is a set of Gabor filters with different frequencies and orientations which is used for feature extraction. A 2D Gabor filter is a Gaussian kernel function that is modulated using sinusoidal plane wave.

The impulse response is defined using sinusoidal wave multiplied by a Gaussian function. Due to multiplication convolution property according to Convolution theorem, the Fourier transform of Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and Gaussian function. Gabor filter has both real and imaginary component which represents orthogonal directions.

Complex form of Component

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma)= \exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right) \exp\left(i\left(2\pi \frac{x'}{\lambda}+\psi\right)\right)$$

Real

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma)= \exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right) \cos\left(2\pi \frac{x'}{\lambda}+\psi\right)$$

Imaginary

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma)= \exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right) \sin\left(2\pi \frac{x'}{\lambda}+\psi\right)$$

where

$x' = x \cos\theta + y \sin\theta$

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

here,

λ – wavelength of the sinusoidal factor,

θ – orientation of the normal to the parallel stripes of a Gabor function,

ψ – phase offset,

σ – sigma/standard deviation of the Gaussian envelope,

γ – spatial aspect ratio

B. Support Vector Machine (SVM):

Support Vector Machines are used in Machine Learning which is associated with supervised learning that analyse data and recognize patterns for classification and regression analyses. SVM can perform non linear classification very efficiently by mapping inputs into high dimensional feature space called Kernel Trick.

Every linear dot product is replaced with non linear kernel function for non linear classification to fit the maximum margin hyper plane in the transformed featured space. Common Kernels used in SVM are as follows:

a) Polynomial (homogeneous): $k(x_i, x_j) = (x_i \cdot x_j)^d$

b) Polynomial (inhomogeneous): $k(x_i, x_j) = (x_i \cdot x_j + 1)^d$

c) Gaussian radial basis function:
$k(x_i, x_j) = \exp(-\gamma \, \| x_i - x_j \|^2)$, for $\gamma > 0$, parametrized to $\gamma = 1/2\,\sigma^2$

VI. SIMULATION AND RESULTS

A. Input Image:

We take two images as input for matching. One image is RGB image or visual image from Gallery dataset and the other one is Thermal Image from probe dataset.

Fig 5.1 Input Image RGB

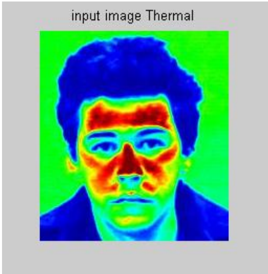

Fig 5.2 Input Image Thermal

B. Preprocessing of Image:

Preprocessing is the process of removing unwanted noise from the image. We use CSDN, Gaussian and DoG along with SIFT to remove noise and enhance the image. SIFT can handle images in various pose and angles.

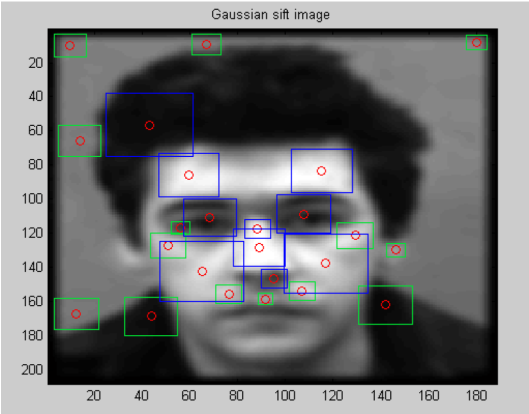

Fig 5.3 Gaussian SIFT image

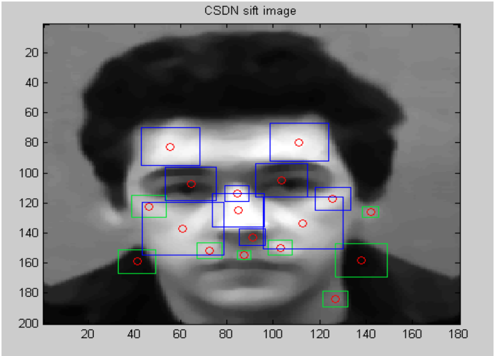

Fig 5.4 CSDN SIFT image

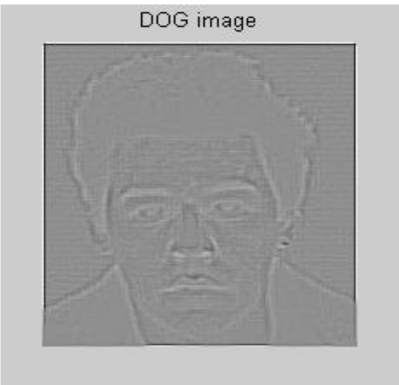

Fig 5.5 Difference of Gaussian (DoG) Image

C. LBP of the Image:

We use Local Binary Pattern algorithm (LBP) along with CSDN, Gaussian and DoG to divide facial components into small regions from which histograms are extracted and concatenated into a single, spatially enhanced feature histogram.

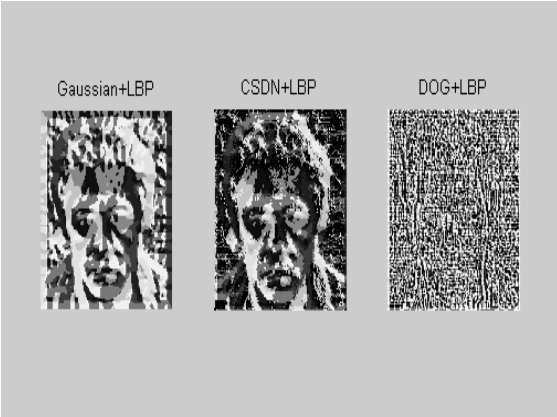

Fig 5.6 LBP of the Image

D. Gabor and SVM:

We propose a novel approach for feature extraction and robustness called G-SVM (Gabor –Support Vector Machine). Gabor helps in edge detection where as SVM helps in Classification of images. The image which is matched gives us an output of image matched else it gives us an output of image mismatched.

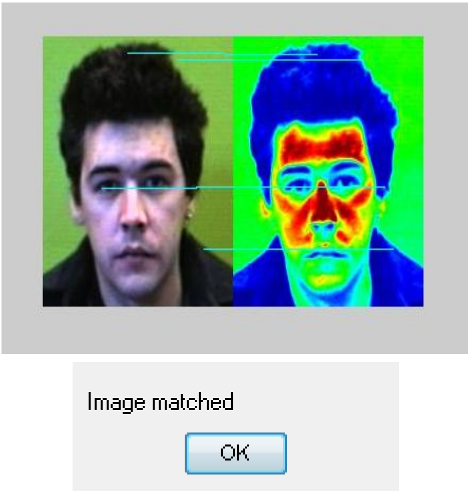

Fig 5.6 Matched Images

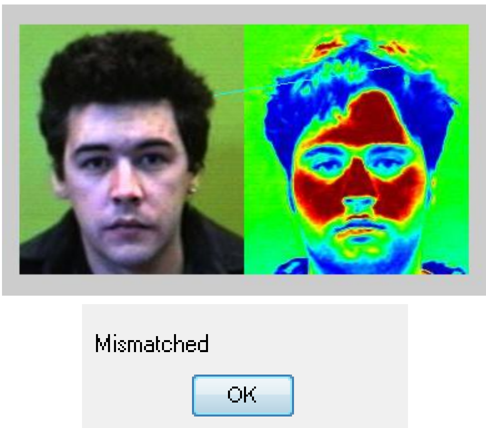

Fig 5.7 Mismatched Images

E. Results:

The graph shows the retrieval rate for thermal image which is higher in our proposed system than in the existing systems.

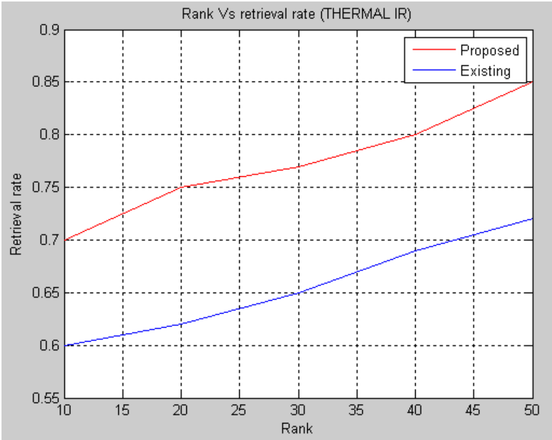

Fig 5.8 Graph of Rank vs Retrieval rate of Thermal IR

VII. CONCLUSION

We have presented a hybrid framework for face recognition based on local binary pattern, multiple Gabor filter and SVM. Designing a good filter and classifier is a crucial step for any successful face recognition system. An average recognition rate of (96.28%) is achieved under environmental variations. This means that our approach achieves a high recognition rate compared to other approaches in published literature. Using multiple Gabor filters rendered the method robust to face variations because each filter has specific property to extract. In addition using generalization property of bagging classifier increased the recognition rate in presence of face class variations. SVM has supported in classification and retrieval. We believe that face recognition under varying conditions is still an interesting area of research, and we anticipate that there will be many further advances in this area.

REFERENCES:

[1] Brendan F. Klare and Anil K. Jain, "Heterogeneous Face Recognition using Kernel Prototype Similarities" *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol 35, no. 6, pp.1410-1422, June 2013.

[2] Wei Zhang, Xiaogong Wang, Xiaoou Tang, "Lighting and Pose Robust Face Sketch Synthesis", Springer, Computer Vision – ECCV 2010, Lecturer Notes in Computer vision, vol.6316, pp. 420- 433.

[3] B. Klare, Z. Li and A. Jain, "Matching Forensic Sketches to Mugshot Photos", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol.33, no.3, pp.639-646, March 2011.

[4] B.Klare and A.Jain, "Heterogeneous Face Recognition: Matching NIR to Visible Light Images," *Proc.Int'l Conf. Pattern Recognition*, 2010.

[5] Juwei Lu, Konstantinos N Plataniotis and Anastasios N Venetsanopoulos, "Face Recognition using Kernel Direct Discriminant Analysis Algorithms", *IEEE Trans. Neural Networks,* vol.14, no.1,pp.117-126, Jan 2003.

[6] Kathryn Bonnen, Brendan Klare, Anil Jain, "Component based Representation in Automated Face Recognition", *IEEE Trans. Information Forensics and Security*, vol.8, no.1, pp. 239-253, Jan 2013.

[7] X.Tan and B.Triggs, "Enhanced Local Texture Feature sets for Face Recognition under Difficult Lighting Conditions", IEEE Trans. Image Processing, vol.19, no.6, pp. 1635-1650,June 2010.

[8] CUHK Face sketch FERET database, http://mmlab.ie.cuhk.edu.hk/datasets.html

[9] Rania Salah EL-Syed, Ahmed El Kholy, Mohamed Youssri El-Nahas, "Robust Facial Expression Recognition via Sparse Representation and Multiple Gabor Filters", *International Journal of Advanced Computer Science and Applications*, vol. 4, no. 3, pp. 82-87 ,2013.

[10] Javier Ruiz-del-Solar, Rodrigo Verschae and Mauricio Correa, "Recognition of Faces in Unconstrained Environments: A Comparative Study" EURASIP Journal on Advances in signal Processing 2009, **2009**:184617 doi:10.1155/2009/184617

[11] M.-F. Balcan, A. Blum, and S. Vempala, "Kernels as Features: On Kernels, Margins, and Low-Dimensional Mappings," Machine Learning, vol. 65, pp. 79-94, 2006.

[12] D. Lowe, "Distinctive Image Features from Scale-Invariant Key points," Int'l Journal Computer Vision, vol. 60, pp. 91-110, 2004.

[13] K.I. Kim, K. Jung, and H.J. Kim, "Face Recognition Using Kernel Principal Component Analysis," IEEE Journal on Signal Processing, vol. 9, pp. 40-42, Feb. 2002.

[14] Dileep Kumar Kotha, Santanu Rath,"Forensic Sketches to Mug Shot Photos using Speeded Up Robust Features". Springer Proceedings of International Conf. on Advance Computing, Vol:174, pp 527-537, 2012

[15] W. Zhang, X. Wang, and X. Tang, "Coupled Information-Theoretic Encoding for Face Photo-Sketch Recognition," Proc. IEEE Conf. Computer Vision and Pattern Recognition, 2011.

[16] Jain,A.K; Klare,B; Unsang Park, "Face recognition: Some challenges in forensics" IEEE International Conf. on Automatic Face & Gesture Recognition, March 2011, pp 726-733

[17] Michael Jahrer, Michael Grabner, and Horst Bischof," Learned local descriptors for recognition and matching", Computer Vision Winter Workshop, Feb 2008.

[18] D. Yi, S. Liao, Z. Lei, J. Sang, and S. Li, "Partial Face Matching between Near Infrared and Visual Images in MBGC Portal Challenge," Proc. Third Int'l Conf. Advances in Biometrics, pp. 733-742, 2009.

[19] J. Li, P. Hao, C. Zhang, and M. Dou, "Hallucinating Faces from Thermal Infrared Images," Proc. Int'l Conf. Image Processing, pp. 465-468, 2008.

[20] A. Quattoni, M. Collins, and T. Darrell, "Transfer Learning for Image Classification with Sparse Prototype Representations," Proc. IEEE Conf. Computer Vision and Pattern Recognition, 2008.

[21] D. Lin and X. Tang, "Inter-Modality Face Recognition," Proc. European Conf. Computer Vision, 2006.

[22] Phillips,P.J., Flynn,P.J.; Scruggs,T; Bowyer, K.W, "Overview of the face recognition grand challenge" ,IEEE Computer Society Conf.on Computer Vision and Pattern Recognition Vol:1, 2005.

[23] Jae Young Choi, Yong Man Ro Konstantinos N. Plataniot i," Color Local Texture Features for Color Face Recognition" IEEE Trans. on Image Processing, vol. 21, no. 3, March 2012

[24] Pavani, S.K; CISTIB/UPF-CIBER_BBN, Sukno, F.M.; Delgado-Gomez, D.Butakoff,C., "An Experimental Evaluation of Three Classifiers for Use in Self-Updating Face Recognition Systems" IEEE Trans. on Biometrics Compendium ,Vol:7 , February 2012

[25] Di Huang, Caifeng Shan, Ardabilian,M , yunhong Wang, "Local Binary Patterns and its Application to Facial Image Analysis" IEEE Trans. on Biometrics Compendium, Vol.41, pp 765-781,Nov 2011.

[26] Brendan Klare, Zhifeng Li, and Anil K. Jain, "On Matching Forensic Sketches to Mugshot Photos" IEEE Trans. on Biometrics Compendium, Vol.33, pp 639-646, March 2011.

[27] Xiaoyang Tan, Nanjing, "Enhanced Local Texture Feature Sets for Face Recognition Under Difficult Lighting Conditions" Image Processing, IEEE Trans. on Biometrics Compendium, Vol.19, pp 1635-1650, June 2010.

[28] Ahonen, T.Hadid, A.Pietikainen, "Face Description with Local Binary Patterns: Application to Face Recognition", IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol.28, pp 2037-2041, Dec 2006.

[29] Q. Liu, H. Lu, and S. Ma, "Improving Kernel Fisher Discriminant Analysis for Face Recognition," IEEE Trans. Circuits and Systems for Video Technology, Vol. 14, pp. 42-49, Jan. 2004.

[30] L. Juwei, K. Plataniotis, and A. Venetsanopoulos, "Face Recognition Using Kernel Direct Discriminant Analysis