Indian Streams Research Journal

ISSN 2230-7850
Volume-3, Issue-7, August-2013

Face Recognition Under Difficult Lighting Conditions

V. Sikanthgoud And M. Venugopal Rao
M. Tech, Dept. of ECE, K. L University, Andhra Pradesh, India
Professor, Dept. of ECE, K. L University, Andhra Pradesh, India.

ABSTRACT.

Face recognition has received a great deal of attention from the scientific and industrial communities over the past several decades owing to its wide range of applications in information security and access control, law enforcement agencies, surveillance and more generally image understanding. Most of these methods were initially developed with face images collected under relatively well-controlled conditions and in practice they have difficulty in dealing with the range of appearance variations that commonly occur in unconstrained natural images due to illumination, pose, facial expression, aging, partial occlusions, etc. Unfortunately, facial appearance depends strongly on the ambient lighting conditions. This paperpresents a robust technique for identifying the faces in the various lighting conditions. The proposed method normalizes the acquired images under different lighting conditions in the first step. In the next step it captures as much as possible of the available information with relatively few training samples. The results show that our proposed method outperforms several existing preprocessors for a range of feature sets, data sets and lighting conditions.

KEYWORDS:

Face recognition, illumination invariance, image preprocessing, kernel principal components analysis, local binary patterns, and visual features.

INTRODUCTION:

For the past few decades face recognition system has received a great deal of attention from the scientific and industrial communities for its wide range of applications in information security and access control, law enforcement, surveillance and more generally image understanding. Various authors developed different techniques having their own advantagesis an important biometric system for security purpose techniques have been proposed to recognize face under uncontrolled lighting conditions. Most of these are frontal faces,Sparse Representations, VADANA,Error Correcting Output Coding[13],[14][15][16]methods were initially developed with face images collected under relatively well controlled conditions and in practice they have difficulty in dealing with the range of appearance variations that commonly occur in unconstrained natural images due to illumination, pose, facial expression, aging, partial occlusions, etc. So for that face recognition system was facing difficult challenges from surveillance security systems, law enforcement agencies and industrial commodities. In this paper, we focus mainly on illumination varying conditions, where the most problematic in the existing face recognition systems.A face verification system for a portable device should be able to verify a client at any time (day or night) and in any place (indoors or outdoors). Facial appearance depends strongly on the ambient lighting. The proposed approach deals with these issues can be broadly classified into three categories: appearance-based, normalization-based, and feature-based methods.

This rest of the paper is organized as follows. Section-II describesthe overview of proposed methods inface recognition system;Section III prescribes the detail explanation and illustrations of three stages in our face recognition system. Theyare as follows preprocessing chain which consistsof

ISSN 2230-7850
Volume-3, Issue-7, August-2013

Gamma Correction, Difference of Gaussian Filtering and Contrast Equalization. Thereafter Robust feature extraction which introducesLocal Binary Patterns and Local Ternary Patterns briefly outlined and also Gabor Feature sets, Section III describes our multiple-feature fusion framework and alsoreportsexperimentalresults in face recognition system Section IV concludes a preliminary description of the methods was presented in the conference papers.

II.Proposed Face Recognition System

To design a reliable face recognition system uncontrolled light conditions it consists of fundamental methods which categorized as(i)Direct-Appearance Based Method, (ii)Normalization-Based Method (iii)Feature-Subspace Analysis Method.The following block diagram describes the step-by-step processes forproposed face recognition system.

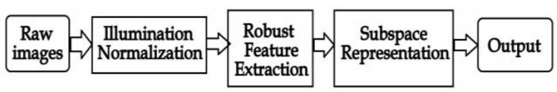


Figure.1 Stages of Full Face RecognitionMethod

A.*Illumination Normalization*

The main approaches with training examples are collected under different lighting conditions and directly (i.e., without undergoing any lighting preprocessing) used to learn a global model of the possible illumination variations, for example a linear subspace or manifold model, which then generalizes to the variations seen in new images[9]. Direct learning of this kind makes few assumptions but it requires a large number of training images and an expressive feature set, otherwise it is essential to include a good Preprocessor to reduce illumination Variations. How, Illumination Normalization takes effect in face recognition was described below it is also the first stage (Preprocessing chain) of face recognition system.

(i)*Detail view of Preprocessing Chain:*

The preprocessing chain run before feature extraction that incorporates a series of stages designed to counter the effects of illumination variations, local shadowing and highlights while preserving the essential elements of visual appearance.

Figure.2Block Diagram of Preprocessing method

Fig.2illustrates the three main stages and their effect on a typical face image. In fig 2.a describes the three main states in preprocessing was shown. Although it was motivated by intuition and experimental studies rather than biology, the overall chain is reminiscent of the first few stages of visual processing in the mammalian retina and LGN(Lateral Geniculate Nucleus).

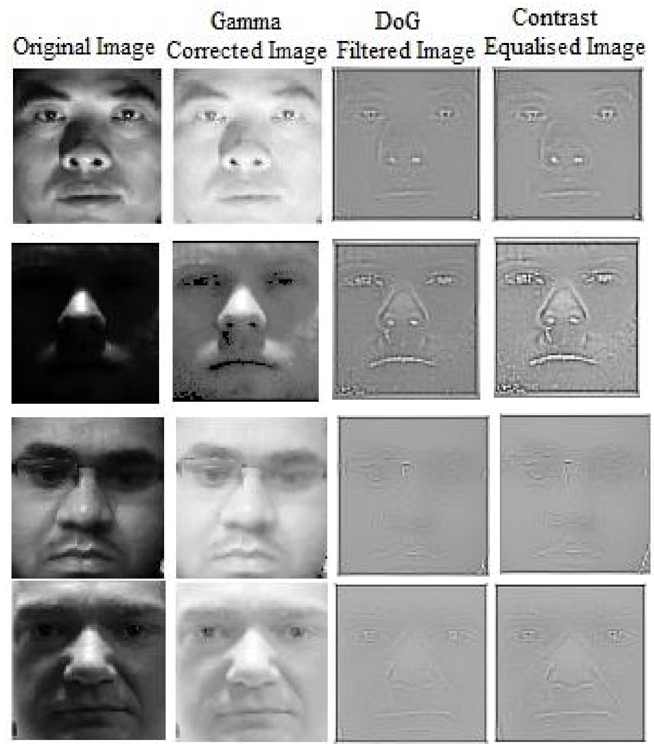


Figure:2.a)Illustration of preprocessed facial image.Column 1 representsOriginal Image, Column 2 represents Gamma Corrected Image, column 3 represents Difference of Gaussian Image and column 4 represents the contrast equalization image

The detailed explanation for these three stages are given as follows

(a) ***Gamma Correction:***

It is a nonlinear gray-level transformation that replaces gray-level I with I^{γ}(for γ>0) or log (I) (for γ = 0), where $\gamma \in [0; 1]$ is a user-defined parameter. This enhances the local dynamic range of the image in dark or shadowed regions while compressing it in bright regions and at highlights. The underlying principle is that the intensity of the light reflected from an object is the product of the incoming illumination L (which is piecewise smooth for the most part) and the local surface reflectance R (which carries detailed object-level appearance information).This curve is valuable in keeping the

ISSN 2230-7850
Volume-3, Issue-7, August-2013

pure black parts of the image black and the white parts white, while adjusting the values in-between in a smooth manner.Thus, the overall tone of an image can be lightened or darkened depending on the gamma value used, while maintaining the dynamic range of the image.

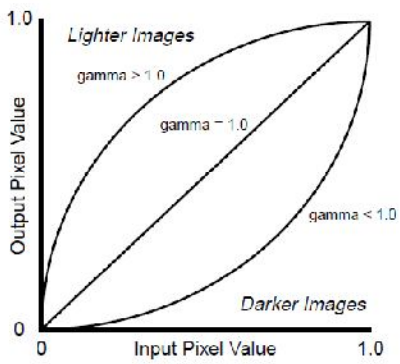


Figure2.b Gamma Curve

The pixel values range from 0.0 represents pure black, to 1.0, which represents pure white. As the fig 2.b shows, gammavalues of less than 1.0 darken an image. Gamma values greater than 1.0 lighten an image and a gamma value equal to 1.0 produces no effect on an image.

We want to recover object level information independent of illumination, and taking logs makes the task easier by converting the product into a sum: for constant local illumination, a given reflectance step produces a given step in log(I) irrespective of the actual intensity of the illumination. In practice a full log transformation is often too strong, tending to over-amplify the noise in dark regions of the image, but a power law with exponent γ in the range [0, 0.5] is a good compromise. Here we use $\gamma = 0.2$[14] as the default setting.

(b)*Difference of Gaussian (Dog) Filtering:*

Gamma correction does not remove the influence of overall intensity gradients such as shading effects. Shading induced by surface structure is a potentially useful visual cue but it is predominantly low spatial frequency information that is hard to separate from effects caused by illumination gradients. High pass filtering removes both the useful and the incidental information, thus simplifying the recognition problem and in many cases increasing the overall system performance. Similarly, suppressing the highest spatial frequencies potentially reduces both aliasing and noise without too much of the underlying recognition signals. Difference of Gaussian filtering is a convenient way to achieve the resulting band pass behavior. Fine details remain critically important for recognition so the inner (smaller) Gaussian is typically quite narrow ($\sigma_0 \leq 1$ pixel), while the outer one might have σ_1 of 2–4 pixels or more, depending on the spatial frequency at which low frequency information becomes misleading rather than informative. Given the strong lighting variations in our datasets we find that $\sigma_1 \approx 2$ typically gives the best results, but values up to about 4 are not too damaging and may be preferable for datasets with less extreme lighting variations. LBP and LTP features do seem to benefit from a little smoothing ($\sigma_0 \approx 1$), perhaps because pixel based voting is sensitive to aliasing artifacts. Below we use $\sigma_0 = 1.0$ and$\sigma_1 = 2.0$ by default.

We implement the filters using explicit convolution. To minimize boundary effects, if the face is part of a larger image the gamma correction and prefilter should be run on an appropriate region of this before cutting out the face image. Otherwise, extend-as-constant boundary conditions should be used: using extend-as-zero or wrap-around (FFT) boundary conditions significantly reduces the overall performance, in part because it introduces strong gradients at the image borders that disturb the subsequent contrast equalization stage. Prior gamma normalization is still required: if DoG is run without this, the resulting images suffer from reduced local contrast (and hence loss of visual detail) in shadowed regions.

Masking is facial regions (hair style, beard . . .) that are felt to be irrelevant or too variable need to be masked out, the mask should be applied at this point. Otherwise, either strong artificial gray-level edges are introduced into the DoG convolution, or invisible regions are taken into account during contrast equalization.

(c) *Contrast Equalization*

The final stage of the preprocessing chain rescales the image intensities. It is important to use a robust estimator because the signal typically contains extreme values produced by highlights, small dark regions such as nostrils, garbage at the image borders, etc. One could use (for example) the median of the absolute value of the signal for this, but here a simple and rapid approximation is preferred based on a two stage process as follows:

$$I(x,y) \leftarrow \frac{I(x,y)}{(mean(|I(x',y')|^{a}))^{1/a}} \quad (1)$$

$$I(x,y) \leftarrow \frac{I(x,y)}{(mean(\min(\tau,|I(x',y')|^{a})))^{\frac{1}{a}}} \quad (2)$$

ISSN 2230-7850
Volume-3, Issue-7, August-2013

Here, α is a strongly compressive exponent that reduces the influence of large values, τ is a threshold used to truncate large values after the first phase of normalization and the mean is over the whole (unmasked part of the) image form equation (1) & (2). By default we use α = 0:1 τ=10[Tan and Trigg's, 2010]. The resulting image is well scaled but it can still contain extreme values. To reduce their influence on subsequent stages of processing, we apply a final nonlinear mapping to compress over-large values. The exact functional form is not critical. Here we use the hyperbolic tangent I(x, y ← τtanh(I(x,y)/T) ,thus limiting *I* to the range(-τ,τ).The proposed technique is tested with the different datasets Yale B, FRGC-204 and Real time-database that has been created under difficult and different illumination conditions. For each person five images are created as normal, bright, very bright, dark and very dark. The images are tested with the proposed algorithm, preprocessing is performed which is the first stage of any face recognition system.

B.*Robust Feature Extraction:*

In this method approaches seek to reduce the image to a more-canonicalform in which the illumination variations are suppressed. Histogram equalization is one simple example, but purpose-designed methods often exploit the fact that (on the Scale of a face) naturally occurring incoming illumination distributions typically have predominantly low spatial frequencies and soft edges so that high-frequency information in the image is predominantly signal (i.e., intrinsic facial appearance).The total processes comes under robust feature extraction which introduces Local Binary Patterns and Local Ternary Patterns. The following figures derive the implementation of robust feature extraction which processes the original image towards the local binary pattern and local binary pattern.

(i) *Local Binary Patterns*

Ojala [14] introduced Local Binary Patterns (LBPs) as a means of summarizing local gray-level structure. The LBP operator takes a local neighborhood around each pixel, thresholds the pixels of the neighborhood at the value of the central pixel and uses the resulting binary-valued image patch as a local image descriptor. It was originally defined for 3X3neighborhoods, giving 8-bit integer LBP codes based on the eight pixels around the central one. Formally, the LBP operator takes the form:

$$\mathrm{LBP}(x_c, y_c) = \sum_{n=0}^{7} 2^n \, s(i_n - i_c) \quad (3)$$

where in this case n runs over the 8 neighbors of the central pixel c, ic and equation (3) in are the gray-level values at c and n and s(u) is 1 if u>=0 and 0 otherwise.The first defined LBPs for neighborhoods of different sizes, thus making it feasible to deal with textures at different scales. The second defined the so-called uniform patterns: an LBP is "uniform" if it contains at most one 0-1 and one 1-0 transitionwhen viewed as a circular bit string. The LBP code in Fig. 3 is uniform. Uniformity is important because it characterizes the patches that contain primitive structural information such as edges and corners.Ojala et al observed that although only 58 of the 256 8-bit patterns are uniform, nearly 90% of all observed image neighborhoods are uniform and many of the remaining ones contain essentially noise.The above figure describes local binary image(LBP) illustrated from original Image.

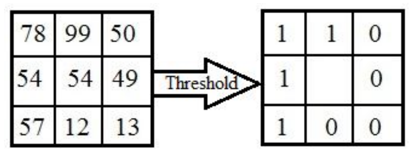


Figure:3. Illustration of the basic LBP operator

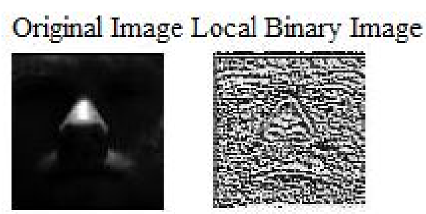
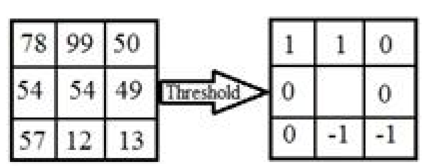


Figure: 3(a). LBP image occurs from original image

Thus, when histogramming LBPs the number of bins can be reduced significantly by assigning all non-uniform patterns to a single bin, typically without losing too much information.

(ii)*Local Ternary Patterns (LTP)*

LBPs have proven to be highly discriminative features for texture classification and they are resistant to lighting effects in the sense that they are invariant to monotonic gray-level transformations.



[54-t,54+t],t=5

ISSN 2230-7850
Volume-3, Issue-7, August-2013

Figure (4) Illustration of the basic LTP operator

However because they threshold at exactly the value of the central pixel i.e., they tend to be sensitive to noise, particularly in near-uniform image regions, and to smooth weak illumination gradients.

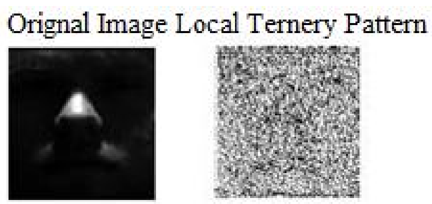


Figure :4.a LTP image occurs after median applies to original image

This section extends LBP to 3-valued codes, LTP, in which gray-levels in a zone of width+-t around ic are quantized to zero, ones above this are quantized to +1 and ones below it to -1, i.e., the indicator s(u) is replaced with a 3-valued function

$$s'(u, i_c, t) = \begin{cases} 1, & u \geq i_c + t \\ 0, & |u - i_c| < t \\ -1, & u \leq i_c - t \end{cases} \quad (4)$$

The binary LBP code is replaced by a ternary LTP code from limit given in equation (4). Here is a user-specified threshold so LTP codes are more resistantto noise, but no longer strictly invariant to gray-level transformations.The LTP encoding procedure is illustrated in Fig.4. Here the threshold was set to 5,so the tolerance intervalis [49, 59].

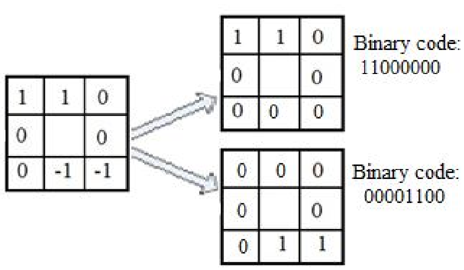


Fig.5. Splitting an LTP code into positive and negative LBP codes.

When using LTP for visual matching, we could use valued codes, but the uniform pattern argument also applies in the ternary case.

For simplicity, the experiments above use a codingscheme that splits each ternary pattern into its positive and negative halves as illustrated in Fig. 5, subsequently treating these as two separate channels of LBP descriptors for which separate histograms and similarity metrics are computed, combining theresults only at the end of the computation.

C.*Feature Subspace Representation*:

It extracts illumination insensitive feature sets directly from the given image. These feature sets range from geometrical features to image derivative features such as edge maps[1], local binary patterns (LBP)[2],[3], Gabor wavelets, and local autocorrelation filters.

(i).*Distance Transform Based Similarity Metric:*

This section details with robust face recognition framework introduced in Section I. The full method incorporates the beforementioned preprocessing chain and LBP or LTP features with distance transform based comparison. However, as mentioned above, face recognition is a complex task for which it is useful to include multiple types offeatures, and we also need to build a final classification stage that can handle residual variability and learn effective models from relatively few training samples.The selection of an expressive and complementary set of features is crucial for good performance. Our initial experiments suggested that two of the most successful local appearance descriptors, Gabor wavelets and LBP (or its extension LTP), were promising candidates for fusion. LBP is good at coding fine details of facial appearance and texture.

(a) *Gabor Features:*

Gabor features encode facial shape and appearance over a range of coarser scales. Both representationsare rich in

Figure 6: Gabor features detected from the original image

Information and computationally efficient, and their complementary nature makes them good candidates for fusion.

When a face image is presented to the system, its Gabor wavelet and LBP features are extracted separately projectedinto their optimal discriminant spaces and used to compute the corresponding distance scores. Each score is normalizedusing the “z-score” method[11].

ISSN 2230-7850
Volume-3, Issue-7, August-2013

$$z = \frac{s-\mu}{\sigma} \quad (5)$$

Where μ,σarerespectively, the mean and standard deviation of over the training set in equation (5). Figure 6 refer to the Gabor features detected from the original image. Finally, the two scores $Z_{Gabor}$and $Z_{LBP}$are fused at the decision level. Not with standing suggestions that it is more effective fuse modalities at an earlier stage of processing, our earlier work found that although feature-level and decision-level fusion both work well, decision-level fusion is better in this application.

Kittler [8] investigated a number of different fusion schemes including product, sum, min, and max rules, finding that the sum rule was the most resilient to estimation errors and gave the best performance overall derived in equation (6).Thus, we fuse the Gabor and LBP similarity scores using the simple sum.The resultingsimilarity score is input to simple Nearest Neighbor (NN) classifier to make the final decision.

Rule: $Z_{Gabor} + Z_{LBP}$(6)

A similar strategy was independently proposed byFig. 7 gives the overall flowchart of the proposed method.Emphasize that it includes a number of elements that improve recognition in the face of complex lighting variations. A combination of complementary visual features LBP and Gabor wavelets is used.The features are individually both robust and information-rich.

Preprocessing which is usually ignored in previous work on these feature sets[10] greatly improves robustness.The inclusion of kernel subspace discriminants increases discriminatively while compensating for any residual variations Described above were each of these factors contributes to the overall system performance and robustness.

(b)*Tensor-Based Feature Representation*

The LBP and Gabor feature sets described here are both very high dimensional (usually over 10 000), and it would be useful to be able to represent them more compactly without sacrificing too much performance. Inspired by recent work on tensor-based decompositions, we tested tensor-based representations for Bland Gabor features using General TensorDiscriminant Analysis (GTDA) as a dimensionality reduction method. The resulting reduced tensors are written as vectors, optionally subjected to additional stages of feature extraction, and then fed to the classifier. Note that there are many other dimensionality reduction methods that could be applied — notably local or manifold-based representations, but in this project we will focus on global linear vector and tensor reductions.

III. Results and Discussion:

To design the proposed method for face recognition system we investigated several aspects of this framework.

(i) *Relation for image normalization and feature sets*

Normalization is known to improve the performance of simple subspace methods (e.g. PCA) or classifiers (e.g. nearest neighbors) based on image pixel representations, but its influence on more sophisticated feature sets has not received the attention that it deserves.A given preprocessing method may or may not improve the performance of a given feature set on a given data set. For example, for Histogram of Oriented Gradient features combining normalization and robust features is useful[12], while histogram equalization has essentially no effect on LBP descriptors, and in some cases preprocessing actually hurts performance [5] presumably because it removes too much useful information.Here we propose a simple image preprocessing chain that appears to work well for a wide range visual feature sets,eliminating many of the effects of changing illumination whilestill

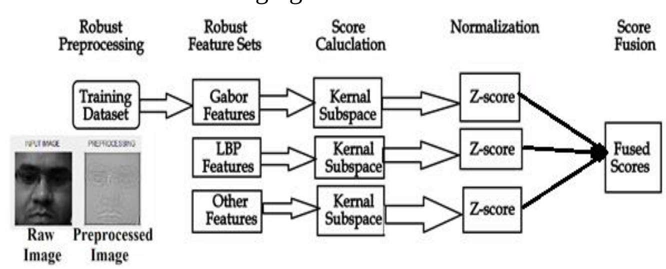


Figure 7: Overall architecture of our multi-feature subspace basedface- recognition method.

preserving most of the appearance details needed for recognition.

(ii) *Robust feature sets and feature comparison strategies*

Current feature sets offer quite good performance under illumination variations but there is still room for improvement. For example, LBP[2] features are known to be sensitive to noise in near-uniform image regions such as cheeks and foreheads. We introduce a

ISSN 2230-7850
Volume-3, Issue-7, August-2013

generalization of LBP called Local Ternary Patterns (LTP) that is more discriminant and less sensitive to noise in uniform regions. Moreover, in order to increase robustness to spatial deformations, LBP based representations typically subdivide the face into a regular grid and compare histograms of LBP[4] codes within each region.This is somewhat arbitrary and it is likely to give rise to both aliasing and loss of spatial resolution. We show that replacing histogramming with a similarity metric based on local distance transforms further improves the performance of LBP/LTP based face recognition.

(iii) ***Fusion of multiple feature sets***

Many current pattern recognition systems use only one type of feature. However in complex tasks such as face recognition, it is often the case that no single class of features is rich enough to capture all of the available information. Finding and combining complementary feature sets hasthus become an active research topic, with successful applications in many challenging tasks including handwritten character recognition [6] and face recognition. Here we show that combining two of the most successful local face representations, Gabor wavelets and Local Binary Patterns (LBP), gives considerably better performance than either alone. The two feature sets are complimentary in the sense that LBP captures small appearance details while Gabor wavelets encode facial shape over a broader range of scales.

(iv)***Results from the proposed face recognition system***

Finally,face recognition system was design from the proposed methods which were explained in detail from above sections. Results of system were as followsFirst stage was show as preprocessing chain was showed in fig.8The Final result concludes the system was recognized the face (acquired) image which was appear as low light condition from that we implemented our proposed method towards the original image.Hence, face (appeared) was recognized by the face recognition system matching patterns which were presented in the (Independent to Facial, Pose etc.,) data base sets. If the face image was not presented in database sets. Hence, user was unable recognize and also unable accessible the service provide by the system which was shown below.

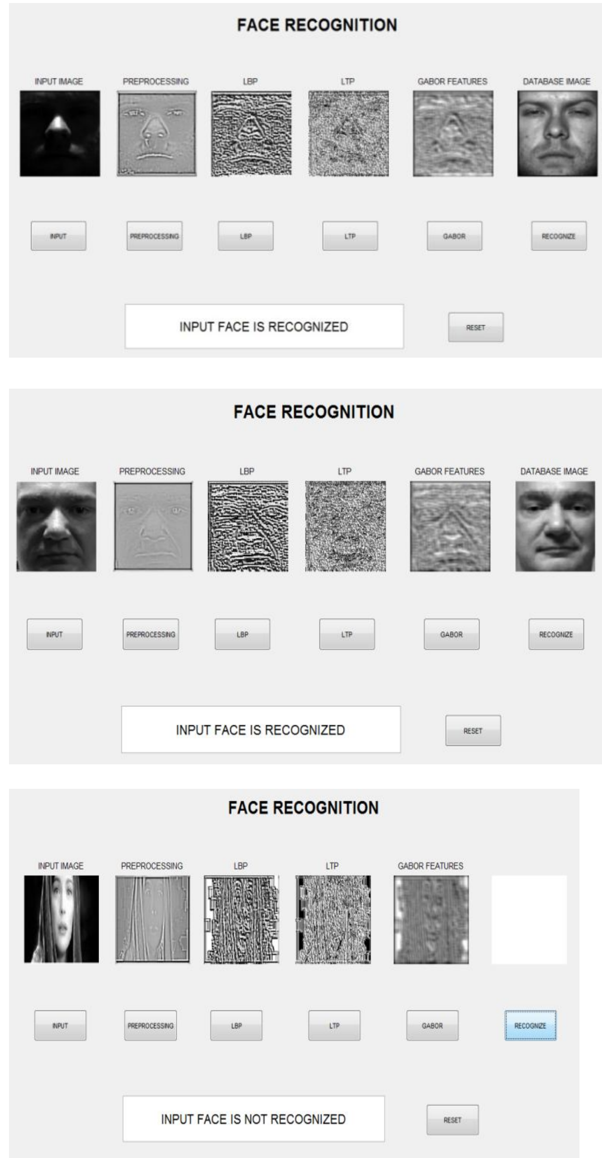


Figure.8 Final result displayed by executing the proposed method, row 1 representsthe user appeared at uncontrolled lighting conditions, row 2 user appeared in different facial expression at uncontrolled lighting condition, row 3 indicates the user was not found in database. Hence from the proposed method face recognition system was excutes perfectly.

(i)***Basic proposed algorithm***

Paging the input image after that preprocess the image to remove noise.In next stage extracting the features using filters.In the final stagenormalizing the levels of contrast displaying the output.Finally, face was recognized by the system.

(ii)***Application for the proposed method***

ISSN 2230-7850
Volume-3, Issue-7, August-2013

This technique implements in Authentication check and Surveillance checking applications. Main advantages are easy of implementation, robust to noise effects, less time of operation and accuracy in operation.

IV.Conclusions

The presented novel new method for face recognitionapplications difficultlighting conditions. It could be achieved by using a simple, efficient image preprocessing chain whose practical recognition performance will be high when compared to the techniques where face recognition is performed without controlled lighting conditions. The technique has been carried out by combining the strengths of gamma correction, Difference of Gaussian filtering and Contrast equalization.Face recognition underuncontrolled lighting based on robust preprocessing and anextension of the LBP local texture descriptor and Gabor feature sets.

The maincontributions are as follows: 1) a simple, efficient image preprocessing chain whose practical recognition performance iscomparable to or better than current (often much more complex) illumination normalization methods; 2) a rich descriptorfor local texture called LTP that generalizes LBP while fragmenting less under noise in uniform regions: 3) a distancetransform based similarity metric that captures the local structure and geometric variations of LBP/LTP face images betterthan the simple grids of histograms that are currently used; and4) a heterogeneous feature fusion-based recognition frameworkthat combines two popular feature sets—Gabor wavelets andLBP—with robust illumination normalization.

The combination ofthese enhancements gives the state-of-the-art performance onthree well-known large-scale face datasets that contain widelyvarying lighting conditions. Moreover, we empirically make a comprehensive analysisand comparison with several state-of-the-art illumination normalization methods on the large-scale FRGC-204 dataset, andinvestigate their connections with robust descriptors, recognition methods, and image quality. This provides new insights intothe role of robust preprocessing methods played in dealing withdifficult lighting conditions and thus being useful in the designation of new methods for robust face recognition. Future scope is to design from blurred, high noise faces which were moving form long distance from face recognition system.

REFERNCES

[1] Y. Adini, Y. Moses, and S. Ullman, “Face recognition: The problem of compensating for changes in illumination direction,”IEEE Trans. Pattern Anal. Mach. Intell.,
vol. 19, no. 7, pp. 721–732, Jul. 1997.

[2] T. Ahonen, A. Hadid, and M. Pietikainen, “Face recognition with localbinary patterns,” inEur. Conf. Comput. Vis., Prague, Czech Republic,2005, pp. 469–481.

[3] T. Ahonen, A. Hadid, and M. Pietikainen, “Face description with localbinary patterns: Application to face recognition,”IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 12, pp. 2037–2041, Dec. 2006.

[4]VenuGoapalRao M., and Vathsal S., “Wavelet methods for Noise reduction in Computed Tomography,” at Belarus-Indian Scientific and technical workshop, New Delhi, 24-26, Feb 2003.

[5] W. Gao, B. Cao, S. Shan, X. Chen, D. Zhou, X. Zhang, and D.Zhao,“The CAS-PEAL large-scale chinese face database and baseline evaluations,”IEEE Trans. Syst., Man, Cybern., A, vol. 38, no. 1, pp. 149–161, Jan. 2008

[6] Y. S. Huang and C. Y. Suen, “A method of combining multiple experts for the recognition of unconstrained handwritten numerals,”IEEE Trans. Pattern Anal. Mach. Intell., vol. 17, no. 1, pp. 90–94, Jan. 1995

[7]VenuGoapalRao M., and Vathsal S., ”Local Adaptive Bivariate Shrinkage Algorithm for Medical Image Denoising,” International Journal of Electronics Engineering (IJEE), 1(1), pp,59-65, Jan 2009.

[8] J. Kittler, M.Hatef, R.Duin, and J.Matas, “On combining classifiers,” IEEE Trans. Pattern Anal Mach. Intell., vol. 20, no. 3, pp. 226–239, Mar. 1998.

[9] K.Lee, J.Ho and D.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] C.Liu,“Gabor-based kernel pca with fractional power polynomial models for face recognition,” IEEE Trans. Pattern Anal. Mach. Intell.,vol. 26, no. 5, pp. 572–581, May 2004.

[11] N. Dalal and B. Triggs, “Histograms of oriented gradients for human detection,” inProc. CVPR, Washington, DC, 2005, pp. 886–893.

[12] A. Jain, K. Nandakumar, and A. Ross, “Score normalization in multimodal biometric systems,” Pattern Recognition, vol. 38, no. 12, pp.2270–2285, 2005.

[13] T. Ojala, M. Pietikainen, and T. Maenpaa, “Multiresolution gray-scaleand rotation invarianat texture classification with local binary patterns,”*IEEE Trans. Pattern al.Mach.Intell.*, vol. 24, no. 7, pp. 971–987,Jul. 2002.

[14] Xiaoyang Tan and Bill Triggs “Enhanced Local Texture Feature Sets for FaceRecognition Under Difficult Lighting Conditions”*IEEE Trans On Image Processing*,vol. 19, no. 6,pp.1635-1650 June 2010.