# Face Recognition under Difficult Lighting Conditions

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## ABSTRACT
Making recognition more reliable under uncontrolled lighting conditions is one of the most important challenges for practical face recognition systems. This paper uses strengths of robust illumination normalization, local texture based face representations, distance transform based matching and multiple feature fusion to tackle this problem. The contributions of this paper include: 1) a simple and efficient pre-processing chain that eliminates most of the effects of changing illumination while still preserving the essential appearance details that are needed for recognition; 2)introduce local ternary patterns (LTP), a generalization of the local binary pattern (LBP) local texture descriptor that is more discriminant and less sensitive to noise in uniform region 3) improve robustness by adding Gabor wavelets and LBP—showing that the combination is considerably more accurate than either feature set alone. The resulting method provides state-of-the-art performance on Extended Yale-B dataset with an acceptance ratio of 85%. This can be used in many applications like surveillance, forensics, banking and login systems.

### Index Terms
Face recognition, illumination invariance, image pre-processing, kernel principal components analysis, local binary patterns, visual features.

## 1. INTRODUCTION
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, surveillance, and more generally image understanding .Numerous approaches have been proposed, including eigenfaces[16] , fisherfaces [3], and laplacianfaces[7], nearest feature line-based subspace analysis[9], neural networks[8], [14], elastic bunch graph matching, wavelets, Multiscale Retinex[15] and kernel methods[11].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[6].

This paper focuses mainly on the issue of robustness to lighting variations.Traditional approaches for dealing with this issue can be broadly classified into three categories: appearance-based, normalization-based, and feature-based methods. In direct appearance-based approaches, training examples are collected under different lighting conditions and directly used to learn a global model of the possible illumination variations. Normalization based approaches seek to reduce the image to a more “canonical” form in which the illumination variations are suppressed. The third approach extracts illumination-insensitive feature sets [3],[12],[14],[17] directly from the given image. These feature sets range from geometrical features [8] to image derivative features such as edge maps[10] , local binary patterns (LBP) , Gabor wavelets [1][4], and local autocorrelation filters. Although such features offer a great improvement on raw gray values, their resistance to the complex illumination variations that occur in real-world face images is still quite limited. For example, even though LBP features are completely invariant to monotonic global gray-level transformations, their performance degrades significantly under changes of lighting direction and shadowing[5].

In this paper, an integrative framework that combines the strengths of all three of the above approaches was proposed. The overall process can be viewed as a pipeline consisting of image normalization, feature extraction, and subspace representation[1]. Each stage increases resistance to illumination variations and makes the information needed for recognition more manifest. The method centres on a rich set of robust visual features that is selected to capture as much as possible of the available information. A well-designed image preprocessing pipeline is prepended to enhance robustness.

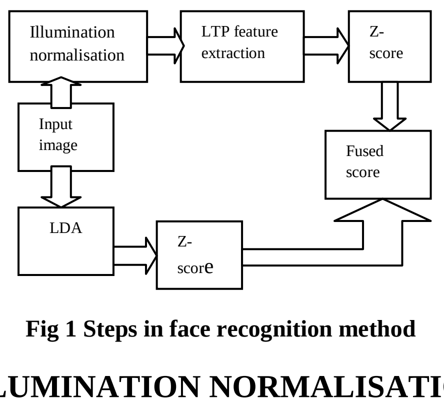


**Fig 1 Steps in face recognition method**

## 2. ILLUMINATION NORMALISATION
This section describes our illumination normalization method. This is a pre-processing 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.

## 2.1 Gamma Correction

It is a nonlinear gray-level transformation that replaces I gray-level with $I^{\gamma}$ where $\gamma$ 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. A power law with exponent $\gamma$ is used. Here we use $\gamma$=0.2.

## 2.2 Difference of Gaussian filtering

Gamma correction does not remove the influence of overall intensity gradients such as shading effects. DoG filtering is a convenient way to achieve the resulting band pass behaviour. 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 $\sigma_1$ might have of 2–4 pixels or more, depending on the spatial frequency at which low frequency information becomes misleading rather than informative.

## 2.3 Masking

If facial regions 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.

## 2.4 Contrast Equalisation

The final stage of our preprocessing chain rescales the image intensities to standardize a robust measure of overall contrast or intensity variation. 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 we have preferred a simple and rapid approximation based on a two stage process as follows:

$$I(x,y) \longrightarrow \frac{I(x,y)}{(\text{mean},(\min(\tau, |I(x',y')|)^{\alpha}))^{1/\alpha}}$$

The exact functional form is not critical. Here we use the hyperbolic tangent $I(x, y) \rightarrow \tau \tanh (I(x, y)/\tau)$, limiting I to the range $(-\tau,\tau)$

**Fig. 2. (Top) the stages of our image preprocessing pipeline, and (bottom) an example of the effect of the three stages—from left to right: input image; image after Gamma correction; image after DoG filtering; image after robust contrast normalization.**

# 3. LTP FEATURE EXTRACTION

## 3.1 Local Ternary Pattern

LBPs have proven to be highly discriminative features for texture classification [1] and they are resistant to lighting effects in the sense that they are invariant to monotonic gray-level transformations. However because they threshold at exactly the value of the central pixel $i_c$ they tend to be sensitive to noise, particularly in near-uniform image regions, and to smooth weak illumination gradients.Here we extend LBP to 3-valued codes, LTP, in which gray-levels in a zone of width ±t around $i_c$ 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.When using LTP for visual matching, we could use $3^n$ valued codes, but the uniform pattern argument also applies in the ternary case.

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

For simplicity, the experiments below use a coding scheme that splits each ternary pattern into its positive and negative halves subsequently treating these as two separate channels of LBP descriptors for which separate histograms and similarity metrics are computed, combining the results only at the end of the computation.

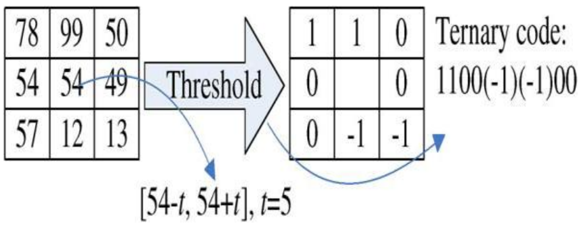


**Fig:4 Local Ternary Pattern conversion**

## 3.2Local Binary Pattern

Ojala et al. 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 3X3 neighborhoods, giving 8-bit integer LBP codes based on the eight pixels around the central one. Formally, the LBP operator takes the form[2]

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

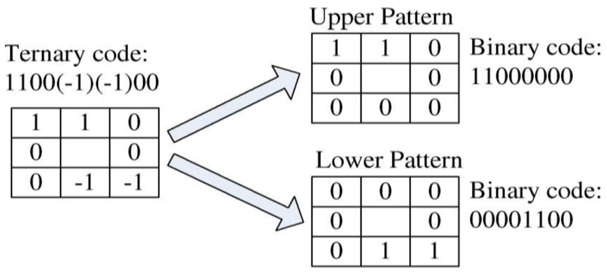


**Fig:3 Local Binary Pattern conversion**

## 3.3 Calculation of Z-score for LBP

It is more appropriate to use a Hausdorff-distance-like similarity metric that takes each LBP or LTP pixel code in image xand tests whether a similar code appears at a nearby position in image y, with a weighting that decreases smoothly with image distance. Given a 2-D reference image x , we find its image of LBP or LTP codes and transform this into a set of sparse binary images $b^k$, one for each possible LBP or LTP code value (i.e., 59 images for uniform codes). Each $b^k$ specifies the pixel positions at which its particular LBP or LTP code value appears. We then calculate the distance transform $d^k$ image of each . Each pixel of gives the distance to the nearest image pixel with code.

$$d^k(x,y)=\min(\max(a^k,b^k))$$

where $a^k$,$b^k$ specifies the pixel positions at which LBP or LTP code value appears.

The distance or similarity metric $d^k$ from image x to image y is then,

$$D(x,y)= \sum_{\text{Pixels(I,j) of y}} d_x{}^k{}_y{}^{(i,j)}(\,i,\,j)$$

The full method incorporates the aforementioned preprocessing chain and LBP or LTP features with distance transform based comparison.

$$Z_{LDA} = \frac{D-\mu}{\sigma}$$

where μ,σ are respectively, the mean and standard deviation ,

D is the distance similarity metric and $Z_{LBP}$ ranges from 0 to 1

## 4. LINEAR DISCRIMINANT ANALYSIS

Linear Discriminant Analysis (LDA) is a commonly used techniques for data classification and dimensionality reduction. Linear Discriminant Analysis easily handles the case where the within class frequencies are unequal and their performance has been examined on randomly generated test data. This method maximizes the ratio of between-class variance to the within-class variance in any particular data set thereby guaranteeing maximal separability. This method also helps to better understand the distribution of the feature data.

Let the training set of images be $Γ_1$ , $Γ_2$,.....$Γ_m$. The average face of the set is defined by

$$\Psi=1/m \sum_{n=1}^{m} Γ_n$$

the between and withinclass scatter matrices $S_b$ and $S_w$ are defined as:

$$S_b=\sum_{n=1}^{m} P_r(C_i)(\mu_i-\mu)(\mu_i-\mu)=\phi_b\phi_b^T$$

where $P_r(C_i)$ is the prior probabilityof class Ci and usually is assigned to 1/m

$$S_w= \sum_{n=1}^{m} P_r(C_i)\,\Sigma_i= \phi_w\phi_w^T$$

$$V=1/m \sum_{n=1}^{m} \phi_b\phi_w^T$$

Then is then subject to principal component analysis which seeks a set of M orthogonal vectors $u_1$.........$u_m$

$$W_k=U_k^T(Γ-\psi)$$

The weights from the vectors $\Omega=(W_1,W_2,\ldots\ldots\ldots W_K)$

Euclidean distance $D_k=\|\Omega-\Omega_k\|$

## 4.1 Calculation of Z-score for LDA

The Z-score for LDA is calculated as follows:

$$Z_{LDA}= \frac{D-\mu}{\sigma}$$

where μ,σ are respectively, the mean and standard deviation , D is the distance similarity metric and $Z_{LDA}$ ranges from 0 to 1.

## 4.2 Calculation of Fused score

We fuse the Gabor and LBP similarity scores using the simple sum rule:

$$Z=Z_{LDA}+Z_{LBP}$$

This fused Z-score is compared with the threshold value 0.5 , if the score is less than the threshold then the face is recognised else it is not recognised.

## 5. DISCUSSION AND CONCLUSION

This project provides a simple, efficient image preprocessing chain whose practical recognition performance is better than current illumination normalization methods and a rich descriptor for local texture called LTP that generalizes LBP while fragmenting less under noise in uniform region is used. Then a distance transform based similarity metric is used to capture the local structure and geometric variations of LBP/LTP face images.A heterogeneous feature fusion-based recognition framework, combines two popular feature sets Gabor wavelets and LBP, is used to provide better efficiency in face recognition. This can be used in many applications like surveillance, forensics, banking and login systems. Also it provides an acceptance ratio of 85%.

The accepatance ratio and rejection ratio are calculated using the following equations:

$$\text{Acceptance ratio} = \frac{1}{N}\sum_{i=1}^{N}(\text{accept ratio})_i$$

$$\text{accept ratio} = \frac{1}{K}\sum_{j=1}^{K}\left(\frac{\text{No. of relevant images retrieved}}{\text{Total no of relevant images}}\right)_j$$

where N and K are the number of image group and the number of images in each group respectively

$$\text{Rejection rate} = \frac{1}{K}\sum_{j=1}^{K}\left(\frac{\text{No. of relevant images rejected}}{\text{Total no of processed images}}\right)_j$$

where S is the total number of images that is processed.
The following table shows the acceptance ratio and rejection ratio for the different number of images.

**Table 1 Acceptance and rejection ratio**

| No. of images | Acceptance ratio | Rejection ratio |
|---|---|---|
| 20 | 90 | 0.01 |
| 40 | 87.5 | 0.025 |
| 60 | 86.7 | 0.033 |
| 80 | 86.25 | 0.047 |
| 100 | 85 | 0.05 |

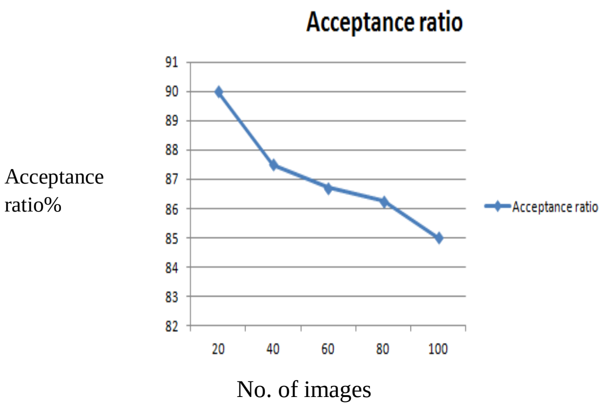


**Fig 4 Acceptance ratio**

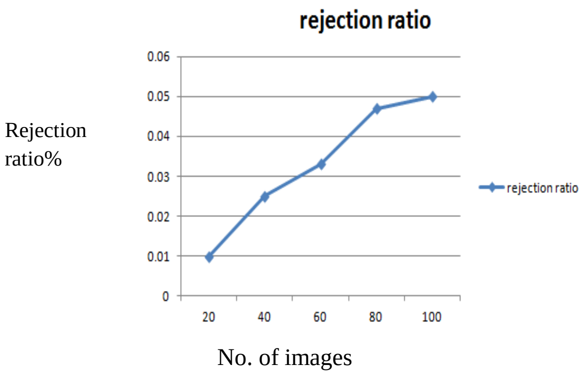


**Fig 5 Rejection ratio**

## 6. FUTURE ENHANCEMENT

This project provides a simple, efficient image pre-processing chain whose practical recognition performance is better than current illumination normalization methods. The complexities of face recognition mainly lie in the constantly changing appearance of human face, such as variations in occlusion, illumination and expression. By using the Self-Organizing Map (SOM) instead of a mixture of Gaussians to learn the subspace that represented each individual, the performance against the partial occlusions and variant expressions can be improved.
Based on the localization of the training images, there are two strategies of learning the SOM topological space, namely to train a single SOM map for all the samples and to train a separate SOM map for each class, respectively. A soft *k* nearest neighbour (soft *k*-NN) ensemble method, can be effectively used to exploit the outputs of the SOM topological space.

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