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# AN ILLUMINATION INVARIANT TEXTURE BASED FACE RECOGNITION

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***Abstract***

***Automatic face recognition remains an interesting but challenging computer vision open problem. Poor illumination is considered as one of the major issue, since illumination changes cause large variation in the facial features. To resolve this, illumination normalization preprocessing techniques are employed in this paper to enhance the face recognition rate. The methods such as Histogram Equalization (HE), Gamma Intensity Correction (GIC), Normalization chain and Modified Homomorphic Filtering (MHF) are used for preprocessing. Owing to great success, the texture features are commonly used for face recognition. But these features are severely affected by lighting changes. Hence texture based models Local Binary Pattern (LBP), Local Derivative Pattern (LDP), Local Texture Pattern (LTP) and Local Tetra Patterns (LTrPs) are experimented under different lighting conditions. In this paper, illumination invariant face recognition technique is developed based on the fusion of illumination preprocessing with local texture descriptors. The performance has been evaluated using YALE B and CMU-PIE databases containing more than 1500 images. The results demonstrate that MHF based normalization gives significant improvement in recognition rate for the face images with large illumination conditions.***

***Keywords:***

***Face Recognition, Texture Analysis, Texture Features***

## 1. INTRODUCTION

Automatic face recognition system has been an active and popular research topic in computer vision and pattern recognition due to its wide applications in security, forensic investigation, access control and law enforcement [1]. Existing face recognition method is mainly classified into appearance (holistic) based method and feature-based method [2]. In holistic method the entire face image is represented as a high dimensional vector. Due to curse of dimensionality such vectors cannot be compared directly. Hence holistic methods use dimensionality reduction techniques to resolve these problems. Examples of this approach are Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA) and Support Vector Machine (SVM) methods, Laplacian Focus and so on. Feature based approaches uses a set of observations obtained from the face image. Some of the well known feature based methods are Elastic Bunch Graph Method (EBGM), Local Binary Pattern (LBP), Gaussian Mixture model and Hidden Markov Model (HMM). As compared to holistic approaches, feature based methods have several advantages. They are robust to variations in pose, illumination, occlusion, expression and localization errors.

The face recognition system has to tolerate the real time challenges due to illumination changes, expression, pose, partial occlusion, ageing and so on. An illumination change is considered as a very crucial factor for face recognition. Several illumination preprocessing methods has been proposed [3] to handle the lighting variations. Among that illumination normalization has strained much attention due to its simplicity and fidelity. Hence, in this paper four admired illumination normalization methods are combined with texture descriptors for face recognition.

### 1.1 MOTIVATION AND JUSTIFICATION FOR THE PROPOSED APPROACH

In real time applications, intensity values of face images are severely affected due to various factors such as surrounding environment and imaging equipment. Illumination variation affects the low frequency component or global appearance of the image [3]. Compared to other real time challenges, lighting variation causes larger differences in the facial images. Lighting variation can sternly alter the appearance of a face in the image and to the extent that facial images with extreme illumination changes appear more different to their individual un-illuminated facial images. Hence pre-processing techniques are preferred to improve the illumination and lighting conditions in images. Hu et al. [4] performed a comparative study of 12 well-known illumination preprocessing methods such as Histogram Equalization (HE), Logarithmic Transform (LT), Gamma Intensity Correction (GIC), Directional Grayscale Deviation (DGS), Laplacian Of Gaussian (LOG), Single Scale Retinex (SSR), Gaussian High Pass (GHP), Self-Quotient Image (SQI), Logarithmic Discrete Cosine Transform (LDCT), Logarithmic Total Variation (LTV), Local Normalization (LN) and Preprocessing chain (referred as TT) for face recognition. Chun et al. [5] proposed Modified Homomorphic filtering (MHF) method for illumination normalization.

Texture features can characterize regularity, randomness, directionality and coarseness properties of patterns. A face can be viewed as a texture pattern exhibiting symmetry and regularity. Hence texture plays an important role in computer vision and pattern recognition. Texture descriptors have gained increasing attention in facial image analysis due to their robustness to challenges such as pose and illumination changes. Ojala et al., proposed LBP features which is initially designed for texture classification [6], [7]. It has proven to be highly discriminative features for facial expression analysis [8], background modeling and face recognition [9] due to its low dimensionality, tolerance against illumination changes, computational simplicity and high efficiency. We performed a comparative analysis of LBP and its derivatives such as Multivariate Local Binary Pattern (MLBP), Center Symmetric LBP (CS-LBP), Local Binary Pattern Variance (LBPV), Dominant LBP (DLBP), Advanced LBP (ALBP) , Local Texture Pattern (LTP) and Local Derivative Pattern (LDP) for face recognition [10]. From the experimental analysis, it is found out that LDP and LTP outperformed the other LBP based models.

Though texture based face recognition are so common, the success of these techniques depends on illumination invariant features of textures. Hence illumination normalization techniques can be applied as preprocessing methods for texture based face recognition. Motivated by this, an attempt is made in this paper to propose illumination invariant face recognition. Since texture feature measures the surface property of image, with lighting variations the textural property will also change. Hence, the preprocessing techniques are applied to remove the lighting variations. It is expected that, it will improve the recognition rate of texture based face recognition system. In earlier researches, preprocessing techniques are used to enhance the performance of Local Binary Pattern for face recognition problem. Still now, such techniques have not been applied for LBP variants such as LTP, LDP and LTrPs. Justified by this, an illumination invariant texture based face recognition is investigated in this paper.

### 1.2 OUTLINE OF THE PROPOSED APPROACH

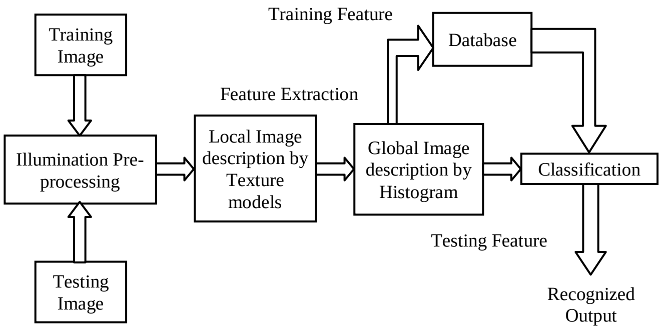



Fig.1. Block Diagram of Face Recognition Process

Overall process of the proposed system is described in Fig.1. Initially all the training and testing images are preprocessed to remove the effect of illumination. In training phase, local texture features are extracted by applying texture descriptors over each region and one dimensional histogram are constructed which are then concatenated together over the region to get the global description of an image. The texture feature of the testing images are computed and compared against the training features stored in the database using Nearest Neighbor classifier which uses log likelihood measure as the distance metric.

### 1.3 ORGANIZATION OF THE PAPER

The rest of the paper is structured as follows. Section 2 briefly describes the different illumination normalization methods. Section 3 focuses the LBP based texture models in detail. Section 4 depicts the face recognition algorithm. Section 5 presents the face databases, experimental settings and extensive experimental analysis. Section 6 presents conclusion and future scope of the paper.

## 2. ILLUMINATION PREPROCESSING METHODS

Illumination preprocessing is an efficient and effective approach in eliminating lighting variation before face recognition. HE, GIC, Normalization chain and MHF techniques are studied in this paper and they are explained below.

### 2.1 HISTOGRAM EQUALIZATION

Histogram Equalization (HE) [11] is still a de facto standard in preprocessing due to its computational simplicity and fidelity. This method is a straightforward and invertible. It increases the global contrast of an image which in turn enhances the discriminative information contained in the facial images. It remaps the histogram of the scene to the histogram of a near-uniform probability density function (pdf). By taking a histogram, the image's pdf is first estimated. Then, cumulative density function (cdf) is calculated. The inverse cdf is then used as mapping function of original image. The histogram manipulation automatically minimizes the contrast in areas too light or too dark of an image. Hence it generates a resulting image whose histogram is approximately uniform.

### 2.2 GAMMA INTENSITY CORRECTION

Shiguang et.al [12] proposed the Gamma Intensity Correction (GIC) method to normalize the overall image intensity to a predefined intensity level. Here $I_{xy}$ represents the overall brightness of the face image which is captured under some unknown lighting conditions and $I_0$ represents the predefined reference face image. The transformed image ($I'_{xy}$) is obtained by a gamma transform (G) over the image I in the image position $x$, $y$.

$$I'_{xy} = G\left(I_{xy} : \gamma^*\right) \tag{1}$$

The Gamma coefficient ($\gamma^*$) is computed by the following optimization process, which intends to minimize the difference between the transformed image and the predefined face image $I_0$.

$$\gamma^* = \arg\min_{\gamma} \sum_{x,y} \left[G\left(I_{xy} : \gamma\right) - I_0(x,y)\right]^2 \tag{2}$$

where,

$$G\left(I_{xy} : \gamma\right) = c.I_{xy}^{1/\gamma} \ . \tag{3}$$

Here $c$ is the gray stretch parameter which has a small positive value. From the above Eq.(2) and Eq.(3), the GIC is expected to make the overall brightness of all the processed images are adjusted to the predefined face image ($I_0$).

### 2.3 NORMALIZATION CHAIN

Normalization chain (TT) proposed by Tan and Triggs [13] incorporates a series of steps include Gamma correction, Difference of Gaussian (DoG) filtering and Contrast Equalization for illumination preprocessing.

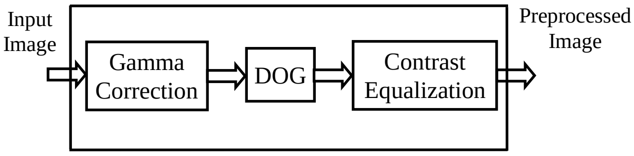



Fig.2. Normalization Chain

#### *2.3.1 Gamma Correction:*

Gamma correction has the effect of enhancing the local dynamic range of the image in dark or shadowed regions, while compressing it in bright regions and at highlights. It is a nonlinear gray-level transformation that replaces gray-level $I$ with $I^{\gamma}$, where $\gamma \in [0, 1]$ is a user-defined parameter. The light reflected from an object is the product of illumination ($i$) and reflectance ($r$). The reflectance component carries object level information which is very useful for face recognition.

#### *2.3.2 Difference of Gaussian (Dog) Filtering:*

Gamma correction does not remove the influence of intensity gradients such as shading effects. Shading induced by surface structure is potentially a useful visual cue but it is predominantly low frequency spatial information that is hard to separate from effects caused by illumination gradients. Hence DoG filtering is used to preserve fine spatial detail essential for recognition.

#### *2.3.3 Contrast Equalization:*

Contrast Equalization is the final process in the normalization chain. It rescales the image intensities to standardize contrast value.

$$I'(x,y) \leftarrow \frac{I'(x,y)}{\left(mean\left(\left\lfloor I'(x',y')\right\rfloor^{\alpha}\right)\right)^{1/\alpha}} \tag{4}$$

In the above Eq.(4), $\alpha$ is a strongly compressive exponent that reduces the influence of large values.

### 2.4 MODIFIED HOMOMORPHIC FILTERING

Chun et.al [5] proposed Modified Homomorphic Filtering (MHF) for illumination normalization. MHF face image not only reduce the illumination effect but also preserved edges and details that will facilitate the further face recognition task. This method improves the appearance of an image by gray level compression and contrast enhancement simultaneously. In MHF, logarithmic transform is first performed on the image followed by Fourier transform. Contrast enhancement is achieved by MHF function and it is given by,

$$H(u,v) = (\gamma_H - \gamma_L)\left[1 - e^{-D^2(u,v)/2D_0^2}\right] + \gamma_L \tag{5}$$

where, $D_0$ is the cutoff frequency from the center. Choose $\gamma_H = 2$ and $\gamma_L = 0.02$.

$$D(u,v) = \left[(u - M/2)^2 - (v - N/2)^2\right] \tag{6}$$

In the above Eq.(6), $M$ and $N$ represents the number of rows and columns of the original image.

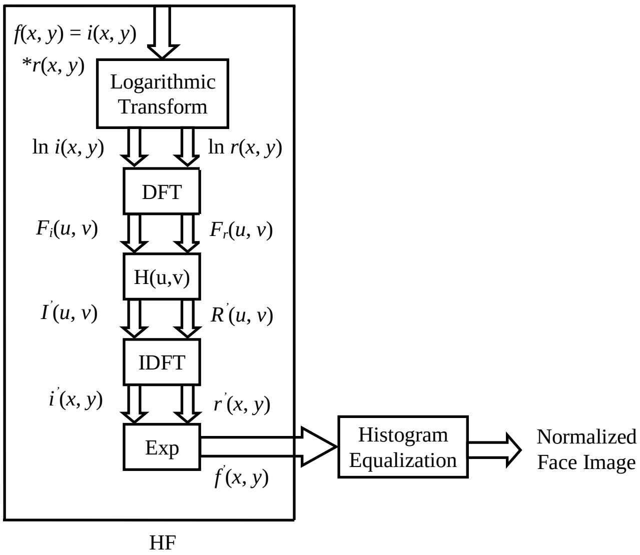



Fig.3. Modified Homomorphic Filtering process

This filter function can be applied separately on illumination and reflectance components. This reduces the illumination effects and exemplifies the reflectance, accordingly. The inverse Fourier Transform and exponential function are used to obtain the enhanced image. The MHF process is represented in Fig.3. HE enhances the contrast of images by transforming the values in an intensity image. Hence the histogram of the output image is approximately uniformly distributed on pixel intensities of 0 to 255.

## 3. TEXTURE MODELS

### 3.1 LOCAL BINARY PATTERN

LBP is computationally simple yet very efficient local texture operator. These features are invariant to monotonic gray scale changes. LBP value of a sample 3 × 3 image is calibrated as,

$$LBP = \sum_{p=0}^{7} s(g_p - g_c) \tag{7}$$

$$s(x) = \begin{Bmatrix} 1, & x \geq 0 \\ 0, & x < 0 \end{Bmatrix} \tag{8}$$

where, $g_c$ is the gray level value of the center pixel, $g_p$ is the grey value of its neighbors around $g_c$ and $p$ is the number of neighbors. A binary code is computed by comparing $g_c$ value with those of its neighborhood. Fig.4 illustrates the basic LBP operator.

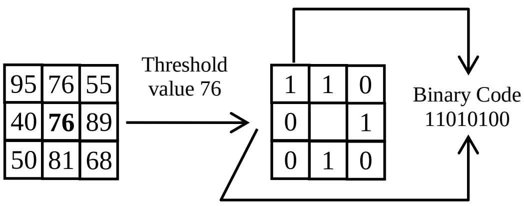



Fig.4. Calculation of LBP pattern

The concepts of uniform patterns are introduced to reduce the number of bins. It effectively captures the fundamental information of textures. A uniformity measure U is defined as,

$$U(LBP) = \left| s(g_{p-1} - g_c) - s(g_0 - g_c) \right| + \sum_{p=0}^{p-1} s(g_p - g_c) - s(g_{p-1} - g_c) \tag{9}$$

The binary code having $U \leq 2$ are nominated as uniform pattern and these are signified by 9 separate bins. The code having $U > 3$ are termed as non-uniform patterns and are represented in a single bin. Hence LBP requires totally 10 bins to store all binary patterns.

## 3.2 LOCAL TEXTURE PATTERN

Conventional LBP is extended to a three – valued code called as LTP. It preserves more textural information than LBP. It was proposed by Suruliandi and Ramar [14] for texture analysis. This descriptor perceives the number of transitions or discontinuities in the circular presentation of the patterns. When such transitions are found to follow a rhythmic pattern, they are recorded as uniform LTP. Considering a local region, the relation between the center pixel $g_c$ and its neighbor is defined by,

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 99 | 106 | 135 | 0 | 1 | 9 | | | |
| 120 | 108 | 86 | 9 | | 0 | | 01900999 | 37 |
| 115 | 135 | 96 | 9 | 9 | 0 | | | |
| | (a) | | | (b) | | | (c) | (d) |

Fig.5. Calculation of LTP and pattern string
(a). 3 × 3 local region; (b). Pattern Units matrix for $\Delta_g = 3$; (c). Pattern String; (d). LTP value

where $g_1, g_2 \ldots g_8$ are the pixel values of a local region, $g_c$ is the value of center pixel and $\Delta_g$ is a small positive value. $\Delta_g$ has more significance in forming the uniform patterns. Fig.5 demonstrates the calculation of LTP over a small region of size 3 × 3. Pattern string values are combined from the top most bit to produce an 8 bit pattern string. The sum of pattern string is the LTP value.

$$P(g_i, g_c) = \begin{cases} 0 & \text{if } g_i < (g_c - \Delta_g) \\ 1 & \text{if } (g_c - \Delta_g) \leq g_i \leq (g_c + \Delta_g) \quad i = 1,2,..8 \\ 9 & \text{if } g_i > (g_c + \Delta_g) \end{cases} \tag{10}$$

Total number of bins required for LTP is 72. Here also, the uniform pattern concept is initiated to condense the number of bins. Uniformity measure $U$ defined in Eq.(9) can be used to find the uniform and non-uniform patterns. The pattern string having $U \leq 3$ are considered as uniform and are represented by 45 bins (3 bins for $U = 0$, 21 bins for $U = 2$ and 21 bins for $U = 3$). The patterns having $U > 4$ are termed as non-uniform and are distinguished by a single bin. Hence uniform LTP requires only 46 bins.

## 3.3 LOCAL DERIVATIVE PATTERN

LDP was implemented by Zhang et.al [15] for robust face recognition. It extracts high order local information by encoding the various distinctive spatial relationships contained in the local region. It carries out two level computations. Hence it contains more discriminative features as compared to standard LBP.

Consider a small region of size 5 × 5, the relations between the center pixel ($g_c$) with its neighbors in a horizontal direction is represented as either a three or four point template. For a 3 point template "0" is assigned to a monotonically increasing or decreasing pattern and "1" is assigned otherwise. Similarly for a 4 point template a gradient turning pattern is labeled as "1" and monotonically increasing or decreasing pattern is labeled as "0". From Fig.6, the second order LDP along $\alpha$ = 0°, 45°, 90° and 135° are represented as,

$$LDP_\alpha^2(g_c) = \sum_{p=0}^{p} 2^{p-1} * f\left(I_\alpha^1(g_c), I_\alpha^1(g_p)\right) \tag{11}$$

where,

$$f(a,b) = \begin{cases} 1, & \text{if } (a,b) \leq 0 \\ 0, & \text{else} \end{cases} \tag{12}$$

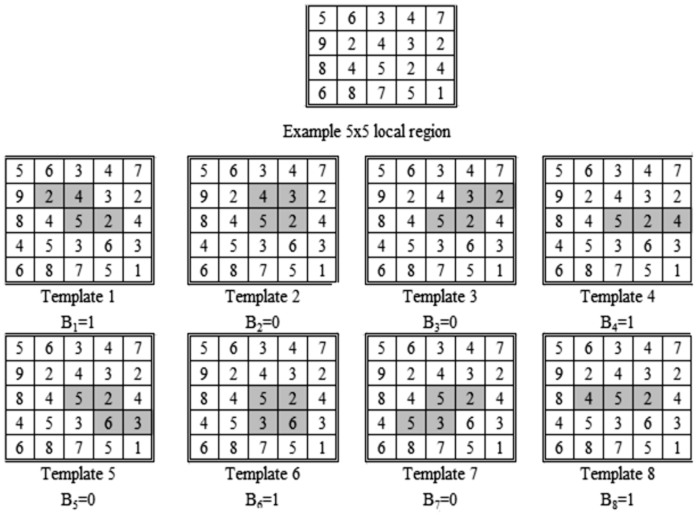



Fig.6. Calculation of LDP micro pattern

The detailed explanation about LDP feature extraction is presented in [15].

## 3.4 LOCAL TETRA PATTERNS

Subramanyam et.al [16] proposed Local Tetra Patterns (LTrPs) for the application of content-based image retrieval. This method encodes the spatial relationship between the referenced pixel and its neighbors based on the first order derivatives along vertical and horizontal directions. Given image $I$, the first-order derivatives along 0° and 90° directions are denoted as $I_\theta^1(g_c)$, where $\theta$ = 0° and 90° is defined by,

$$I_{0^o}^1(g_c) = I(g_h) - I(g_c) \tag{13}$$

$$I_{90^o}^1(g_c) = I(g_v) - I(g_c) \tag{14}$$

where, $g_c$ represents the center pixel, $g_h$ and $g_v$ – horizontal and vertical direction of center pixel. Based on the first order derivatives, the direction of every pixel can be premeditated as,

$$I_{Dir}^{1}(g_c)=\begin{cases}1, & I_{0^0}^{1}(g_c)\geq 0 \text{ and } I_{90^0}^{1}(g_c)\geq 0\\ 2, & I_{0^0}^{1}(g_c)< 0 \text{ and } I_{90^0}^{1}(g_c)\geq 0\\ 3, & I_{0^0}^{1}(g_c)< 0 \text{ and } I_{90^0}^{1}(g_c)< 0\\ 4, & I_{0^0}^{1}(g_c)\geq 0 \text{ and } I_{90^0}^{1}(g_c)< 0\end{cases} \tag{15}$$

From Eq.(15), it is obvious that the possible direction for each center pixel can be 1, 2, 3 or 4.

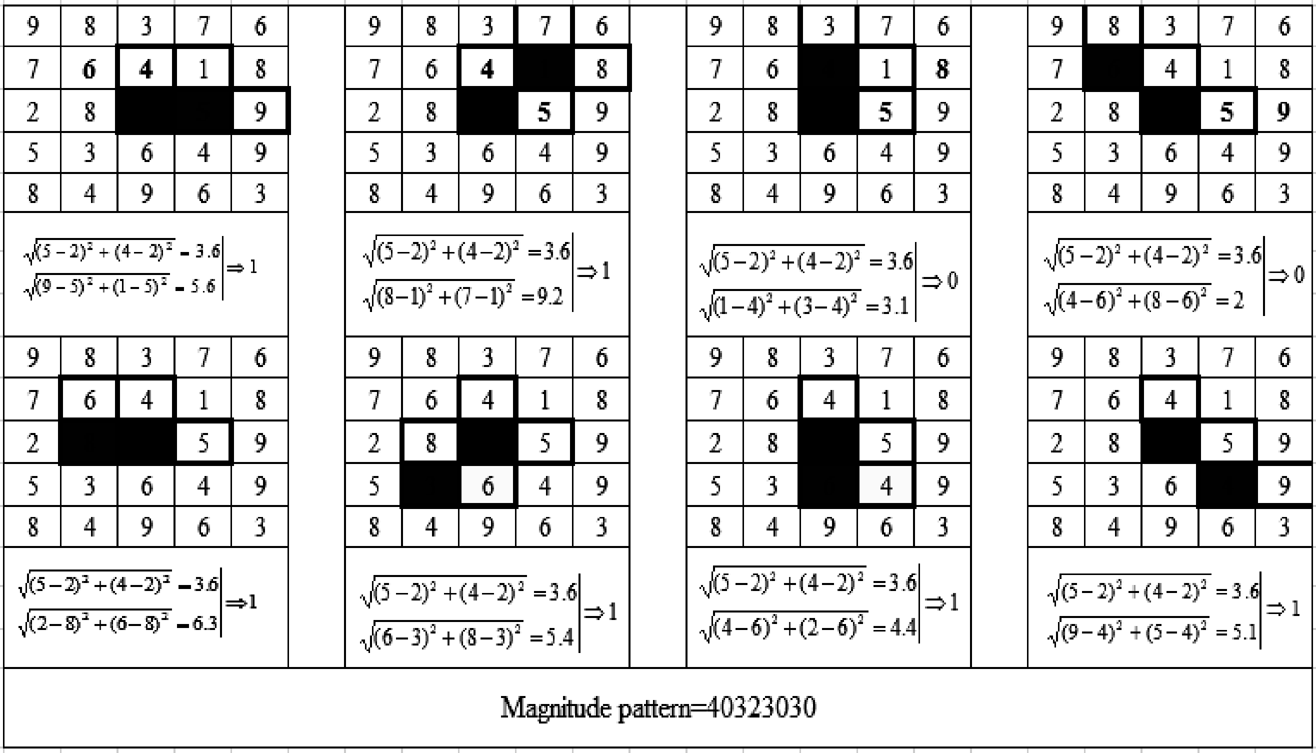



Fig.7. Calculation of magnitude and tetra pattern

The second-order LTrPs ($g_c$) is defined as,

$$LTrP^2(g_c)=\left\{\begin{array}{l} f_1\left(I_{0^0}^{1}Dir(g_c), I_{0^0}^{1}(g_1)\right),\\ f_1\left(I_{0^0}^{1}Dir(g_c), I_{0^0}^{1}(g_2)\right),\\ \ldots f_1\left(I_{0^0}^{1}Dir(g_c), I_{0^0}^{1}(g_p)\right)\end{array}\right\}\Bigg|_{p=8} \tag{16}$$

$$f_1\left(I_{Dir}^{1}(g_c), I_{Dir}^{1}(g_p)\right)=\begin{cases}0, & I_{Dir}^{1}(g_c)=I_{Dir}^{1}(g_p)\\ 1, & \text{else}\end{cases} \tag{17}$$

From Eq.(16) and Eq.(17), we get the 8 bit tetra pattern for each center pixel. Then we separate all patterns into four parts based on the direction of center pixel. Finally, the tetra patterns for each direction are converted into three binary patterns. Similarly, the other tetra patterns for remaining three directions (2, 3 and 4) are converted to 12 (4 × 3) binary patterns. Fig.7 illustrates the calculation of magnitude and tetra patterns for a small region of size 5 × 5. The combination of sign and magnitude mechanism provides better recognition rate. Hence 13 binary patterns (1 magnitude component and 12 binary patterns) are used to calculate the feature vector. The comprehensive explanation about LTrPs feature extraction is offered in [16].

## 4. FACE RECOGNITION ALGORITHM

Face recognition algorithm consists of two phases namely training phase and testing phase.

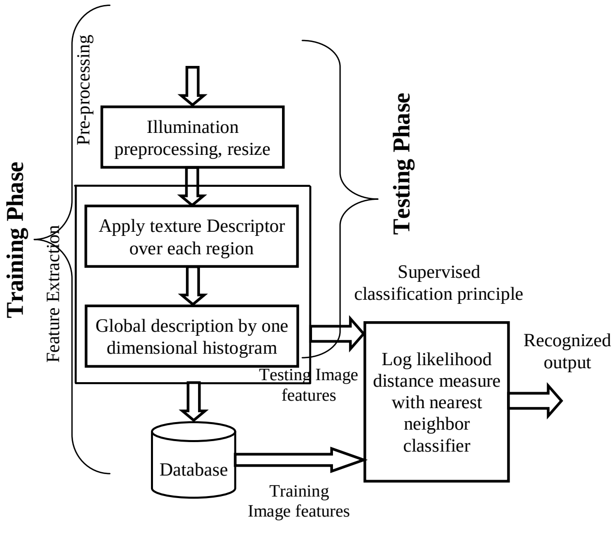



Fig.8. Block diagram of Face Recognition Algorithm

### 4.1 TRAINING PHASE

1. Load the image
2. Apply any one of the illumination normalization techniques among HE, GIC, normalization chain and MHF over an image.
3. Divide the image into non overlapping region of size $N \times N$.
4. Apply any one of the local texture descriptor such as LBP, LDP, LTP and LTrPs over the sub region.
5. Construct a one dimensional histogram for each sub region.
6. Concatenate the histogram over each sub regions to get global description.
7. Store this training feature in the database.

### 4.2 TESTING PHASE

1. Steps 1 to 6 of training phase are repeated to extract the testing feature from an image.
2. Retrieve the training features from the database.
3. Find the similarity between training and testing features using G statistic distance.

$$G = 2\left[\begin{array}{l}\left[\sum_{s,m}\sum_{i=1}^{n} f_i \log f_i\right] - \left[\sum_{s,m}\left(\sum_{i=1}^{n} f_i\right)\log\left(\sum_{i=1}^{n} f_i\right)\right] - \\ \left[\sum_{i=1}^{n}\left(\sum_{s,m} f_i\right)\log\left(\sum_{s,m} f_i\right)\right] + \\ \left[\left(\sum_{s,m}\sum_{i=1}^{n} f_i\right)\log\left(\sum_{s,m}\sum_{i=1}^{n} f_i\right)\right]\end{array}\right] \quad (18)$$

where, $s$ is the histogram of the test sample and $m$ is a histogram of the texture measure distribution of the train sample, $n$ is the total number of bins in a histogram and $f_i$ is the frequency at bin $i$.

4. Choose the nearest neighbor as correct match for the corresponding training image.

## 5. PERFORMANCE EVALUATION

### 5.1 PERFORMANCE METRIC

In order to evaluate the performance of the proposed model, an extensive experimental investigation is carried out, covering face recognition under different lighting variations. The experiments were conducted on Yale B and CMU-PIE databases which contain face images under different lighting conditions appropriate for face recognition. The closest match of the testing sample with any one of the training sample has been identified using nearest neighbor classifier and such match is validated as either correct or incorrect based on the supervised knowledge.

The Recognition Rate is calculated by,

$$\text{Recognition Rate}(\%) = \frac{\text{No. of correct matches}}{\text{No. of test images}} \times 100 \quad (19)$$

### 5.2 EXPERIMENTAL ANALYSIS

#### *5.2.1 Results on CMU-PIE Database:*

(a)

(b)

(c)

Fig.9.(a). Sample Images of different subjects; (b). Images of one subject under different illumination; (c). Images obtained by HE, GIC, normalization chain and MHF

The CMU-PIE database [17] contains 68 subjects with different pose, illuminations and expressions. Frontal face images with controlled illumination variation are taken for training. Five samples per subject are kept in the training set and remaining images per individual are kept in the testing set. Fig.9 represents sample images from CMU-PIE database.

Table.1. Recognition Rate under Different Illumination Condition on CMU-PIE database

| Texture model | Recognition Rate (%) | | | | |
|---|---|---|---|---|---|
| | Without pre-Processing | With preprocessing | | | |
| | | HE | GIC | TT | MHF |
| LBP | 78.5 | 83 | 85 | 86.6 | 88.3 |
| LTP | 86.7 | 87 | 89 | 90.4 | 92 |
| LDP | 86.6 | 87 | 88.7 | 91 | 91.5 |
| LTrPs | 89 | 90 | 90.7 | 91 | 95 |

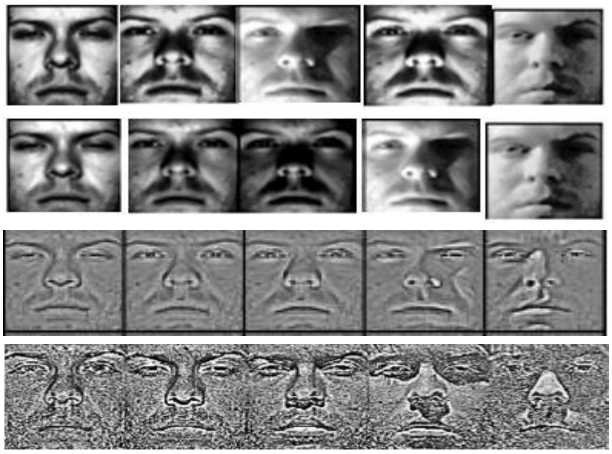
In order to analyze the performance of various illuminations preprocessing methods, an experiment is carried out in this section on CMU-PIE database. The local texture descriptors used are LBP, LTP, LDP and LTrPs. The results obtained for the experiment is listed in Table.1. Preprocessed images preserve more facial feature than non-preprocessed images. Hence, face recognition rate on original face image without illumination preprocessing also included.

The results in Table.1 demonstrate that the illumination preprocessing method MHF performs better among the tested methods due to its ability in preserving edges and details which enhances the face recognition task. It can also reduce the illumination effect tremendously. It is also noted that HE offers poor recognition rate for all the texture models tested along with it. HE fails to produce good results because it normalizes only the contrast which is not sufficient to preserve the micro details present in the image.

#### *5.2.2 Results on Yale B Database:*

(a)

(b)



(c)

Fig.10.(a). Sample Image different subjects; (b). Images of one subject under different illumination conditions; (c). Images obtained by HE, GIC, normalization chain and MHF

Yale face database from Yale centre for Computational Vision and control [18] contains images of 38 subjects in 9 poses and 64 illuminations per pose. We only use the frontal face images under 64 illumination conditions for evaluation. In our experiments, the images which are captured under the azimuth angle of $12^\circ$ from the optical axis are considered for experimental investigation.

The Fig.10 shows the sample images from the database. The original image size is $320 \times 243$. All images are rescaled to the size of $240 \times 240$. It is of importance to pay attention to different factors that manipulate the performance of face recognition system. The number of training images per subject is recognized as one of the key factor for a face recognition problem. This database is used for performance analysis of different preprocessing methods with different number of training and testing images. Number of training images per subject is varied from 1to 5 where as the testing image is kept as constant value of 12. None of the training and testing images is overlapped.

Table.2. Recognition Rate under Different Illumination Condition on YALE-B database

| **No. of Training Images** | **Texture model** | **Recognition Rate (%)** | | | | |
|---|---|---|---|---|---|---|
| | | **Without pre processing** | **With preprocessing** | | | |
| | | | **HE** | **GIC** | **TT** | **MHF** |
| 1 | LBP | 52 | 59 | 63 | 69 | 75 |
| | LTP | 56 | 62 | 66 | 72 | 76 |
| | LDP | 58 | 69 | 71 | 75 | 78 |
| | LTrPs | 59 | 70 | 72 | 76 | 79.5 |
| 2 | LBP | 60 | 63 | 67 | 71 | 76 |
| | LTP | 62 | 64 | 67 | 75 | 78 |
| | LDP | 65 | 69 | 73 | 78 | 81 |
| | LTrPs | 70 | 73 | 75 | 78 | 82.5 |
| 3 | LBP | 72 | 78 | 80 | 82 | 82 |
| | LTP | 77 | 80 | 83 | 86 | 87 |
| | LDP | 78 | 80 | 83 | 87 | 89 |
| | LTrPs | 80 | 86 | 87 | 89 | 91 |
| 4 | LBP | 76 | 78 | 81 | 84 | 87 |
| | LTP | 79 | 83 | 83 | 87 | 89 |
| | LDP | 80 | 83 | 86 | 90 | 91 |
| | LTrPs | 83 | 85 | 89 | 92 | 96 |
| 5 | LBP | 80.4 | 82 | 84.3 | 86 | 89.5 |
| | LTP | 86 | 87 | 89 | 91 | 92 |
| | LDP | 87.5 | 87.6 | 89 | 92 | 93 |
| | LTrPs | 89 | 90 | 92 | 94.5 | 96.5 |

Table.2 represents the recognition rate of different methods with different number of training and testing images per subject. The performance of individual methods gradually increases with the increase in number of training images per subject. LTrPs offers better results among others because it encodes the images with four distinct values. Hence it is able to extract more detailed information from the images among all other methods considered for exploration. MHF normalization techniques performs superior than other normalization methods. It combines illumination normalization and contrast enhancement techniques together.

## 6. CONCLUSION AND FUTURE SCOPE

In this paper, efficient illumination normalization techniques for face recognition are presented. Illumination preprocessing techniques HE, GIC, Normalization chain and MHF are exercised prior to facial feature extraction. These methods effectively eliminate unwanted illumination effect and enhance the local features of facial images, which play a vital role in recognition. Texture based face recognition are most successful and recently used techniques. Hence local descriptors LBP, LTP, LDP and LTrPs are used for face recognition. The combination of normalization techniques and local descriptors provides very promising performance on Yale B and CMU-PIE datasets that contain face images of widely varying lighting conditions. Among all the normalization methods considered MHF offers superior results because it captures micro pattern information of face images. It eliminates illumination effect and enhances the contrast by histogram equalization. In future the effect of directional illumination variation can also be experimented by the proposed approach to prove the efficiency of our method for face recognition.

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