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Normalization Techniques Fusion for Face Recognition under Difficult Illumination Changes

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Abstract: *face recognition is the one of the robust technology compared to other biometric technologies but it has a challenging problem in computer vision. To eliminates this problem and enhance the recognition rate we propose the fusion of normalization techniques rather than single normalization technique .Due to great success of texture features to face recognition Local binary pattern and Local ternary patterns are used for feature extraction. These patterns are more robust to different illumination changes lastly neighbhourhood classifier used for feature vector comparison, these methods are experimented under difficult lighting changes. In this paper these methods performed on Extended Yale database containing total images 2247 and size of each image is 32X32. The experimental results shows that fusion of preprocessing technique and local texture descriptor gives better recognition rate compared to single preprocessing technique used. The face recognition system has a lot of applications such as remote sensing, access control, surveillance systems etc.*

Key words: *Face recognition, different lighting condition, Normalization, local texture patterns, nearest neighborhood classifier.*

I. INTRODUCTION

Face recognition is the one of the most successful application in biometric technologies like, fingerprint recognition, iris recognition, retina recognition; voice recognition etc.In has newly received significantly attention, especially during the past few years. The problem of machine recognition of human faces continues to attract researchers from disciplines such as image processing, pattern recognition, neural networks, computer vision, computer graphics, and psychology [1]. The strong user-friendly systems need for secure our assets and protect our privacy because now a day's technology is increased, so there is a chance of increasing robbery is possible. At present, in ATM to get money needs a personal identification number. A password for a computer and so on. Although very reliable methods of biometric personal identification exist, for example, fingerprint analysis and retinal or iris scans, these methods depends on the Physical interaction of the participants, whereas a face recognition system based on analysis of frontal or profile images of the face is effective system without physical interaction of the participants. But face recognition is a difficult task when photos are taken in uncontrolled environments. Lot of problems occur, which are pose, different illumination changes, aging, facial expressions, occlude faces etc. among these problems Illumination changes is frequently occurred on faces.

Fig1:different lighting conditions on same persons

An image is a smooth object will typically exhibit smooth variation in brightness from one point in the image to another known as shading. These smooth changes in brightness can be a cue to local changes in surface orientation and thus to depth. For example below figure shown that gradual changes in brightness across surface of the person's face. We observed that from left image the brightness is increased, second image brightness decrease and remaining images there is a change in a brightness, these are all conditions are called illumination conditions.

Different methods have been proposed to deal with the illumination invariant face recognition technique. Some methods are elastic bunch graph matching (EBGM) [2] principal component analysis (PCA)[3,4,5,6,7], Kernel principal component analysis , linear discriminate analysis (LDA)and independent component analysis (ICA),these techniques are also called holistic approaches. The main shortcoming of holistic approaches is that they assume that any given pel in the image corresponds to the same position in the person's face. Therefore, they are suitable scenarios where the faces image have the same illumination conditions, same pose, and the same expression and are well aligned. Even small violations of these conditions dramatically reduce performance. In this paper we propose fusion of illumination normalization techniques such as Logarithmic transformation and Weber faces, and compare them and also propose local approaches instead of holistic approaches for robust feature extraction and nearest neighbhourhood classifier used for efficient face recognition.

2 ILLUMINATION NORMALIZATION METHODS

Illumination Normalization is an efficient approach in eliminating illumination changes before face recognition.

2.1 Logarithmic Transformation:

The logarithmic transformation is given by

$$g(m,n) = c\log_2(f(m,n)+1) \qquad (1)$$

This type of mapping spreads out the lower gray level. For an 8-bit image, the lower gray level is zero and the higher gray level is 255.it is desirable to map 0 to 0 and 255.The above mentioned function spreads out the lower gray levels.

2.2 Weberfaces normalization technique

The illumination changes in face images are normalized using Weber's law based normalization technique [8, 9]. The goal of this law is to overcome the illumination factor and represent each image by its reflectance only, thus making this law illumination invariant. Ernst Weber, experimental studied that the ratio of the increment threshold to the background intensity is a constant. This relationship, Known since as Weber's Law. This can be mathematically represented as

$$\frac{\Delta I}{I} = K \qquad (2)$$

Where ΔI represents the increment I represents the initial stimulus intensity and k represents the left side of equation is remains constant .despite of changes in the I term. The fraction $\Delta I/I$ are known as the Weber fraction. The Weber's Law descriptor (WLD) represents an image as a histogram of differential excitations and gradient orientations, and has several motivating properties like robustness to noise and lighting changes, well-designed detection of edges and dominant image representation. WLD descriptor is based on Weber's Law. According to this law the ratio of the increment threshold to the background intensity is constant. The computation of WLD descriptor involves three steps i.e. finding differential excitations, gradient orientations and building the histogram. An each granule will be separated into overlapping blocks to evaluate the differential excitation with current coefficient and neighbourhood matrix.

3. FEATURE EXTRACTION

3.1Local Binary patterns:

Motivation behind Local binary patter is texture of face because face has a composition of micro pattern which also called texture patterns. Local binary pattern is first introduced by ojala [10]. The LBP description of a pixel is created by thresholding the values of a 3 ×3 surrounding pixels with respect to its central pixel and interpreting the result as a binary number. if the surrounding pixel is greater than center pixel it can be treated as a one and if the surrounding pixel is less than center pixel it can be treated as a zero. This can be described as shown below function

$$y = \sum_{i=1}^{s} 2^{i-1} I(c,n_i) \qquad (3)$$

Where $I(c,n_i) = \begin{cases} 1 \ if \ c < n_i \\ 0 \ otherwise \end{cases}$ (4)

For this patterns first Image devide into regions and computes binary patterns for each region and each pixel in that region. Compute the histogram for each region.concatinated these regional histograms into single histogram to form a feature Vector. The Local binary pattern operator $LBP_{P,R}$ produces 2^P different output values, corresponding to the 2^p different binary patterns that can be formed by the P pixels in the neighbor set. If all the 2^p patterns are adopted, computation will be very complex. Studies find that some patterns appear in a low frequency; and some patterns contain more information than others. Therefore, it is possible to use only a subset of the 2^P Local Binary Patterns to describe the texture of images. This type patterns are called uniform pattern [11], the formula definition as follow: Uniform pattern has a common point which there are two changes from 0 to 1 at most in the circular binary code, for example, 11111111 has none code changes, and 00111100 has two code changes. Local binary pattern exhibits 256 patterns but Uniform local binary pattern produces only 59 possible patterns. This can be explained as shown below

$$U(G_p) = |S(X_{P-1} - X_C) - S(X_0 - X_C)| + \sum_{p=1}^{P-1} |S(X_p - X_C) - S(X_{P-1} - X_C)| \le 2 \qquad (5)$$

A code that has the value equal or less than 2 are considered uniform. In practice this can be done with the binary XOR function between the codes. The number of possible codes by only using uniform codes reduced to P

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(P+1)/2, number of where p is the points of the neighbourhood.

2	6	3
7	5	4
1	8	9

0	1	0
1	x_c	0
0	1	1

Fig2:3X3 image

LBP pattern: 01001101
Decimal value: 178
Fig3: computation of LBP value

3.2 Local Ternary pattern:

Local binary pattern encodes the pixel difference between the neighboring pixels and the center pixel. It is a 2-valued code that is successfully used in lot of applications [12] .The LBP operator is based on just two bit values either 1 or 0. This basis does not tolerate the LBP operator to discriminate between patterns. The drawbacks of Local binary patterns are mainly ,which are: The LBP operator cannot differentiate between two pels values if the first pel is near the central pel but a little bit below that pel and the second undistinguishable one is extreme below the center pel value [13]. LBP is sensitive to noise .To overcome this draw backs a new 3-valued texture operator, Local Ternary Patterns (LTP) that can be considered as an extension to LBP was introduced recently.LTP is less sensitive to noise, as t encodes the small pixel difference into a separate state. The LTP code obtained as shown below

$$LTP = \sum_{P=0}^{P-1} S(g_p - g_c)\, 3^P \quad (6)$$

Where s(x, y) is the threshold function and t is a pre defined threshold.

$$s(x,t) = \begin{cases} 1 \text{ if } x \geq t \\ 0 \text{ if } |x| < t \\ -1 \text{ if } x \leq -t \end{cases} \quad (7)$$

The dimensionality of LTP histogram is very large. Suppose $LTP_{8,2}$ will result in a histogram of 3^8=6561 bins. Thus in [14], LTP code is split into a positive LBP code and a negative code as shown below

$$s_n(x,t) = \begin{cases} 1 \text{ if } x \leq t, \\ o \text{ if } x < t. \end{cases} \quad (8)$$

$$s_n(x,t) = \begin{cases} 1 \text{ if } x \leq -t \\ 0 \text{ if } x > -t \end{cases} \quad (9)$$

In this way, each threshold pixel has one of the three values. Neighboring pixels are combined after thresholding into a ternary pattern. Computing a histogram of these ternary values will result in a large range, so the ternary pattern is split into two binary patterns. Histograms are concatenated to generate a descriptor double the size of LBP.

31	19	46
27	25	72
16	29	52

.

Fig4: 3x3digital image

Positive pattern

1	0	1
1		0
0	0	1

Pattern: 10101001

1	-1	1
1		0
-1	0	1

Pattern: 0100010

0	1	0
0		0
1	0	0

Negative pattern

Fig5: splitting the spectral features

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The ternary decision leads to two separate histograms, one representing the distribution of the patterns resulting in a, the other representing the distribution of the patterns resulting in b. Two separate histograms are computed

$$H_{1,lower}(i) = \sum_{x,y}(LBP_{r,p}(x,y) = -i$$

i=0, 1……,2^p-1 (10)

$$H_{1,lower}(i) = \sum_{x,y}(LBP_{r,p}(x,y) = i)$$

i=0, 1… 2^{p-1} (11)

The neighbor information of pixels that lie within the threshold is encoded implicitly by this splitting. Finally, both histograms are concatenated and treated as a single histogram, also called as feature vector.

4. FEATURE VECTOR COMPARISON

After construction of feature vector from the query image. These feature vectors compare with the images in the training database. In this work used nearest neighbhourhood classifier for feature vector comparison. For example, the distance can be defined as in which X and ε are the normalized enhanced histograms to be compared, indices I and j refer to i^{th} bin in histogram corresponding to the j^{th} local region and is the weight for region.

$$X_w^2(x,\varepsilon) = \sum_{j,i} w_j \frac{(x_{i,j}-\varepsilon_{i,j})^2}{x_{i,j}+\varepsilon_{i,j}} \quad (12)$$

.

5. METHODOLOGY

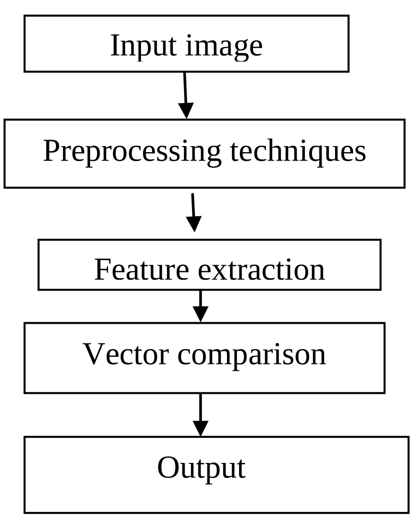

Fig6: Methodology

In this paper, the work consists of 5 steps as mentioned above those are 1.image is given as a input 2.preprocessing techniques 3.feature extraction 4.vector comparison, these all are explained above.

6. RESULTS AND DISCUSSION

In this paper above mentioned methods performed on extended Yale data base which contain 2414 images of size 32X32. Devide this database into two sets,which are train set contain 1140 images and test set ,which contain 1274 images. The experimental results as shown below, which having a few images of train set and test set.

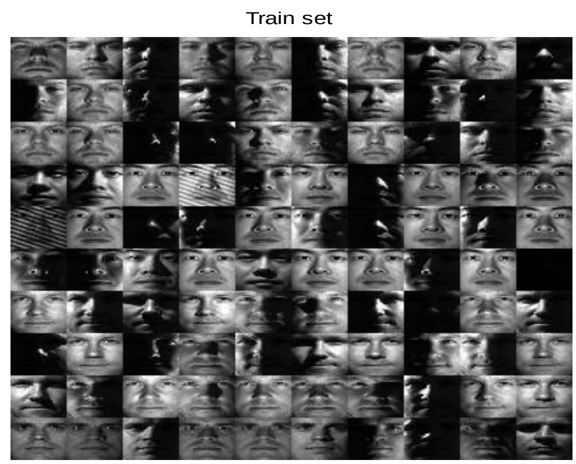

Fig7:Trainset

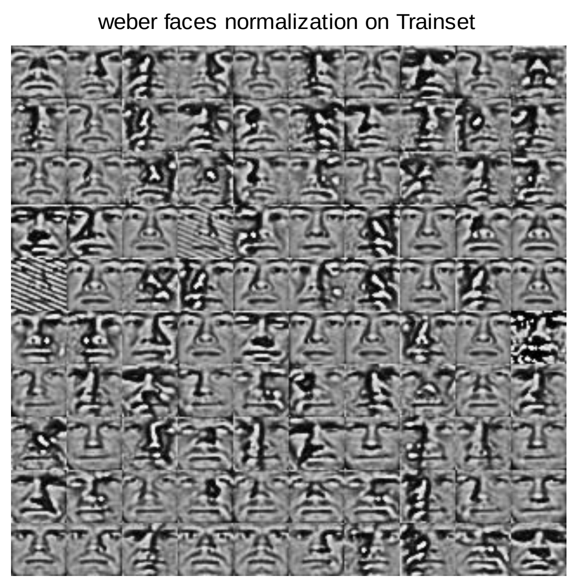

Fig8:weber faces on trainset

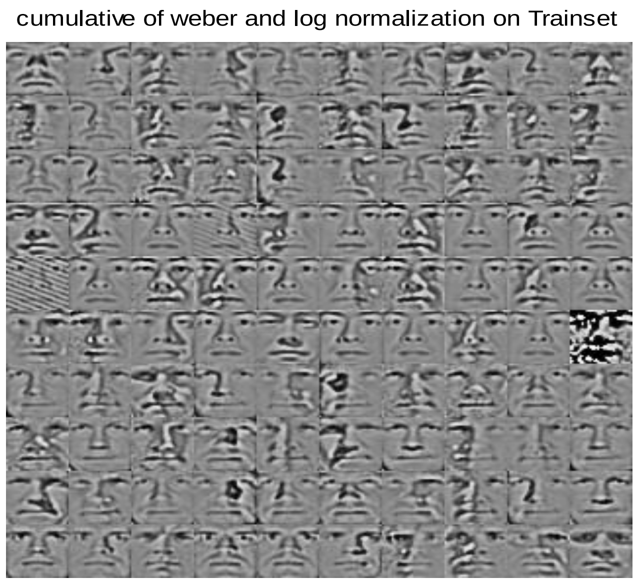

Fig9: Fusion of Log and Weberfaces normalization techniques

Fig10: Test set

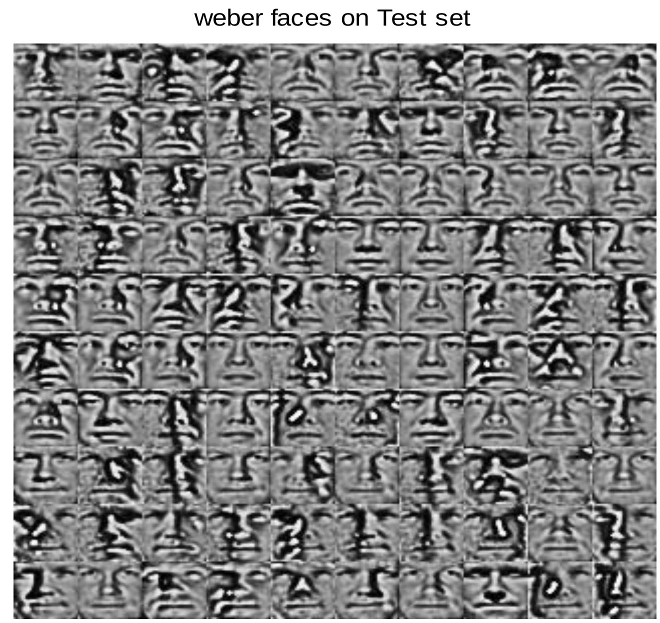

Fig11:weber faces on Testset

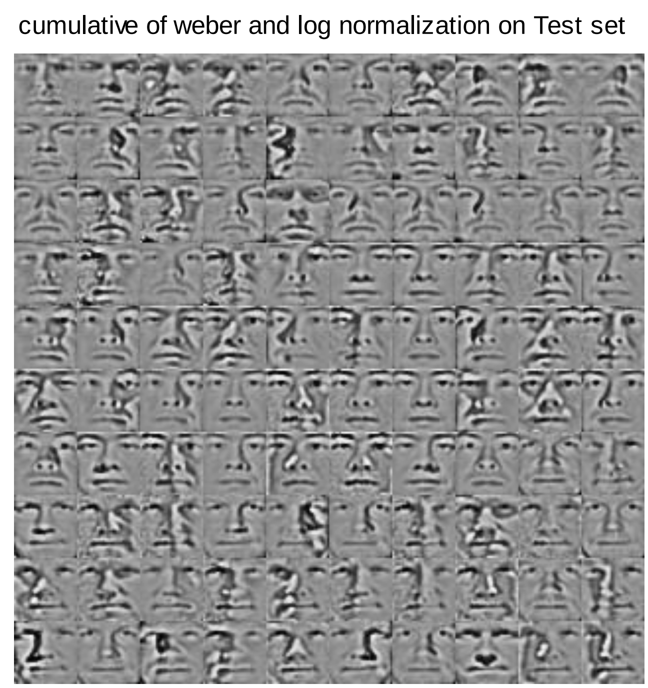

Fig12: Fusion of Log and Weberfaces normalization techniques

Recognition rate of normalization technique and fusion of normalization technique as ahown in Table 1.this table shown that recogntion rate of preprocessed images achieved good recognition rate compared to the no processed images.The graphical representation of this recogniton rate shown in figure 13.

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MEHTOD	Total number of images	Total number of recognized images	Recognition rate
	NO processed		
LBP/NNC	1247	850	66.7248
LTP/NNC	1247	869	69.7434
	Weberfaces normalization method		
LBP/NNC	1247	1096	86.0283
LTP/NNC	1247	1126	88.4376
	New normalization method		
LBP/NNC	1247	1140	91.4194
LTP/NNC	1247	1167	93.5846

Table1:comparision of recognition rate for different normalization techniques

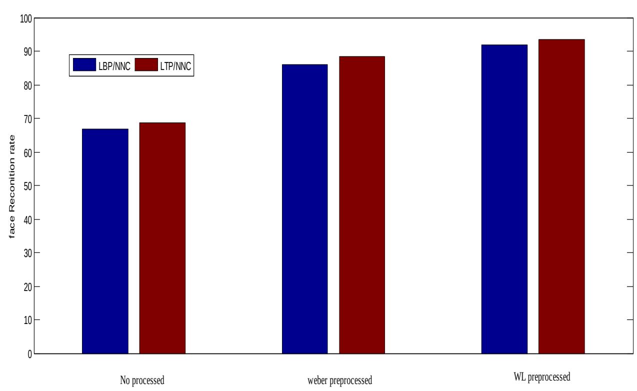

Fig13:recognition rate of different normalization techniques

CONCLUSION

In this paper evaluated the recognition rate of Weberfaces and new normalization (fusion of log and Weberfaces) technique using texture features and neighborhood classifier. The experimental results shown that new normalization technique achieved better recognition rate .This experimental results are showing that Local ternary pattern achieved good recognition rate than that of Local binary patterns.

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