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Gray level Local Derivative Texture Pattern _ A Texture Descriptor For Face Recognition Using Various Distance Metrics

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Abstract

Face Recognition by a robot or machine is one of the challenging research topics in the recent years due to diversity in faces and variations caused by expressions, illuminations, pose, occlusion, aging and other challenges. Since face can be perceived as composition of micro patterns of textures, a new texture based descriptor which can withstand most of the challenges is proposed in this paper. Multiresolution based preprocessing is employed to diminish the effect of facial variations. The strength of the descriptor is tested in various dimensions by using the variety of distance measures and performance metric. The proposed method is experimented on JAFFE, ORL and Yale databases containing more than 2000 face images. From the results, it is observed that, the proposed descriptor consistently performs better for both face identification and face verification under various circumstances.

Keywords: Face recognition, texture analysis, Graylevel Local Derivative Texture Pattern (GLDTP), Contourlet, Distance metrics

Introduction

Automatic face recognition by reasoning about similarity of facial images is a hard computer vision task. Face recognition by a computer system is one of the most promising and potentially widespread areas in the field of computer vision. Existing face recognition methods are mainly classified as holistic based methods and feature based methods [1]. The holistic method uses the whole face region as input to the face recognition system. Examples of this approach are Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis

(ICA), Support Vector Machine (SVM) methods, Laplacian Focus and so on. Feature based approaches use 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). Compared to holistic based methods feature based methods achieve better recognition rate due to 1) Low dimensional local feature vectors represent the original image 2) Common and class specific features of face are easily identified and 3) Usage of different facial features improves the classifiers accuracy.

The performance of face recognition system in controlled environments has achieved a satisfactory level. However, in real time, there are still some challenging issues to address in face recognition under uncontrolled conditions. The challenges that may depreciate the face recognition are poor illumination, facial expression and pose variations. Hazim and Bulent [2] utilize the multiresolution techniques to diminish the loss in face recognition. Multiresolution techniques are used to obtain multiple evidences from the same face and search for those components that are less sensitive to intrinsic deformations due to expression or due to extrinsic factors, like illumination and pose. Most of the techniques either consider few real time challenges or they perform better in a controlled environment. Hence, the objective of this paper is to propose a new texture descriptor that can overcome the above mentioned issues and also to prove that the performance can be improved by introducing multiresolution based preprocessing [3]. This paper also deals with finding appropriate distance metric for the proposed descriptor.

Motivation and Justification of The Proposed Approach

Texture is a term that characterizes the contextual property of an image. Textural features play an important role in recognizing objects and scenes. Texture descriptor is applied on face images to get accurate results because every pixel is classified based on the collective relationship of the pixel with its neighbors [4]. In recent years, the texture descriptor attained a golden line in face recognition. Among them, LBP based method has shown its superiority in face recognition. It was originally proposed as a descriptor for texture classification [5]. Due to its computational simplicity, it was successfully applied for background modeling [6] and face expression recognition [7]. Because of the great success of LBP, recently many models, which are variants of LBP has been proposed for texture analysis [8].

It is crucial to evaluate the performance of LBP and its variants for face recognition under different real time challenges. Suruliandi et al., [9] performed an analysis over 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 LDP for face recognition and they concluded that LTP and LDP outperformed the other LBP based models for face recognition**.**

One of the main challenges with facial recognition is to achieve illumination invariance. It has been proven that, differences caused by illumination variations are more significant than differences between individuals [10]. Facial expression which changes face geometry usually has an adverse effect on the performance of a face recognition system. Recognizing faces reliably across changes in pose has proved to be a much harder problem. Rotation of face image induces very large changes in face appearance. Hence it degrades the recognition rate. Hazim and Bulent [2] prove that multiresolution techniques effectively capture the intrinsic features such as lines and curves of a face image. For comparing the faces the distance metric plays a crucial role in finding the similarity. An empirical evaluation of distance measures on texture classification was previously taken up by Yossi Rubiner [11].

The success of face recognition mainly depends on feature extraction techniques and classification algorithm. Texture based face recognition are so common in recent years. Motivated by this, a new texture based descriptor Graylevel Local Derivative Texture Pattern (GLDTP) is proposed for face recognition. It extracts second order derivative facial features using three descriptions such as -1, 0 and +1. It is already proved that multiresolution can withstand all the real time disputes that occur in uncontrolled environment. Hence Contourlet based preprocessing is adopted in this paper to overcome the challenges. The success of the classification algorithm heavily depends on the distance metric that it uses. Extensive experiments are carried out in this paper using various distance metric to prove the efficiency of the proposed technique.

Face Recognition Process

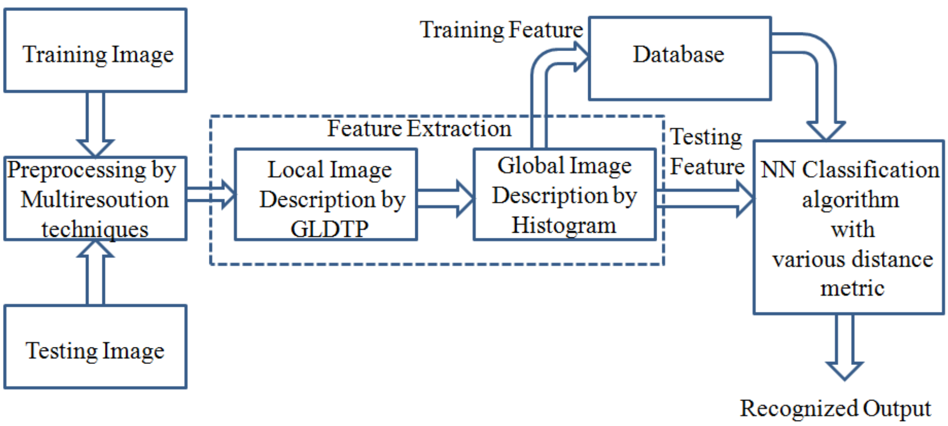
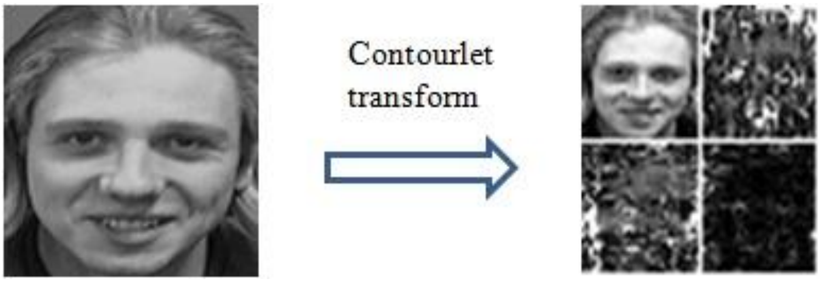


Figure 1: Block Diagram of Face Recognition Task

Overall process of the proposed system is illustrated in Figure 1. The training images are preprocessed by Contourlet transform to remove the facial variation effects. In training phase, local texture features are extracted by applying GLDTP descriptor over the image and one dimensional histogram is constructed to get the global description, which is then stored as training feature. The texture feature computed in a similar manner for the testing images are compared against the training features using Nearest Neighbor classifier. The classifier uses any one of the distance measures such as G-statistic, Euclidian, Manhattan, Chi-square, Minkowski or Bhattacharya as the distance metric.

Organization of The Paper
The rest of the paper is organized as follows: Section 2 shows the Contourlet transform for preprocessing. Section 3 briefly describes the proposed descriptor. Section 4 describes the distance measures used in this study. Section 5 presents the face recognition algorithm. Section 6 focuses databases, experimental settings and extensive experimental results. The conclusions are presented in Section 7.

Preprocessing Techniques
Contourlet transform [12] is a new image representation scheme which owns a powerful ability to efficiently capture the smooth contours of images. Contourlet based preprocessing techniques are employed to mitigate the facial variation effects. This transform consists of two main steps as Laplacian Pyramid decomposing and Directional Filter Banks. The original image is decomposed to a low pass image and a band pass image by LP decomposing. Each bandpass image is further decomposed by DFB. Repeating the same steps upon the low pass image, the multiscale and multi direction decomposition of the image is obtained. Figure 2 shows the single level Contourlet transform of an image.



(a) (b)

Figure 2: Contourlet decomposition (a) Input image (b) Single level decomposition of an image

GLDTP Texture Descriptor
One of the main goals of texture analysis is to provide a robust mathematical description of the spatial behavior of intensity values in any given neighborhood. These local distributions called textures, characterize object surfaces and are used for pattern identification and recognition of images. A face image can be viewed as a texture pattern exhibiting symmetry and regularity. A texture descriptor can characterize an image as a whole as in Gray Level Co-occurrence Matrix (GLCM) or it can also be characterized by local texture descriptor at micro level and through histogram of occurrence frequency of such local descriptors at the macro level. The global description of the image is obtained by constructing the one dimensional histogram in which abscissa indicates the number of the texture patterns and ordinate indicates the occurrence frequency of such patterns.

The proposed descriptor is applied over a small local region of size 5×5 in the image and local texture pattern value which corresponds to that region will be calculated. This proposed descriptor reveals second order local derivative information by encoding the various distinctive spatial relationships contained in the local region. Given, local region I (Z) as shown in Fig 3(a), I represents the gray value of the pixel at position Z. Let Z_0 be a center point and Z_i, i=1, 2, 3…8 be the neighboring pixels around Z_0. The first order derivative is defined as the absolute difference between a pixel and its immediate neighbor in the right side. For example, the first order derivative Y_0 is given as,

$$Y_0 = |I(Z_0) - I(Z_4)| \qquad (1)$$

In a similar manner, the first order derivatives can be determined for all the neighbors of Z_0. The second order derivative of the center pixel is computed between the first order derivative of center pixel and first order derivatives of all other pixels in its eight neighborhoods. The second order derivatives are calculated as,

$$B_i = f(Y_0, Y_i) \qquad , i = 1,2...8 \qquad (2)$$

The ternary coding function is defined as,

$$f(Y_0, Y_i) = \begin{cases} 0 \ , Y_i \le (Y_0 - T) \\ +1 \ , (Y_0 - T) < Y_i < (Y_0 + T) \\ -1 \ , Y_i > (Y_0 - T) \end{cases} \qquad (3)$$

In Eqn.(3),the threshold value (T) is empirically evaluated. The GLDTP for the pixel Z_0 is computed as follows.

$$GLDTP(Y_o)^+ = \sum_{i=1}^{8} B_i * 2^i \qquad where\, B_i \in 0\, or +1 \qquad (4)$$

$$GLDTP(Y_o)^- = \sum_{i=1}^{8} B_i * 2^i \qquad where\, B_i \in -1 \qquad (5)$$

GLDTP $(Y_0)^+$ and GLDTP $(Y_0)^-$ will be the two values that characterize the textures of the pixel Z_0. Equivalent decimal value is computed for both positive and negative codes and subsequently treating them as two separate channels of local descriptors for which separate histograms and similarity metrics are computed. The computation of GLDTP is illustrated in Figure 4.

$I(Z_{20})$	$I(Z_{21})$	$I(Z_{22})$	$I(Z_{23})$	$I(Z_{24})$
$I(Z_{19})$	$I(Z_{1})$	$I(Z_{2})$	$I(Z_{3})$	$I(Z_{9})$
$I(Z_{18})$	$I(Z_{8})$	$I(Z_{0})$	$I(Z_{4})$	$I(Z_{10})$
$I(Z_{17})$	$I(Z_{7})$	$I(Z_{6})$	$I(Z_{5})$	$I(Z_{11})$
$I(Z_{16})$	$I(Z_{15})$	$I(Z_{14})$	$I(Z_{13})$	$I(Z_{12})$

(a)

Y_{20}	Y_{21}	Y_{22}	Y_{23}	Y_{24}
Y_{19}	Y_{1}	Y_{2}	Y_{3}	Y_{9}
Y_{18}	Y_{8}	Y_{0}	Y_{4}	Y_{10}
Y_{17}	Y_{7}	Y_{6}	Y_{5}	Y_{11}
Y_{16}	Y_{15}	Y_{14}	Y_{13}	Y_{12}

(b)

Figure 3: (a) Local Region (b) First Order Derivatives

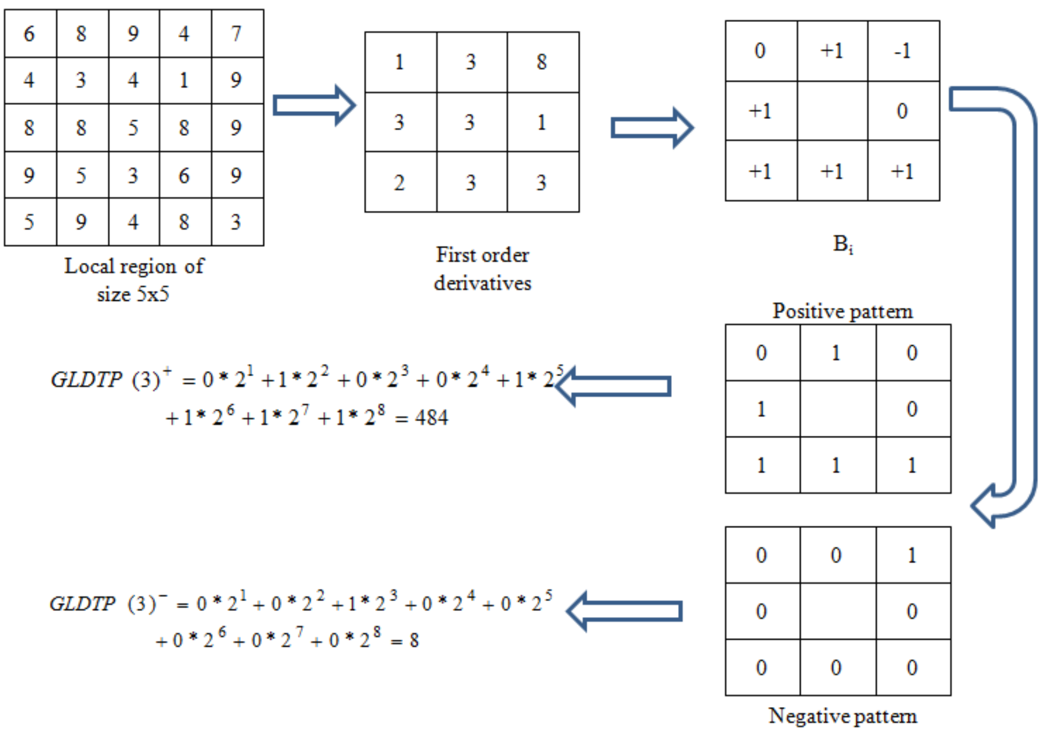


Figure 4: Computation of GLDTP from a Local Region

Distance Measures

An important problem in computer vision is measuring the dissimilarity between distributions of texture features of training and testing samples. When the training and testing features are represented either in one dimensional or two dimensional histograms then distance metric can be employed to find the similarity and dissimilarity between the samples. Distance metrics considered in this paper are G-Statistics, Euclidean Distance, Manhattan, Chi-square, Minkowski and Bhattacharya.

G- Statistics Distance measure

In classification, the dissimilarity between a training samples and a testing samples are measured by a nonparametric statistical measure and is given by,

$$D = 2\left[\begin{array}{l}\left[\sum_{s,m}\sum_{i=1}^{n} f_i \log f_i\right] - \left[\sum_{s,m}\left(\sum_{i=1}^{n} f_i\right)\log\left(\sum_{i=1}^{n} f_i\right)\right] \\ -\left[\sum_{i=1}^{n}\left(\sum_{s,m} f_i\right)\log\left(\sum_{s,m} f_i\right)\right] + \left[\left(\sum_{s,m}\sum_{i=1}^{n} f_i\right)\log\left(\sum_{s,m}\sum_{i=1}^{n} f_i\right)\right]\end{array}\right] \tag{6}$$

where‘s’ is the histogram of the test sample, ‘m’ is the histogram of the training sample, ‘n’ is the total number of bins in a histogram and ‘fi’ is the frequency at bin ‘i’.

Euclidean Distance

It was often called Pythagorean metric since it is derived from the Pythagorean Theorem. The distance between training and testing samples in Euclidean space generally means the shortest distance between them. If ‘s’ and ‘m’ are histograms of the test and training samples and ‘n’ is the number of bins, then Eqn.(7) is used for finding Euclidean distance.

$$D = |s - m| = \sqrt{\sum_{i=1}^{n} |s_i - m_i|^2} \tag{7}$$

Manhattan Distance Metric

The Manhattan distance between two histograms is the sum of the differences of their corresponding components and is defined as,

$$D = \sum_{i=1}^{n} |s_i - m_i| \tag{8}$$

Where‘s’ and ‘m’ are the histograms of testing and training samples.

Chi-Square Distance Metric

The chi-squared distance between training and testing histograms are defined as,

$$D = \frac{1}{2}\sum_{i} \frac{(s_i - m_i)^2}{(s_i + m_i)} \tag{9}$$

Minkowski Distance Metric

Minkowski distance is defined as the generalized distance between two histograms. Minkowski distance of order p (p-norm distance) is defined as,

$$D = \left(\sum_{i=1}^{n} |s_i - m_i|^p\right)^{\frac{1}{p}} \tag{10}$$

When p=1, the performance of Minkowski distance is equal to the performance of Manhattan distance. P may vary from 1 to ∞.

Bhattacharya Distance metric

Bhattacharyya distance measure can be used to evaluate the degree of similarity between two histograms as follows. Let s_i to the frequency coded quantity in bin i for the test sample histogram and m_i a similar quantity for the training sample histogram. Then, Bhattacharya distance measure is given by.

$$D = -\ln\left(\sum_{i=n}\sqrt{s_i m_i}\right) \tag{11}$$

Face Recognition Algorithm

Nearest Neighbor algorithm is used for face recognition. It consists of two phases namely training phase and testing phase.

Training Phase

1. For all the training images repeat the steps 2 to 7.
2. Apply the Contourlet transform over the image.
3. Divide the image into non overlapping sub region of N×N.
4. Apply GLDTP over each sub region using a 5×5 sliding window and compute GLDTP $(.^{+})$ and GLDTP $(.^{-})$ for the center pixel value of the sliding window.
5. For each region, construct two dimensional histograms of GLDTP positive and negative values computed in step no.4.
6. Concatenate the histograms separately for all the regions to get global description of the image.
7. Store this training feature in the database.

Testing Phase

1. Steps 2 to 6 of training phase are applied to extract testing feature of the image.
2. Find the similarity between testing and training features stored in the database using any one of the distance metric described in this paper.
3. Choose the nearest neighbor as correct match for the corresponding training image.

Experiments and Performance Evaluation

Experimental Setup and Performance Metric

In order to demonstrate the strength of the proposed descriptor, an extensive experimental investigation is carried out covering face recognition under all challenges. Level4 Contoutlet transform is used for preprocessing. At this level, it can capture edge information in more detail. In Eqn.(3), the threshold (T) is experimentally evaluated and set to 2 for all the experiments in this paper. Minkowski distance of order 3 is used in this paper.

The following performance metrics are used to show the effectiveness of the proposed technique. Recognition rate (RR) is defined as,

$$RR = \frac{Number\ of\ correct\ images}{Number\ of\ test\ images} * 100 \tag{12}$$

The Average Recognition Rate (ARR) of N databases are calculated by,

$$ARR = \frac{\sum_{i=1}^{N} \mathrm{Re}cognition\ \ rate\ of\ \ database\ \ i}{N} \tag{13}$$

$$\mathrm{Pr}ecision = \frac{True\ Positive}{(True\ Positive + False\ Positive)} \tag{14}$$

$$\mathrm{Re}call = \frac{True\ \ Positive}{(True\ \ Positive + True\ \ Negative)} \tag{15}$$

True Positive signifies that case was positive and predicted as positive, True Negative means that case was negative and predicted also negative and False Positive means case was negative but predicted as positive. Precision is the average probability of relevant retrieval. Recall is the average probability of complete retrieval. The higher value of precision and recall indicates the better performance of the system.

Database Description

JAFFE

JAFFE database [13] consists of images of 10 subjects and each subject has seven types of facial expressions: angry, disgust, fear, happy, neutral, sadness, and surprise. There are three samples corresponding to each facial expression of each subject. The original images having the size 256x256 are registered using eye coordinates and resized to 120x120. Normal face recognition and face expression recognition experiments were carried out by using this database. Figure 4 shows the sample images from the database.

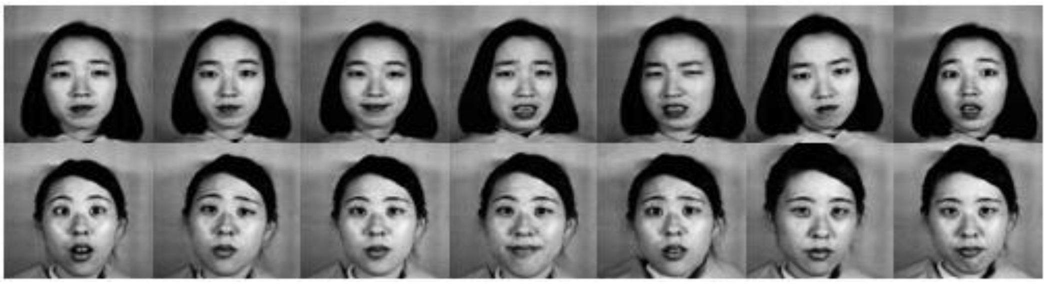


Figure 4: Sample Images From JAFFE Database For Facial Expression

ORL

The ORL database [14] contains a set of face images taken between 1992 and 1994 at the Ollivetti Research Laboratory in Cambridge. It contains 400 images of 40 subjects. Some images were captured at different times and have different variations including expression, lighting and facial details. The images were taken with a tolerance for some tilting and rotation of the face images up to 20 degrees, and the image size is 92x112 pixels. These images are used to validate the performance of the proposed technique under expression and pose variation conditions.Figure 5 shows sample images of two subjects and each subject has ten images.

Figure 5: Sample Images From ORL Database For Pose and Expression Variations

YALE B

The YALE B [15] face database contains 5760 single light source images of 10 subjects each seen under 576 viewing conditions (9 poses x 64 illumination conditions). For every subject in a particular pose, an image with ambient illumination was also captured. Hence, the total number of images is in fact 5760+90=5850. Table 1 illustrates the database description and Figure 6 shows the sample images from the database. An illumination invariant property of the proposed technique is examined by using this dtaabase.

Table 1: Database Description

Subsets	1	2	3	4	5
Lighting Angle (in degrees)	0~12	12~25	26~50	51~75	76~100
No. of images	70	120	120	120	120

Subset 1

Subset 2

Subset 3

Subset 4

Subset 5

Figure 6: Sample Image From Yale Database With Illumination Variation

Experimental Evaluation and Analysis

Results on normal face recognition

This experiment calculates the performance of GLDTP for normal face recognition. The normal faces are the frontal images with average illumination and neutral facial expressions. N fold cross validation principle is used for classification. JAFFE and ORL databases were divided into ten folds, taking 20 images of a person in a fold. From each fold, 40% of the images were used for training and 60% for testing. The subjects represented in the training set were not included in the testing set of images, thus ensuring a person–independent classification of facial expressions. Each test was performed three times and an average was calculated. The performance of GLDTP is experimented with various distance measure and the results are tabulated in Table.2.

Table 2: Recognition Rate For Normal Faces With Different Databases

Data-base	Recognition Rate (%)						
	GLDTP with various Distance measure						Contourlet based GLDTP with G statistics
	G Statistics	Euclidian	Manhattan	Chi-square	Minkowski	Bhattacharya	
JAFFE	94	86	89	92	88	92	98
ORL	95	87	90	91	90	91	98.5

From the experimental results, it is concluded that the GLDTP with G statistics distance measure provides better results than the other distance measure tested along with it. It extracts micro detail information of face images and provides signifcantly better results for face recognition. In the next experiment, GLDTP is preprocessed by Contourlet and the performance is evaluated using G statistics. The results shows the improvement in recognition rate. It indicates the significance of preprocessing. Hence, Contourlet based GLDTP is used as the proposed technique for all experiments.

Results on Illumination Variation

Illumination is one of the basic characteristics of a visible surface and it provides information for scene interpretation. The appearance of face image is severely affected by illumination condition that will hinder the performance of face recognition. A reliable face recognition algorithm should be able to process face images under various lighting and shading conditions [16]. To prove the illuminant invariant property of the proposed technique, an experimented is conducted with different distance measure and the results are exhibited in Figure 7.

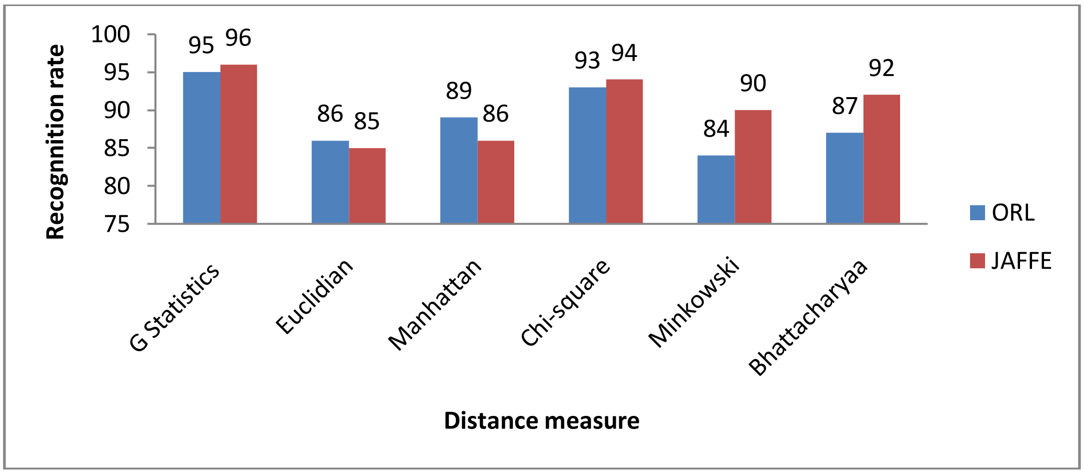


Figure 7: Recognition Rate With Different Distance Measure

From the results, it is concluded that G-statistic distance measure yields better recognition rate under face images of different illumination conditions. Euclidian distance measure gives poor results compared to other metrics.

The direction of camera position is considered as one of the major factor affecting the recognition rate. The face images are divided into five subsets according to the angle between the light source direction and the camera axis. From Fig 4, subset 1 is used as training set and other subsets are used for testing. Table 3 presents the recitation results of proposed technique with G-statistic as the distance metric.

Table 3: Recognition Rate of face images under different illumination conditions using proposed technique with G-statistic distance metric

Technique	Recognition Rate (%)			
	Subset 2	Subset 3	Subset 4	Subset 5
Contourlet based GLDTP with G-statistic distance metric	98	92	90	85

From Table 3, it is observed that the proposed technique provides better results for subset2. The recognition rate gradually decreases when the camera angle is increased from 0° to 100°. The direction of light source induces very large changes in face appearance. Hence face features are not simultaneously and accurately aligned, which dramatically affects the performance of face recognition system.

Results on Expression Variation

Expression variation is another problem that plays a predominant role in face recognition. Adjoining of dynamic expression in face causes a broad range of discrepancies in recognition systems. The proposed technique is experimented with well known distance metrics and the results are presented in Table 4.

Table 4: Recognition Rate of Face Images Under Different Expression With Various Distance Metrics

Proposed Technique	Distance measure	Images used		Performance metric				
		Total Images	No of correct images	True Positives (TP)	True Negatives (TN)	False Positives (FP)	Precision (TP/(TP+FP))	Recall (TP/(TP+TN))
Contourlet based GLDTP	G Statistics	150	143	136	7	14	0.91	0.95
	Euclidian	150	130	121	9	29	0.81	0.93
	Manhattan	150	135	125	10	25	0.83	0.93
	Chi-square	150	145	140	5	10	0.93	0.97
	Minkowski	150	136	123	13	27	0.82	0.90
	Bhattacharya	150	142	136	6	14	0.91	0.96

From the results, it is observed that precision and recall values are high for the proposed technique with chi-square.

One more experiment is conducted for the proposed approach with different distance measure by varying the number of training and testing samples. The number of training images per subject is varied as 1, 5 and 10 whereas the testing image is kept as 12, none of the training and testing image is overlapped. The results are tabulated in Figure 8.

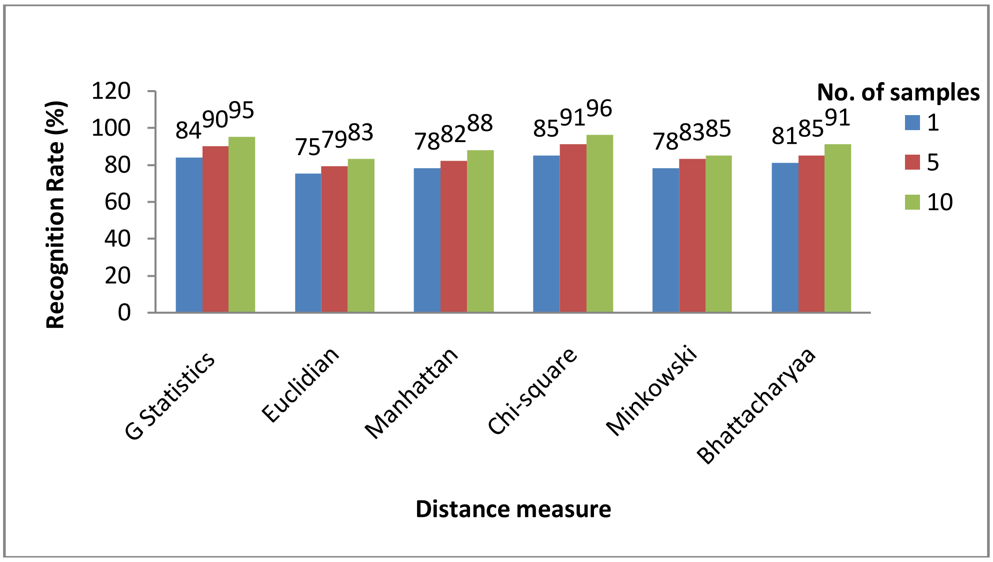


Figure 8: Recognition Rate of Face Images Under Different Expression With Different Number of Training Images

From the results, it is observed that the performance of the proposed techniques gradually increases with the increase in number of training images per subjects. In this case also chi-square performs better than others.

Results on Pose Variation

Multiview face recognition is a challenging task of deformable pattern recognition.In real world applications, the image will be collected at various rotation angles of camera direction. It changes the facial features of an image. In the present work, the effect of variation of poses on the overall performance of face recognition is investigated by the proposed approach with different distance measures. The rotation angle is varied from 0º to ± 25º and the average is considered. The results of this experiment are presented in Table 5.

From the tabulated results, it is concluded that G-statistic distance metrics yield better results at 0° and the recognition rate progressively decreases when the angle increased from 0º to ± 25º. It is due to the facts that, the appearance of a face can vary drastically if the intensity or the direction of the light source changes.

Table 5: Recognition Rate of Face Images Under Different Poses With Various Distance Metrics

Rotation angle (in degrees)	Recognition Rate (%)					
	Contourlet based GLDTP with various distance metric					
	G Statistics	Euclidian	Manhattan	Chi-square	Minkowski	Bhattacharya
-25	94	75	85	91	81	86
-20	95	77	86	93	82	86
-15	96	78	86	94	85	87
-10	96.5	79	87	95.5	88	89
-5	97	83	89	97	88	91
0	98	86	90	97	89	93
5	97	82	89	96	88	90
10	96.5	80	86	96	87	89
15	96	78	85	95	84	87
20	95	76	84	94	83	84
25	95	74	83	92	81	86
Average Recognition Rate	96	79	86	95	85	88

Conclusion and Future Enhancement

In this paper, a novel and efficient local texture descriptor GLDTP is proposed for face recognition. Face recognition experiments under (1) controlled/ideal condition, (2) varying lighting condition (3) facial expression (4) pose variation have been systematically performed. Contourlet based preprocessing is used to diminish the facial variation effects. The proposed descriptor is experimented with various distance metric such as G- Statistics, Euclidean, Manhattan, Chi-square, Minkowski and Bhattacharya.

The proposed approach with G-statistics distance yield 98.5% recognition for normal face recognition. It also gives 96% recognition rate for illumination variations and pose variation conditions. The proposed approach with Chi-square provides 95% for facial expression. In general, the proposed technique with G-statistics distance enhances the performance of face recognition.

For future work, the proposed method can be used for texture synthesis, texture classification, segmentation and other texture based application like Content Based Image Retrieval (CBIR), Classification of remotely sensed images and medical images. GLDTP can also be extended for gender classification and age varying problem. The performance of GLDTP can be improved by incorporating neural network for classification.

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