FACE RECOGNITION BASED ON LOCAL DERIVATIVE TETRA PATTERN

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Abstract

This paper proposes a new face recognition algorithm called local derivative tetra pattern (LDTrP). The new technique LDTrP is used to alleviate the face recognition rate under real-time challenges. Local derivative pattern (LDP) is a directional feature extraction method to encode directional pattern features based on local derivative variations. The nth -order LDP is proposed to encode the first (n-1)th order local derivative direction variations. The LDP templates extract high-order local information by encoding various distinctive spatial relationships contained in a given local region. The local tetra pattern (LTrP) encodes the relationship between the reference pixel and its neighbours by using the first-order derivatives in vertical and horizontal directions. LTrP extracts values which are based on the distribution of edges which are coded using four directions. The LDTrP combines the higher order directional feature from both LDP and LTrP. Experimental results on ORL and JAFFE database show that the performance of LDTrP is consistently better than LBP, LTP and LDP for face identification under various conditions. The performance of the proposed method is measured in terms of recognition rate.

Keywords:

Local Binary Pattern (LBP), Local Ternary Pattern (LTP), Local Derivative Pattern (LDP), Local Tetra Pattern (LTrP)

1. INTRODUCTION

In recent years, face recognition plays an important role in intensive research. With the current discerned world security situation, governments as well as private require reliable methods to accurately identify individuals, without overly contravene on rights to privacy or requiring significant compliance on the part of the individual being recognized. Face recognition extends an acceptable solution to this problem. A number of techniques have been applied to face recognition and they can be divided into two categories 1) Geometric feature matching and 2) Template matching. Geometric feature matching [1][5][6] involves segmenting the different features of the face: eyes, nose, mouth, etc. and extracting illustrative information about them such as their widths and heights. Values of these measures can then be stored for each person and it can be compared with those of the known individuals. Template matching is a non-segmentation approach to recognize the face. Each face is treated as a two dimensional array of intensity values, which is then compared with other face's intensity arrays. Earliest methods treated faces as points in very high dimensional space and then the Euclidean distance between them is calculated. Dimensional reduction techniques including Principal Component Analysis (PCA) [2][3] have now been successfully applied to the problem, hence reducing complexity of the recognition process without negatively infringing on accuracy.

Nowadays different patterns are used for feature extraction. The Local Binary Pattern (LBP) is designed to encode the relationship between the referenced pixel and its surrounding pixels [17]. LBP is applied successfully to all facial expression analysis. Its performance is much better than Eigen face. LBP produces micro patterns. The center pixel is subtracted from the eight neighbouring pixels. Assign 0 for negative values and assign 1 for the positive values. These micro patterns are constructed by combining eight neighbouring bits clockwise. Due to the simplicity and robustness, it has been widely used in face recognition [13][14]. However this LBP can fail in some situations.

In order to avoid such situation, the Local Tetra Pattern (LTP) was introduced to capture more detailed information than LBP. LTP is an extension of LBP. LTP is less sensitive to noise than LBP as well as small pixel difference is encoded into a separate state. To reduce its dimensionality, the ternary code constructed by LTP is split into two binary codes: a positive LBP and a negative LBP [14]. A threshold value is added with the center pixel (u) and is subtracted from the center pixel(l) and generate a boundary [l,u]. Assign -1, if the neighbouring pixel is lesser than l, assign 1 if the neighbouring pixel is greater than u and assign 0 if it is lies between l and u [13]. This ternary code is split into two. Assigns 0 to -1's to construct higher bit pattern. Assign 1 to -1's to construct lower bit pattern and construct higher and higher bit pattern. LTP only encodes the texture features of an image depending on the grey level difference between center pixel and its neighbours, which are coded using two directions.

Local tetra pattern (LTrP) is an extension of LBP and LTP. It is able to extract more detailed information than LBP and LTP. The LTrP encodes the relationship between the center pixel and its neighbours by using the first-order derivatives in vertical and horizontal directions not like LTP. Local tetra pattern (LTrP) extracts information based on the distribution of edges which are coded using four directions (1,2,3,4). LTrP encodes the relationship depends on the direction of the center pixel and its neighbours, which are calculated by combining (n-1)th - order derivatives of the 0 degree and 90 degree directions.

Local Derivative Pattern was proposed by Baochang Zhang [4] for face recognition with high order local pattern descriptor. It encodes directional bit pattern based on local derivative variations. It can capture more detailed information including different angles than the first order LBP. LDP is a micro pattern representation which can also be modeled by histogram. Histogram is used to preserve the information about the distribution of the LDP micro patterns [6]. LBP is always considered first-order local pattern operator, because LBP encodes all-direction first-order derivative binary result whereas LDP encodes directional higher-order derivative information. So it extracts more distinctive features than LBP.

This paper proposes the new method Local derivative tetra pattern (LDTrP). Which combines the feature directional and neighbouring patterns from both LDP and LTrP. LBP can only be considered as a non-directional 8-neighbour pattern. LTP is also a non-directional pattern. The turning point in the LTrp and LDP is the direction and n-order derivations. The proposed LDTrP is a micro pattern which can also be modeled by histogram.

The rest of this paper is organized as follows. Section 2 introduces and discusses various feature extraction methodologies. In section 3 explains the proposed method in detail. Section 4 discusses the histogram intersection. In section 5 an extensive experiments over JAFFE and ORL databases are conducted to evaluate the performance of the proposed method on face recognition. Finally, conclusion and future work is drawn in section 6 with some discussions.

2. METHODOLOGIES

The popular methods designed for feature extraction are Local Binary Patterns, Local Ternary Patterns, Local Derivative Pattern and Local Tetra Pattern.

2.1 DIFFERENT PATTERNS USED TO EXTRACT TEXTURE FEATURE

Texture is an image feature that describes about the structural arrangement of the surface. It defines the surface properties of an object and their relationship to the neighbouring environment. Although several algorithms are available, LBP follows a simple algorithm where as LTP is more resistant to noise and small pixel variations. However, LDP extracts higher order information by encoding various spatial relationships contained in a given local region. The LTrP check the relationship between the reference pixel and its neighbours in both vertical and horizontal directions. These methods are summarized in the following section.

2.1.1 Local Binary Pattern (LBP):

The standard local binary pattern (LBP) searches the relationship between the referenced pixel and its surrounding 8-neighbours and then calculates the gray-level difference.

LBP is a grayscale invariant texture measure and is a useful tool to model texture images. In LBP, it labels the pixels of an image by thresholding the 3×3 neighbourhood of each pixel with the value of central pixel and concatenating the bits from top left. The thresholding function for $f(\cdot,\cdot)$ for the basic LBP can be represented by Eq.(1).

$$f\left(I\left(N_0\right),I\left(N_i\right)\right)=\begin{cases}0 & \text{if } I\left(N_0\right)-I\left(N_i\right)\le \text{threshold}\\ 1 & \text{if } I\left(N_0\right)-I\left(N_i\right)> \text{threshold}\end{cases} \tag{1}$$

where, N_i, i = 1,2,...8 is an eight neighbourhood point around N_0 is shown in Fig.1. Concatenation of the binary gradient direction is called a micro pattern. The Fig.2 shows LBP micro pattern, when the threshold is set to zero.

N_1	N_2	N_3
N_8	N_0	N_4
N_7	N_6	N_5

Fig.1. Eight neighbourhoods around N_0

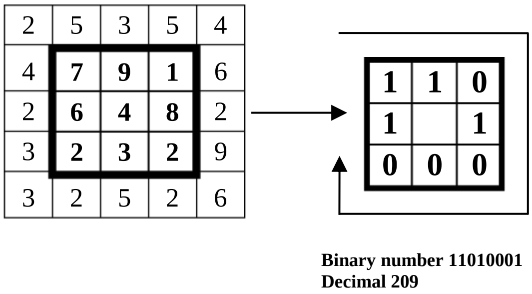

Fig.2. Micropattern obtained from the black square

2.1.2 Local Ternary Pattern (LTP):

Local Ternary Pattern is an advanced version of LBP. It has three-valued code with relation to grey values of its neighbours [15]. Unlike LBP, it does not threshold the pixels into 0 and 1, but it uses a threshold constant to threshold pixels into three values 1, 0 and -1. As shown in Fig.3 considering t as the threshold constant, N_0 as the value of the center pixel and the value of the neighbouring pixels N_i, i = 1,2,..8. The result of the thresholding function for $f(\cdot,\cdot)$ for the basic LTP can be represented in Eq.(2):

$$f\begin{pmatrix}I\left(N_0\right),\\ I\left(N_i\right)\end{pmatrix}=\begin{cases}1 & \text{if } I\left(N_i\right)>I\left(N_0\right)+t\\ 0 & \text{if } I\left(N_i\right)\ge I\left(N_0\right)-\text{t} \;\&\; I\left(N_i\right)\le I\left(N_0\right)+\text{t}\\ -1 & \text{if } I\left(N_i\right)<I\left(N_0\right)-t\end{cases}$$

N_6	N_7	N_8
N_5	N_0	N_1
N_4	N_3	N_2

Fig.3. Eight – Neighbourhood around N_0

Assign 0 in a cell when the pixel value is between N_0-t and N_0 + t, where N_0 is the center intensity of the pixel. Therefore, because the intensity is 45 in the centre of this window, the range is between [40, 50], where value of t is 5. Any cells that are above 50 get assigned 1 and any cells that are below 40 get assigned -1. Once construct the ternary code [13], and then split up the code into higher and lower patterns. Basically, any values that get assigned a -1 get assigned 0 for higher patterns and any values that get assigned a -1 get assigned 1 for lower patterns. The Fig.4 shows local ternary pattern, when the threshold is set to 5. Also, for the lower pattern, any value of the cell that is 1 in the original window gets mapped to 0. The final bit pattern starts from the second row third column, then going around anti-clockwise. Therefore, when this modification is made the gives both lower patterns and higher patterns as output to the given image.

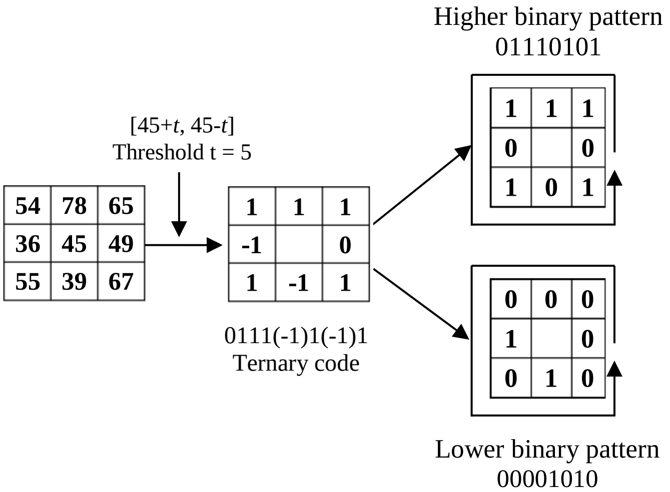

Fig.4. Steps to obtain ternary pattern

2.1.3 *Local Derivative Pattern (LDP):*

LDP creates the higher-order derivative information. LBP and LDP consider only the center pixels 8-neighbours but, it considers directional neighbours in 4 degrees. So, it captures more discriminative features than LBP [4]. Given an image, the first-order derivatives along 0°, 45°, 90° and 135°. Directions are denoted as $I'_{\alpha}(N)$ where, α = 0°, 45°, 90° and 135°. Let N_0 be a point in $I(N)$, and N_i, i = 1,..,8 be the neighboring point around N_0 (Fig.1). The four first-order derivatives at $N = N_0$ can be written as,

$$\begin{aligned} I'_{0}\cdot(N_0) &= I(N_0) - I(N_4) \\ I'_{45}\cdot(N_0) &= I(N_0) - I(N_3) \\ I'_{90}\cdot(N_0) &= I(N_0) - I(N_2) \\ I'_{135}\cdot(N_0) &= I(N_0) - I(N_1) \end{aligned}$$

The second order derivative in α direction at $N = N_0$ can be defined as:

$$LDP_{\alpha}^{2}(N_0) = \left\{ \begin{array}{l} f\left(I'_{\alpha}(N_0), I'_{\alpha}(N_1)\right), \\ f\left(I'_{\alpha}(N_0), I'_{\alpha}(N_2)\right), ..., \\ f\left(I'_{\alpha}(N_0), I'_{\alpha}(N_8)\right) \end{array} \right\} \tag{2}$$

where, $f\left(I'_{\alpha}(N_0), I'_{\alpha}(N_i)\right)$ is a binary coding function. It encodes the co-occurrence of two derivative directions at different neighbouring pixels as:

$$f\left(I'_{\alpha}(N_0), I'_{\alpha}(N_i)\right) = \begin{cases} 0 \text{ if } I'_{\alpha}(N_i), I'_{\alpha}(N_0) > 0 \\ 1 \text{ if } I'_{\alpha}(N_i), I'_{\alpha}(N_0) \leq 0 \end{cases} \tag{3}$$

Finally, the second-order Local Derivative Pattern, LDP^2(N), is defined as the concatenation of four 8-bit directional LDPs.

$$LDP^2(N) = \left\{ LDP_{\alpha}^{2}(N) \mid \alpha = 0^{\circ}, 45^{\circ}, 90^{\circ}, 135^{\circ} \right\} \tag{4}$$

The LDP operator labels the pixels of an image by comparing two derivative directions at neighbouring pixels and concatenates the transition result as a 32 bit binary string.

2.1.4 *Local Tetra Pattern (LTrP):*

The LBP, LDP, and LTP extract the texture features of an image based on the distribution of edges, which are coded using only two directions. The possible directions may be either positive or negative direction. It is clear that the performance of these methods can be improved by differentiating the edges in more than two directions. So, the local tetra patterns (LTrPs) are used to encode information based on the four directions [8][9].

The idea of LTrP is based on local patterns described in LBP, LTP & LDP. The LTrP are the spatial structure of the local texture using the direction of the center gray pixel [10][11]. Consider an image I, the first-order derivatives along 0° and 90° directions are denoted as:

$$\left. \begin{array}{l} I_{0^{\circ}}^{1} = I(n_h - n_c) \\ I_{90^{\circ}}^{1} = I(n_v - n_c) \end{array} \right\} \tag{5}$$

where, n_h and n_v denotes the horizontal and vertical neighbourhoods of the central pixel n_c. The direction of the central pixel can be calculated as:

$$I_{Dir}^{1}(n_c) = \begin{cases} 1 & I_{0^{\circ}}^{1}(n_c) \geq 0 \text{ and } I_{90^{\circ}}^{1}(n_c) \geq 0 \\ 2 & I_{0^{\circ}}^{1}(n_c) < 0 \text{ and } I_{90^{\circ}}^{1}(n_c) \geq 0 \\ 3 & I_{0^{\circ}}^{1}(n_c) < 0 \text{ and } I_{90^{\circ}}^{1}(n_c) < 0 \\ 4 & I_{0^{\circ}}^{1}(n_c) \geq 0 \text{ and } I_{90^{\circ}}^{1}(n_c) < 0 \end{cases} \tag{6}$$

Depending on first order derivatives the above equation produces four directions. The values of the four directions are 1,2,3,4. Finally the image is converted into image four values.

$$LTrP^2(n_c) = \left\{ \begin{array}{l} f\left(I_{Dir}^{1}(n_c), I_{Dir}^{1}(n_1)\right), \\ f\left(I_{Dir}^{1}(n_c), I_{Dir}^{1}(n_2)\right), \\ f\left(I_{Dir}^{1}(n_c), I_{Dir}^{1}(n_3)\right), .., \\ f\left(I_{Dir}^{1}(n_c), I_{Dir}^{1}(n_p)\right), \end{array} \right\} \tag{7}$$

$$f\left(I_{Dir}^{1}(n_c), I_{Dir}^{1}(n_p)\right) = \begin{cases} 0 & \text{if } I_{Dir}^{1}(n_1) = I_{Dir}^{1}(n_p) \\ I_{Dir}^{1}(n_p) & \text{otherwise} \end{cases} \tag{8}$$

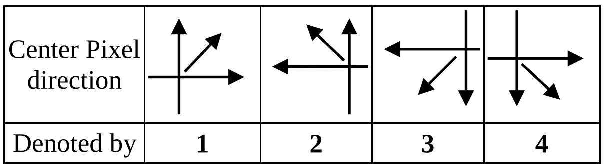

Fig.5. shows the LTrP estimates the four direction of bit pattern

The 8 bit tetra pattern is constructed from the Eq.(7) and Eq.(8). The Fig.7 shows the way of obtaining tetra bit pattern, where the center pixel's direction is 3. The way of combining center bit pattern 3 with the neighbouring is shown in Fig.6.

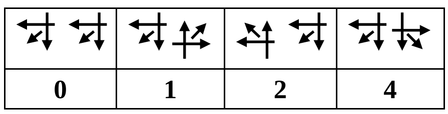

Fig.6. Tetra bit pattern calculation for the center pixel direction "3" using neighbour pixels direction

2	**3**	**3**	**5**	**8**
5	**7**	**9**	**4**	**1**
5	**6**	**7**	**8**	**9**
2	**3**	**4**	**6**	**5**
8	**6**	**7**	**4**	**5**

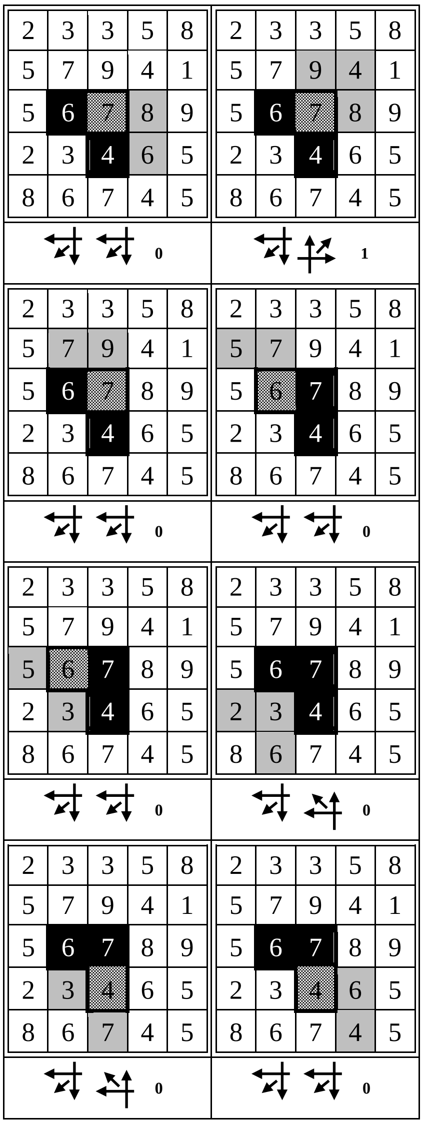

Fig.7. Tetra pattern obtained when the direction of center pixel=3

Check all the neighbouring pixels with direction of center pixel and generate the tetra bit using Fig.6. Finally the tetra bit pattern generated for center pixel's direction 3 is 01000220. If both the center and neighbouring pixel's direction are the same then the direction is 0. If not the final direction is the direction of the neighbouring pixel. In the example cited above, the direction of the second row first column is the same. Therefore the third tetra pattern is also 0. All the remaining are in different directions so it gets only to its neighbouring pixel's direction.

In the same way change the direction of center pixel into 1,2 and 4 and construct three more tetra patterns. If the direction of the center pixel is 1 then the tetra pattern generated is 42340002. When the direction of the center pixel is 2 then the LTrP can generate 31330000 bit pattern. The tetra pattern 02300113 is generated when the direction of the center pixel is 4.

3. PROPOSED METHOD

The proposed system combines the directional features of both LDP and LTrP. The LDTrp consider 900 direction from LDP and horizontal and vertical directional feature from the LTrP.

3.1 LOCAL DERIVATIVE TETRA PATTERN (LDTRP):

This section provides a brief review of the second-order local derivative pattern (LDP) to calculate the first-order derivative direction variation and the LTrP extract the texture features of an image based on the distribution of edges. After that, the definition and feasibility of the second-order LDP $I^1_{90^\circ}(Z_0)$, $I^1_{90^\circ}(Z_i)$ from Fig.5, where, LTrP are presented and discussed. Finally, the spatial histogram is described for modeling the distribution of LDP of a face.

LBP is incapable of describing more detailed information. LDP is a high-order local pattern for face representation. LBP is a no directional first-order local pattern operator, but LDP encodes the higher-order derivative information which contains more detailed features than the LBP. Local Derivative Pattern representation for face recognition, provide a strong discriminative capability in describing detailed texture information. The higher-order LDP can capture more detailed information. LDP encodes directive pattern features from local derivative variation. The main process of this method is that an LDP captures local features in four directions: 0°, 45°, 90° and 135°.

The goal of the proposed method is to match the most relevant images from the databases. In this paper, the LDP includes LTrP, and the Pattern generated which is used to retrieve feature from the images.

This proposed method considers only the 90°, because human face is vertically symmetrical (Fig.8). Given an image $I(N)$, first-order derivatives along 90° direction is denoted as $I^1_{90^\circ}(N)$. Let N_0 be a point in $I(N)$ and N_0, i = 1,2,...8 be the neighbouring point around N_0 (see Fig.1). The first order derivatives at $N = N_0$.

$$I^1_{90^\circ}(N_0) = I(N_0) - I^1_{90^\circ}(N_2) \tag{8}$$

The proposed LDP operator labels the pixels of an image by comparing two derivative directions at neighbouring pixels. The derivative direction defined in Eq.(8) is performed on 4 templates (Fig.9) reflecting various distinctive spatial relationships in a local region.

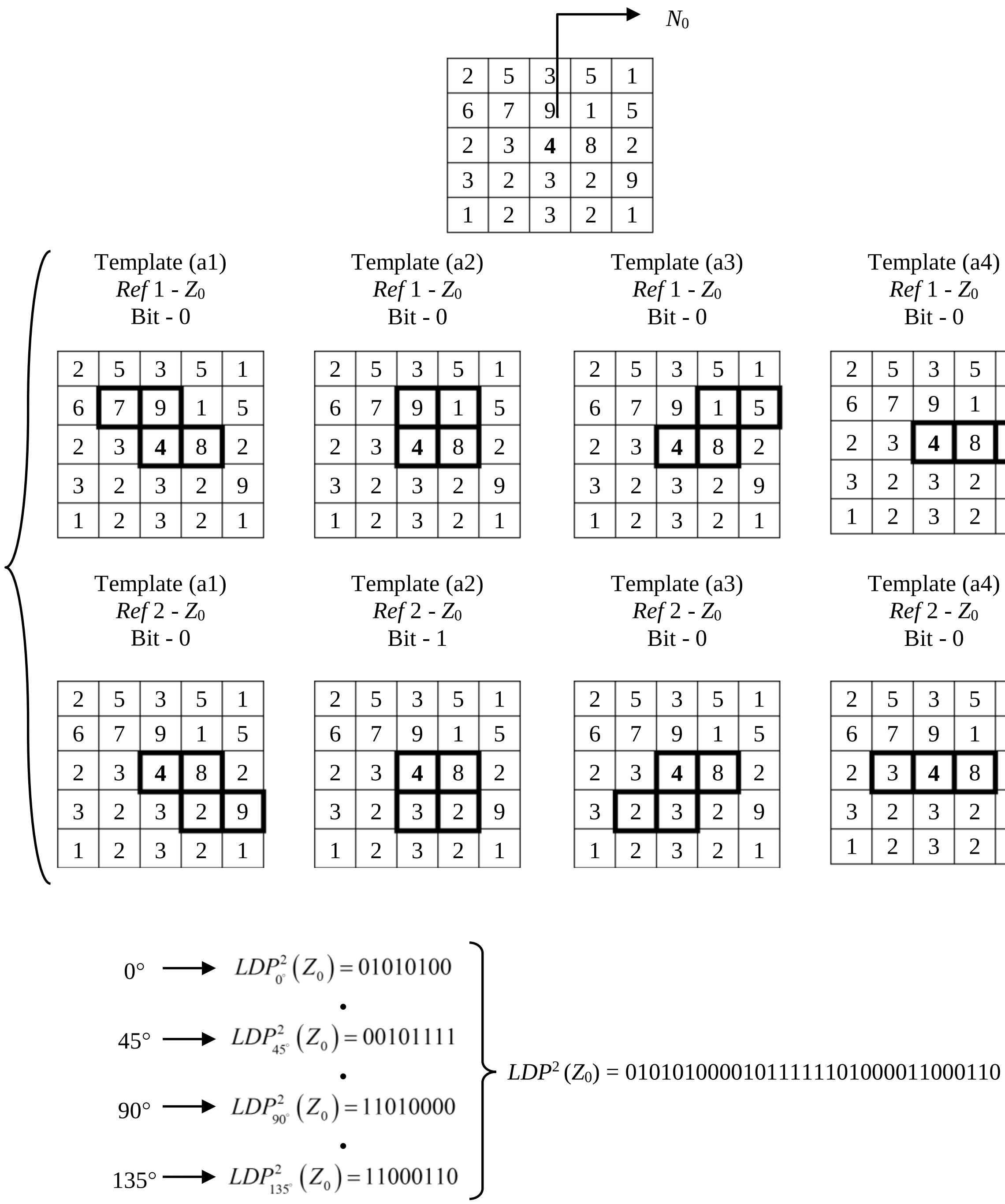

Fig.8. Steps to obtain second-order LDP Micropattern

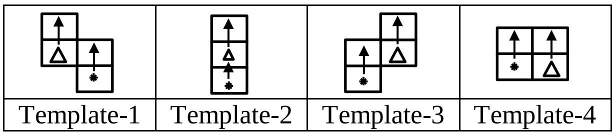

Fig.9. 4 templates for 4 various distinctive spatial relationships ref1 and ref2 are the reference points to be aligned to the point of N_0 with $\alpha = 90^\circ$, ref1 = * and ref2 = Δ

$$LDP^2_{90^\circ}(N_0) = \left\{ \begin{array}{l} f\left(I'_{90^\circ}(N), I'_{90^\circ}(N_1)\right), \\ f\left(I'_{90^\circ}(N_0), I'_{90^\circ}(N_2)\right), .., \\ f\left(I'_{90^\circ}(N_0), I'_{90^\circ}(N_F)\right), \end{array} \right\} \tag{9}$$

where f (s) is a coding function. It encodes the co-occurrence of two derivative directions at different neighbouring pixels as

$$\begin{array}{ll} f^1\left(I'_{90^\circ}(N_0), I'_{90^\circ}(N)\right) = \left(I'_{90^\circ}(N_0), I'_{90^\circ}(N_i)\right) & ref1 = N_0 \\ f^1\left(I'_{90^\circ}(N_0), I'_{90^\circ}(N)\right) = \left(I'_{90^\circ}(N_0), I'_{90^\circ}(N_i)\right) & ref2 = N_0 \end{array} \tag{10}$$

Unlike many existing face recognition systems, where conventional feature descriptors, such as local derivative patterns and Local Tetra Patterns (LTrP), are used for face recognition, where the LTrP extract the texture features of an image based on the distribution of edges, which are coded using only Eq.(10).

Consider an image I, the second-order derivatives along 90° direction denoted as f^1 and f^2 where, f^1 and f^2 are calculated from the first order derivatives at $N = N_0$ and $ref1 = N_0$ and $ref2 = N_0$ for all pixels in I. The direction of the center pixel can be formulated as:

$$f\left(N_0\right)=\begin{cases}1 & f^1 \geq 0 \text{ and } f^2 \geq 0\\ 2 & f^1 < 0 \text{ and } f^2 \geq 0\\ 3 & f^1 < 0 \text{ and } f^2 < 0\\ 4 & f^1 \geq 0 \text{ and } f^2 < 0\end{cases} \quad (11)$$

From Eq.(11) four possible directions are derived depending on the first order derivatives of all the center pixels. The possible values can be 1, 2, 3, or 4, and finally, the image is converted into four values, i.e., directions. In this paper, those patterns which have 1's, 2's, 3's, 4's are collected separately and set that bits only 1 and the remaining all are set into 0. Calculate their decimal equivalent. The Fig.10, demonstrates the LDTrP operator extracts detailed high-order information than the others.

4. HISTOGRAM INTERSECTION

In this paper LDP and LTrP methods are used for face recognition. The procedure to recognize face is, the second-order LDP is applied on each pixel to extract discriminative features from its neighbours. Model the distribution of higher-order LDP and LTrP by spatial histogram [1], [7] because it is more robust against variations in pose or illumination than other methods. Given a direction (90°), LDTrP is spatially divided into rectangular regions represented by $R_1, R_2,...,R_L$ from which spatial histograms are extracted, which can be denoted as HLDPLDTrP (i,α)

$$\text{HLDPLDTrP}(i,\alpha)= \{\text{H}_{LDPLTrP\ \alpha}\ (R_i)|\ i = 1,2,3,...,L\} \quad (12)$$

where, $\alpha = 90^{\circ}$

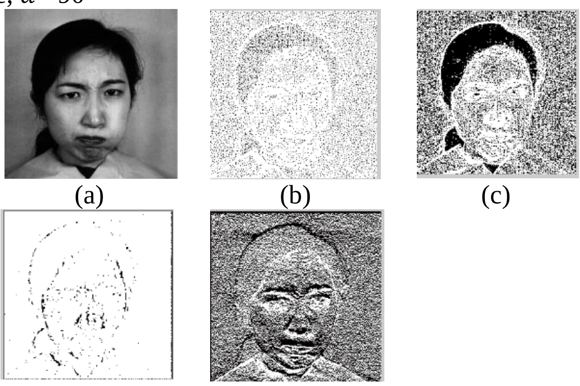

Fig.10. Visualization of LBP, LTP, LDP (in 0 degree) and LDTrP representations. (a) Original face image (b) LBP (c) LTP (d) The second-order LDP (e) The LDTrP

The LDTrP histogram feature extracted from the local region R_i is $\text{H}_{LDTrP\ \alpha}(R_i)$. Notice that region do not have any fixed shape. If the region selected is circle, then spatial histogram can be extracted from circular region with different radius. Many similarity measures for histogram matching have been proposed. In this paper histogram intersection is used to measure the similarity between two histograms.

$$S_{HI}\left(H,S\right)=\sum_{i=1}^{B}\min\left(H_i,S_i\right) \quad (13)$$

In this equation $S_{HI}(H,S)$ is the histogram intersection with $H = (H_1, H_2, H_3,...,H_A)^{\mathrm{T}}$ and $S = (S_1, S_2, S_3,...,S_A)^{\mathrm{T}}$. The Eq.(6) is used to calculate the similarity of the nearest neighbour classifier. This measure is a useful method for the calculation of common parts of two histograms. This is a very simple equation with simple operations.

5. EXPERIMENTAL ANALYSIS

The performance of the proposed system is computed by using the test images in the database. This section uses two databases (JAFFE and ORL) for testing purpose.

5.1 DATASET

This section conducts experiment on two data sets JAFFE and ORL. This experiment conducts comparative performance evaluations on all the forty subsets of the ORL database with expression, lighting and aging variations. Each subset contains ten faces. All the faces were cropped into 92×112 pixels. It can also conduct comparative performance evaluations on all the 10 subsets of the JAFFE database with expression, lighting and aging variations. Each subset of JAFFE dataset contains 13 faces. All the faces were resized into 256×256 pixels.

The goal of the proposed system is to detect the most relevant images from the database. In this paper, LDTrP includes the features of LTrP and LDP. This is used to retrieve features from the images. The query image and images in the database are compared by using histogram intersection for obtaining the same measurement and best matched images are retrieved from the database of images in response to query image. The database was retrieved from [9], [16] URLs as a ZIP file of same sizes. For the implementation, they should be converted into tiff files.

5.1.1 JAFFE Dataset:

The database contains 130 images of 7 facial expressions (6 basic facial expressions + 1 neutral) posed by 13 Japanese female models. The images are shown in Fig.11.

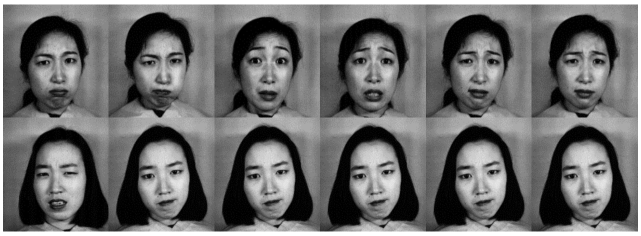

Fig.11. Images from JAFFE dataset

5.1.2 ORL Dataset:

There are ten different images of each of 40 different people. For some subjects, the images were taken at different times, varying the lighting, facial expressions (open, closed eyes, smiling or not smiling) and facial detail (glasses, no glasses). The Fig.12 shows some sample faces from ORL.

Fig.12. images from ORL dataset

5.2 PERFORMANCE METRICES

The performance of the proposed method can be evaluated by several performance metrics are available. This paper uses the Accuracy, Precision Rate, Recall Rate, F-Measure and error rate to analyses the performance.

where,

TP = True Positive

FP = False Positive

TP = True Positive

FP = False Negative

Prate = Precision rate

Rrate = Recall rate

Mathematically, this can be stated as:

The *Accuracy* of a test is its ability to differentiate the match and mismatch correctly. To estimate the accuracy of a test, we should calculated cases.

$$Accuracy = TP / \text{Number of files}$$

The *Precision* is the fraction of retrieved instances that are relevant to the find.

$$Precision = TP / (TP + FP)$$

The *Recall* is the fraction of relevant instances that are retrieved according to the query.

$$Recall = \mathrm{TP} / (\mathrm{TP} + \mathrm{FN})$$

F-measure is the ratio of product of precision and recall to the sum of precision and recall. The f-measure can be calculated as,

$$F\text{-}measure = (Prate \times Rrate) / (Prate + Rrate)$$

Calculating error used to compare an estimate to an exact value. The *Percentage Error* calculates the difference between the approximate and exact values as a percentage of the exact value.

$$Error\ rate = 1 - TP$$

Moreover comparison is also made regarding the performance between the proposed LDT'rP and LDP, LBP, LTP, LTrP approach using extensive variations in images in varying pose, and expression. LDTrP performs effectively under different performance measurements were conducted on the standard data set ORL and JAFFE.

Experimental result in Fig.13-Fig.17 demonstrate that the recognition accuracy, error rate, Precision Rate, Recall Rate, and F-Score were better in LDTrP when compared to LBP, LTP, LTrP and LDP.

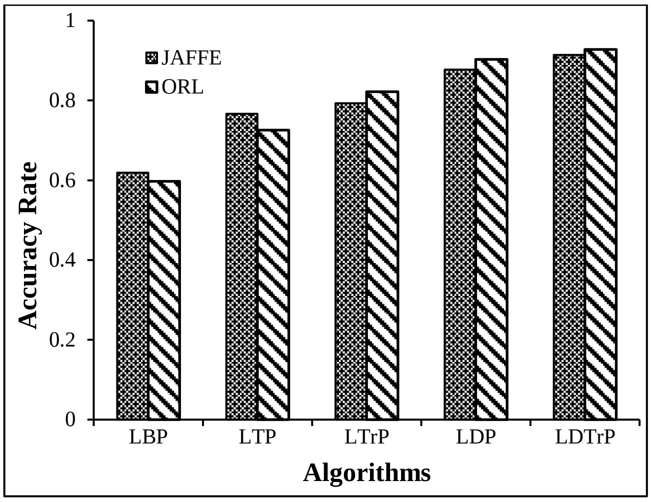

Fig.13. Accuracy comparison of LBP, LTP, LTrP, LDP, LDTrP on the FERET and ORL dataset

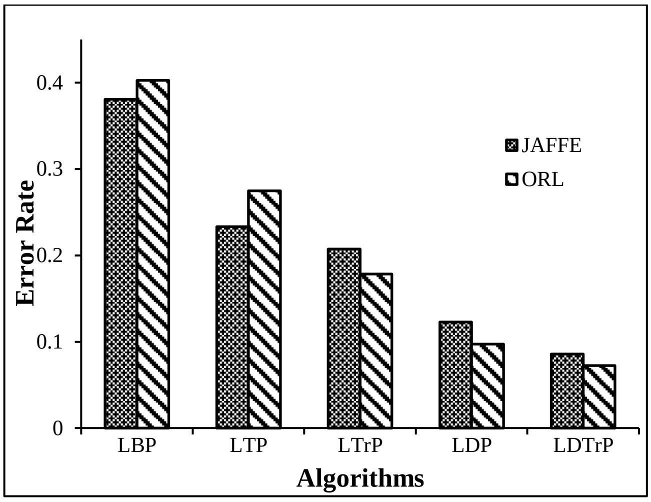

Fig.14. Error Rate comparison of LBP, LTP, LTrP, LDP, LDTrP on the FERET and ORL dataset

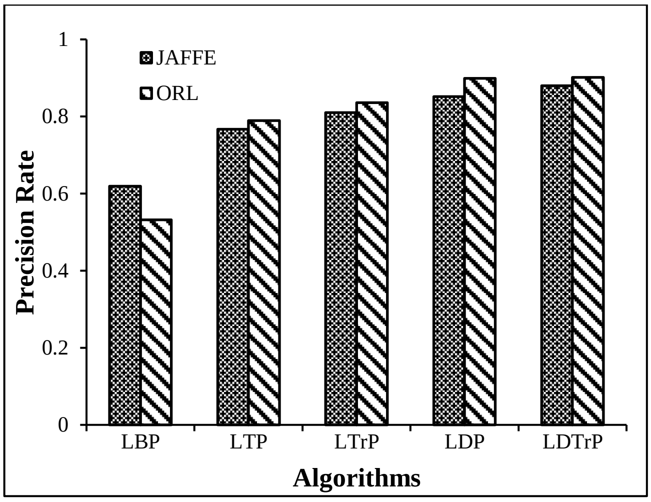

Fig.15. Precision Rate comparison of LBP, LTP, LTrP, LDP, LDTrP on the FERET and ORL dataset

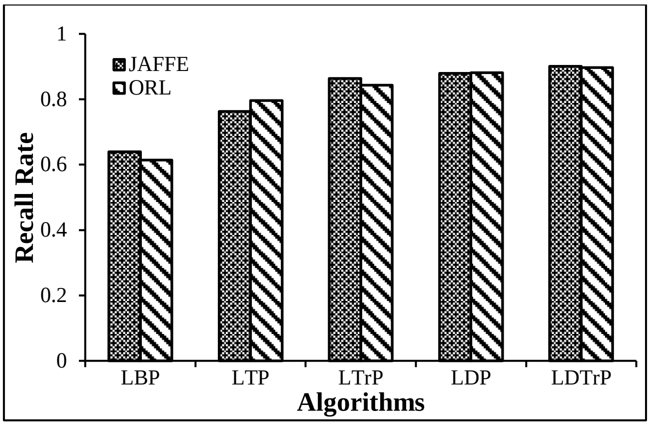

Fig.16. Recall Rate comparison of LBP, LTP, LTrP, LDP, LDTrP on the FERET and ORL dataset

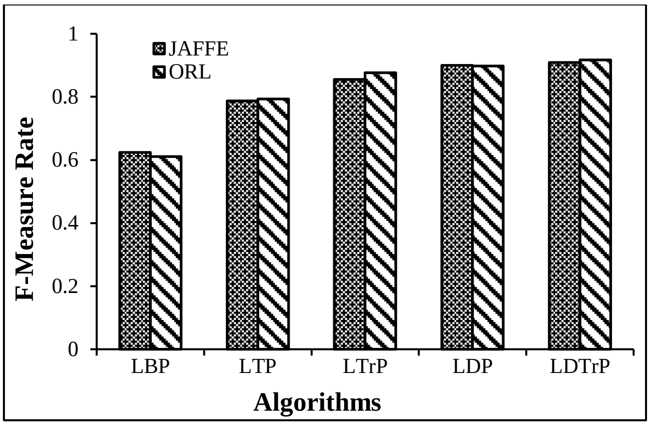

Fig.17. F-Measure Rate comparison of LBP, LTP, LTrP, LDP, LDTrP on the FERET and ORL dataset

6. CONCLUSIONS AND FUTURE WORK

This paper investigates accuracy, error rate, Precision Rate, Recall Rate, and F-Score of using LDTrP for face recognition. Local derivative patterns are used to capture higher-order local derivative variations. To model the distribution of micropatterns, the histogram intersection is used as similarity measurement. The experiments conducted on the database ORL and JAFFE demonstrate, the proposed higher-order LDTrP achieves better performance than LBP, LDP, LTrP and LTP.

Due to the effectiveness of the proposed method, it can be also be used in colour images. The proposed method has focused on higher accuracy rate. But, it can also be improved to reduce space and time consumption.

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