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Face Recognition Techniques in Image Processing: A Survey

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ABSTRACT

Face recognition is one of the most important tasks in computer vision and Biometrics. Texture is an important spatial feature useful for identifying objects or regions of interest in an image. Texture based face recognition is widely used in many applications. LBP method is most successful for face recognition. It is based on characterizing the local image texture by local texture patterns. In this paper performance evaluation of Local Binary Pattern (LBP) and its modified models Multivariate Local Binary Pattern (MLBP), Center Symmetric Local Binary Pattern (CS-LBP), uniform local binary patter, multi block local binary pattern, SOBEL-LBP, Elliptical LBP Rule based local binary pattern and Local Binary Pattern Variance (LBPV) are investigated.

Keywords: Face recognition, Biometrics, Person Identification

1.INTRODUCTION

Image processing is a technique [a] to perform some operations on image data to get enhanced or upgraded image to separate or extract some helpful data or information from it. The image data is growing rapidly in the social networks and World Wide Web. So, these days, image processing is among quickly developing advancements. It structures center examination territory inside designing and software engineering disciplines as well. Image processing essentially incorporates the accompanying six stages:

1.1 *Process of Image processing*

There are two kinds of strategies [b] utilized for image processing specifically, digital, and analogue image processing. Analogue picture processing can be utilized for the printed versions like printouts and photos. Due to huge growth of digital data and media on the internet, face recognition in image processing is need of the hour as subtask.

1.2 *Data collection*

Numerous biometric frameworks or image processing techniques are being utilized to distinguish transactions which increase security levels [c]. These frameworks break down the various registers that can perceive an individual, for instance, face, voice, finger impression, face, voice, and iris. The learning system needs data and that data collected as observational, experimental, simulation, and derived.

1.3 *Data preprocessing*

Pre - processing improves the picture information that smothers reluctant bends or upgrades some image features. Some of the image

pre-processing techniques are for example scaling, revolution, and interpretation.

1.4 ***Data Transformation***

An operator or function [d] that accepts an image or picture as its input and produces an image as its yield. After transformation, the input image and output image may have different interpretations and may look completely different. Some example data transformation techniques in image processing are Korhonen-Loeve analysis or principal component analysis, Fourier transforms and various/numerous spatial filters.

1.5 ***Data analysis***

The data analysis [e] performed on the images collected using techniques like image segmentation, classification approaches, clustering approaches, Interactive visual analysis based on MDS projections etc.

1.6 ***Evaluation***

Many typical performance evaluation techniques used in face recognition and image processing tasks. For example[f], accuracy, robustness, sensitivity, adaptability, reliability and efficiency are some traditional performance evaluation indicators.

2. IMAGE PROCESSING TECHNIQUES

1. Principles of Local Binary Patterns

The original LBP operator was introduced by Ojala et al. [12]. This operator works with the eight neighbors of a pixel, using the value of this center pixel as a threshold. If a neighbor pixel has a higher gray value than the center pixel (or the same gray value) than a one is assigned to that pixel, else it gets a zero. The LBP code for the center pixel is then produced by concatenating the eight ones or zeros to a binary code (figure 1.0).

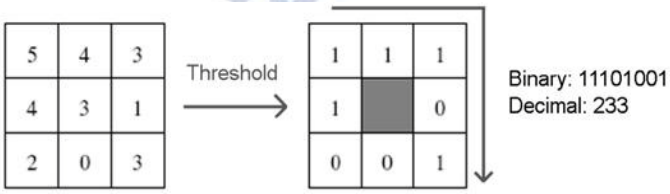

Figure 1.0: The Original LBP Operator

Later the LBP operator was extended to use neighborhoods of different sizes. In this case a circle is made with radius R from the center pixel. P sampling points on the edge of this circle are taken and compared with the value of the center pixel. To get the values of all sampling points in the neighborhood for any radius and any number of pixels, (bilinear) interpolation is necessary. For neighborhoods, the notation (P, R) is used. Figure 1.1 illustrates three neighbor-sets for different values of P and R.

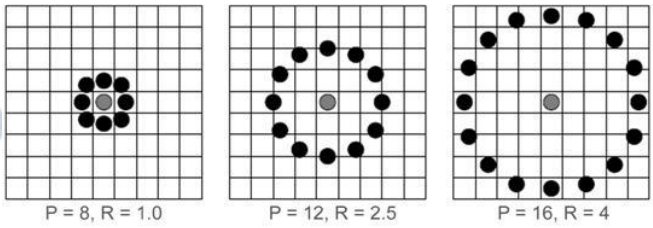

Figure 1.1: Circularly neighbor-sets for three different values of P and R

If the coordinates of the center pixel are (xc, yc) then the coordinates of his P neighbors (xp, yp) on the edge of the circle with radius R can be calculated with the sinus and cosines:

$xp = xc + Rcos(2\pi\pi p/P)$ (1)

$yp = yc + Rsin(2\pi\pi p/P)$ (2)

If the gray value of the center pixel is gc and the gray values of his neighbors are gp, with p = 0, ..., P – 1, then the texture T in the local neighborhood of pixel (xc, yc) can be defined as:

$T = t(g_c, g_0, \ . \ . \ . \ , g_{P-1}$ (3)

Once these values of the points are obtained is it also possible do describe the texture in another way. This is done by subtracting the value of the center pixel from the values of the points on the circle. On this way the local texture is represented as a joint distribution of the value of the center pixel and the differences:

$T = t(g_c, g_0, -g_c, . \ . \ . \ , g_{P-1} - g_c)$ (4)

Since t(gc) describes the overall luminance of an image, which is unrelated to the local image texture, it does not provide useful information for texture analysis. Therefore, much of the information about the textural characteristics in the original joint distribution (Eq. 3) is preserved in the joint difference distribution (Ojala et al. 2001):

$T \approx (g_0 - g_c, . \ . \ . \ , g_{P-1} - g_c)$ (5)

Although invariant against gray scale shifts, the differences are affected by scaling. To achieve invariance with respect to any monotonic transformation of the gray scale, only the signs of the differences are considered. This means that in the case a

point on the circle has a higher gray value than the center pixel (or the same value), a one is assigned to that point, and else it gets a zero:

$$T \approx (s(g_0 - g_c), \ldots, s(g_{P-1} - g_c)) \quad (6)$$

Where $s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$

In the last step to produce the LBP for pixel (xc, yc) a binomial weight 2p is assigned to each sign. $s(g_p - g_c)$. These binomial weights are summed:

$$LBP_{P.R}(x_c, y_c) = \sum_{p=0}^{p-1} s(g_p - g_c) 2^p \quad (7)$$

The Local Binary Pattern characterizes the local image texture around (xc, yc). The original LBP operator in figure 1.3 is very similar to this operator with P = 8 and R = 1, thus LBP8,1. The main difference between these operators is that in LBP8,1 the pixels first need to be interpolated to get the values of the points on the circle.

2. Uniform of Local Binary Patterns

In [13] A Local Binary Pattern is called uniform if it contains at most two bitwise transitions from 0 to 1 or vice versa. In a matter of fact this means that a uniform pattern has no transitions or two transitions. Only one transition is not possible since the binary string needs to be considered circular. The two patterns with zero transitions, with for example eight bits, are 00000000 and 11111111. Examples of uniform patterns with eight bits and two transitions are 00011100 and 11100001. For patterns with two transitions are P(P -1) combinations possible. For uniform patterns with P sampling points and radius R the notion *L*BPu2*P*, is used.

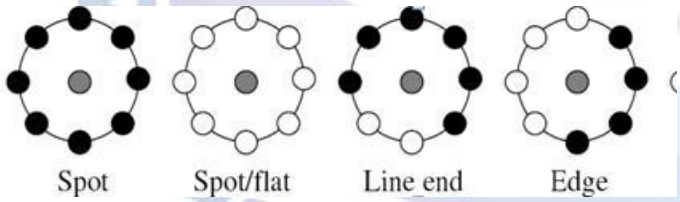

Figure 1.3: Different texture primitives detected by the *L*BPu2*P*, using just uniform Local Binary Patterns has two significant advantages. The first is that it saves memory. With non-uniform examples there are 2P potential mixes. With *L*BPu2*P*, there are (P − 1) + 2 examples conceivable. The quantity of potential examples for a neighborhood of 16 (introduced) pixels is 65536 for standard LBP and 242 for LBPu2. The subsequent advantage is that LBPu2 identifies just the significant nearby surfaces, similar to spots, line closures, edges and corners. See figure 1.5 for instances of these surface natives.

3. Multi-Block Local Binary Pattern Features

In [14] Traditional Haar-like square shape highlight estimates the contrast between the normal forces of rectangular districts (See Fig.1). For instance, the worth of a two-square shape channel is the distinction between the amounts of the pixels inside two rectangular districts. On the off chance that we change the position, size, shape, and plan of rectangular locales, the Haar like features can catch the force slope at various areas, spatial frequencies, and bearings. Viola a Jones [15] applied three sorts of such highlights for distinguishing front facing faces. By utilizing the vital picture, any square shape channel types, at any scale or area, can be assessed in steady time [15]. Be that as it may, the Haar-like highlights appear excessively basic and show a few cutoff points [16]. In this paper, we propose another square shape highlights, called Multi-block Local Binary Pattern (MB-LBP) include. The fundamental thought of MB-LBP is that the

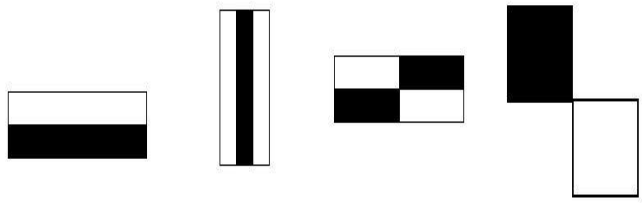

Fig. 1.4 Traditional Haar-like features. These features measure the differences between rectangular regions' average intensities.

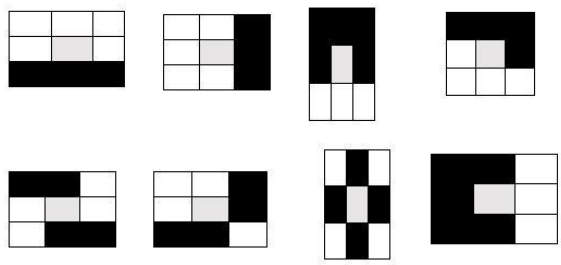

Fig. 1.5 Multi-block LBP include for picture portrayal.

As demonstrated in the figure, the MB-LBP highlights encode rectangular areas' powers by neighborhood double example. The subsequent parallel pattern scan portrays assorted picture structures. Contrasted and unique Local Binary Pattern calculated in a nearby 3×3 neighborhood between pixels, MB-LBP can catch huge scope structure. Basic distinction rule in Haar-like

highlights is changed into encoding rectangular districts by neighborhood double example administrator. The first LBP, presented by Ojala [8], is characterized for every pixel by thresholding the 3×3 neighborhood pixel esteem with the middle pixel esteem. To encode the square shapes, the MB-LBP administrator is characterized by contrasting the focal square shape's normal force gc with those of its local square shapes {g0, ..., g8}. Thusly, it can give us a double grouping. A yield worth of the MBLBP administrator can be gotten as follows:

$$MB - LBP = \sum_{i=1}^{8} s(g_i - g_c)2^i$$

where gc is the normal force of the middle square shape, gi (I = 0, ・, 8) are those of its local square shapes,

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$$

A nittier gritty depiction of such MB-LBP administrator can be found in Fig. 2. We straightforwardly utilize the subsequent parallel examples as the element worth of MB-LBP highlights. Such parallel examples can identify assorted picture constructions like edges, lines, spots, level regions and corners [8], at various scale and area. Contrasting and unique Local Binary Example determined in a nearby 3×3 neighborhood between pixels, MB-LBP can catch huge scope structures that might be the prevailing aspects of pictures. Absolutely, we can get 256 sorts of parallel examples, some of them can be found in Fig. 3. In segment 4.1, we direct a test to assess the MB-LBP highlights. The trial results show the MB-LBP highlights are more unmistakable than Haar-like highlights and unique LBP highlights.

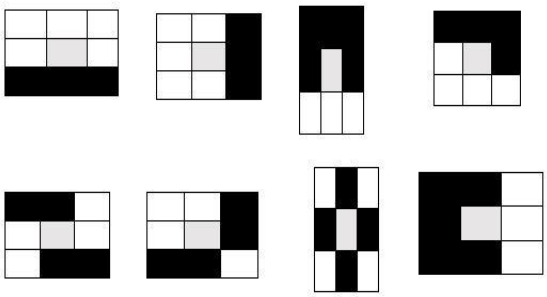

Fig. 1.6 A randomly chosen subset of the MB-LBP features

Another benefit of MB-LBP is that the quantity of thorough arrangement of MB-LBP highlights (square shapes at different scales, areas and angle proportions) is a lot more modest than Haar-like highlights. Given a sub-window size of 20 × 20, there are absolutely 2049MB-LBP highlights, this sum is around 1/20 of Haar-like highlights (45891). Individuals typically select critical highlights from the entire list of capabilities by Adaboost calculation, and build a twofold classifier. Attributable to the enormous list of capabilities of haar-like component, the preparation cycle generally invests a lot energy. The less number of MB-LBP highlight set makes the execution of highlight choice essentially simple. It is ought to be underlined that the worth of MB-LBP highlights is non-metric. The yield of LBP administrator is only an image for addressing the parallel string. In the following segment, we will depict how to plan the frail classifiers dependent on MB-LBP includes, and apply the Adaboost calculation to choose huge highlights and build classifier.

4. RLBP operator: rule based local binary pattern

In [18] Rule Based LBP can be by and large depicted as unique method totally characterized by the arrangement of rules around there. The worth of procedure is addressed in standard cover on which the guidelines are applied to reap another worth. An intriguing property of rule based nearby paired example is that basic standard that can be brought about exceptionally complex conduct. Presently consider test window S3X3and contrast every pixel and focuses of the example window of size 3x3. All adjoining pixels which in any case more noteworthy than the middle supplant them with esteem 1 supplant them with 0 to such an extent that dim picture is changed over to parallel picture. On the paired picture the accompanying guidelines have been applied to eliminate the vulnerability of surface arrangement.

1) The section savvy tallies (CSi) are determined on example space S3X3

$$C_i = \sum_{i=1}^{3} S(CS_i, n); where\ n = 1, 2, 3 \qquad (1)$$

$$C_i = \begin{cases} 1 & C_i \geq 2 \\ 0 & C_i < 2 \end{cases}$$

2) The column shrewd checks (RSi) are determined on example space S3X3

$$R_i = \sum_{i=1}^{3} S(RS_i, m)\ where\ m = 1, 2, 3 \quad (2)$$

$$C_i = \begin{cases} 1 & R_i \geq 2 \\ 0 & R_i < 2 \end{cases}$$

3) The means left askew D1 and right inclining D2 are registered on example space S3x3

4) From the new sample counts the matrix like is giving blow.

R1	D1	C1
R2		C2
R3	D2	C3

5 work out the LBP administrator on new example space and supplant the middle pixel.

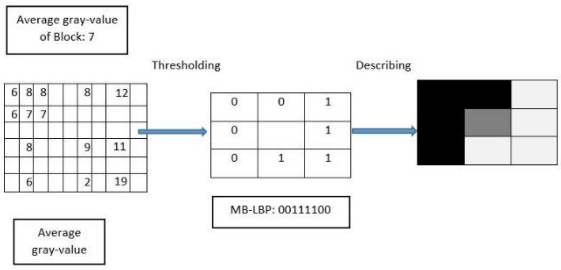

Fig 1.6

6)Reiteration step1 to step5 on entire pictures and structure the new unambiguous picture.

The result of this technique can be helpfully introduced as a two-dimensional example utilized in picture handling, particularly with equal registering. RLBP of 8-digit, sections the Image in better path in any event, for Noisy Images and relatively better than customary methods.in the fig5a), b), c) and d) pictures are yield of RLBP.

Local Gradient Patterns

In the proposed LGP for face recognition a middle pixel in a picture the LGP esteem is figured by contrasting its dim scale worth and its neighbors dependent on conditions (3) and (4).

$$LGP_{pr} = \sum_{i=0}^{p} 2^{(i=1)} * f1(|g_i - g_c|) - Th \quad (3)$$

$$Th = 1/p \sum_{i=0}^{p} (|g_i - g_c|) \quad (4)$$

The proposed LGP is virtual homogeneous to the fulfilled LBP extent (CLBP_M).The just qualification between these two highlights is that, the LGP ascertains the edge (Th) from the mean/normal of the whole picture LDO.

Local Orientation Gradient XOR Patterns

The origination of RLBP, LGP, and LGXP has been adjusted to characterize the LOGXORP. Given a middle pixel in a picture, the inclinations (p=8) are determined as,

$$I_{gc}^{G} = g1 - g9 \quad (5)$$

$$I_{gc}^{V} = g3 - g7 \quad (6)$$

where {g1,g2,g3,g4,g5,g6,g7,g8}|p=8 are the dark upsides of neighbors for a given place pixel gc. The direction and angle esteems are determined as

$$I_{gc}^{G} = \sqrt{((I_{gc}^{h})^2 + (I_{gc}^{v})^2) \div 2} \quad (7)$$

$$\theta_{gc} = tan^{-1}\left(\frac{I_{gc}^{v}}{I_{gc}^{h}}\right) \quad (8)$$

$$(I_{gc}^{G}) = \begin{cases} 0^0 + \theta_{gc} & I_{gc}^{h} \geq 0 \; and \; I_{gc}^{v} \geq 0 \\ 180^0 + \theta_{gc} & I_{gc}^{h} \geq 0 \; and \; I_{gc}^{v} \geq 0 \\ 180^0 + \theta_{gc} & I_{gc}^{h} < 0 \; and \; I_{gc}^{v} < 0 \\ 360^0 - \theta_{gc} & I_{gc}^{h} \geq 0 \; and \; I_{gc}^{v} < 0 \end{cases}$$

The nearby inclination XOR designs (LGXORP) neighborhood arranged XOR designs (LOXORP) are determined as:

$$LOXORP = \begin{bmatrix} \{Q(I_{g1}^{G}) \; X \; (I_{gc}^{G})\}, \\ \{Q(I_{g2}^{G}) \; X \; (I_{gc}^{G})\}, \\ . \\ . \\ \{Q(I_{gp}^{G}) \; X \; (I_{gc}^{G})\} \end{bmatrix} \quad (10)$$

$$LOXORP = \begin{bmatrix} \{Q(I_{g1}^{G}) \; X \; (I_{gc}^{G})\}, \\ \{Q(I_{g2}^{G}) \; X \; (I_{gc}^{G})\}, \\ . \\ . \\ \{Q(I_{gp}^{G}) \; X \; (I_{gc}^{G})\} \end{bmatrix} \quad (11)$$

Where Q(x) means the quantized worth of x and addresses the elite or (xor) activity. Essentially, direction and angle designs are determined using askew bearings also. For the nearby example with p areas, 2p blend of RLBPs is conceivable bringing about a component vector length (2p). The element Vector computational expense is very high the uniform examples are utilized to diminish the computational expense the uniform examples allude to the uniform appearance design that has restrained discontinuities in the roundabout paired.

5. Multivariate Local binary pattern (MLBP)

In [19] The Multivariate Local Binary Pattern administrator, MLBP c was created by Arco Lucifer [1]

which portrays nearby pixel relations in three groups. Notwithstanding the spatial cooperation of pixels inside one band, associations between groups are thought of. In this manner, the local set for a pixel comprise the nearby neighbors in each of the three groups (Fig 1.7).

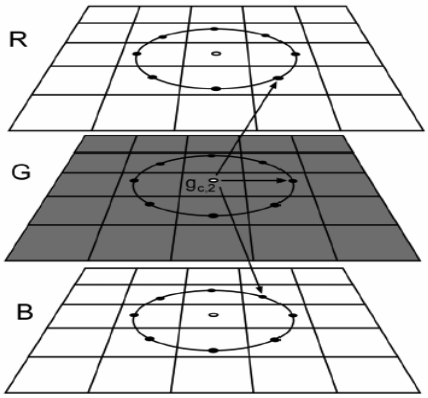

Fig. 1.7.MLBP texture measure describes spatial relations within a band and between bands

$$MLBP = \sum_{i=0}^{p-1} sign(g_i^{b1} - g_c^{b1}) + sign(g_i^{b2} - g_c^{b1}) + sign(g_i^{b3} - g_c^{b1}) + sign(g_i^{b1} - g_c^{b2}) + sign(g_i^{b2} - g_c^{b2}) + sign(g_i^{b3} - g_c^{b2}) + sign(g_i^{b1} - g_c^{b3}) + sign(g_i^{b2} - g_c^{b3}) + sign(g_i^{b3} - g_c^{b3})$$

From the above equation the neighborhood limit is taken from these groups, which makes up an aggregate of nine unique mixes. This outcomes in the accompanying administrator for a neighborhood shading surface depiction. The shading surface measure is the histogram of MLBP c event, figured over a picture or an area of a picture. This single dispersion contains P ×32bins (for example P =8 brings about 72 canisters).

6. Center Symmetric Local binary pattern (CS-LBP)

In [20] The CS-LBP is another adjusted variant of LBP. It model was created by Marko Heikkila [21] for the acknowledgment of item in PASCAL data set. The first LBP was extremely long its element isn't hearty on level pictures. In this technique, rather than contrasting the dark level worth of every pixel with the middle pixel, the middle symmetric sets of pixels are looked at (Fig.1.8). CS-LBP is firmly identified with angle administrator. It thinks about the dim level contrasts between sets of inverse pixels around there. So CS-LBP exploit both LBP and slope based highlights. It additionally catches the edges what's more, the striking surfaces.

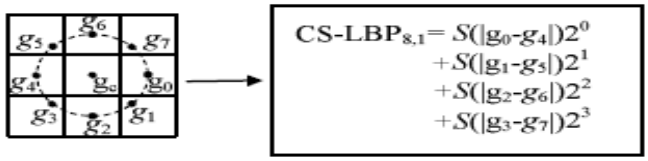

Fig.1.8 CS-LBP feature for a neighborhood of 8 pixel

The CS-LBP features can be computed by

$$CS - LBP_{p,r,t} = \sum_{i=0}^{N/2-1} s(|g_i - g_i(N/2)|2^i, s(x) = \begin{cases} 1, if \ \ x \geq t \\ 0 \ otherwise \end{cases} \quad (1)$$

Where gi and gi+n/2 relate to the dark degree of focus symmetric sets of pixels (N altogether) similarly dispersed on a circle of sweep r. It additionally lessens the computational intricacy when contrasted and fundamental LBP [21].

Local binary pattern variance (LBPV)

The LBPV descriptor proposed by Zhenhua [14] offers a preferred outcome over LBP. Neighborhood invariant highlights have the downside of losing worldwide spatial data, while worldwide highlights protect minimal nearby surface data. LBPV proposes an elective cross breed conspire; worldwide revolution invariant coordinating with locally variation LBP surface highlights. It is a rearranged yet productive joint LBP and differentiation dissemination strategy. LBPp,r/VARp,r is incredible in light of the fact that it misuses the correlative data of spatial example. Furthermore, neighborhood contrast. Edge esteems are utilized to quantize the VAR of the test pictures processed to parcel the all-out appropriation into N canisters with an equivalent number of passages.

$$LBPV_{P,R}(K) = \sum_{i=0}^{N} \sum_{j=1}^{M} W\left(LBP_{P,R}(i,j), k\right) \quad k \in [0,k] \quad (2)$$

$$where \ W\left(LBP_{P,R}(i,j), k\right) = \begin{cases} var_{P,R}(i,j), & LBP_{P,R}(i,j) = k \\ 0, & otherwise \end{cases} \quad (3)$$

These limit esteems are utilized to quantize the change of test pictures.

7. SOBEL-LBP

In [22] LBP really encodes the miniature level data of edges, spots and other nearby highlights in a picture. In view of this perception, we contend that consolidating Sobel administrator with LBP can upgrade the neighborhood highlights, and consequently more nitty gritty data can be removed from LBP activity. This new administrator is named as Sobel-LBP. Since Sobel administrator is simple and proficient to execute, it just somewhat builds the computational work of LBP include extraction measure. The Sobel administrator contains two 3×3 bits (flat portion x S and vertical bit y S which are convolved with the first picture i to ascertain angle approximations:

$$I^x = s_x * I = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} * I, I^y = S_y * I = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * I$$

Where I x and I y address the on a level plane and in an upward direction separated outcomes, individually. Typically I x and I y are joined to give the inclination greatness (I x)2 ◎ (I y)2 Here the Sobel-LBP administrator is characterized as the connection of LBP procedure on I x and I y :

$$sobel - LBP_{P,R} = \{sobel - LBP^x_{P,R}, \quad sobel - LBP^y_{P,R}\}$$

$$where \;\; sobel - LBP^x_{P,R} = \sum_{P=0}^{P-1} s(I^x_{P,R} - I^x_c)2^p$$

$$sobel - LBP^y_{P,R} = \sum_{P=0}^{P-1} s(I^y_{P,R} - I^y_c)2^p$$

Histogram of Sobel-LBP

The histograms of the Sobel-LBP miniature examples contain the appropriation data of the neighborhood highlights in a picture. To save spatial data, a face picture is isolated into a few non-covering rectangular subregions. Fig. 2 outlines an illustration of face picture separated into 3×3 sub-locales. A spatial histogram, which connects the histograms of the relative multitude of sub-districts, is utilized to address the face. The spatial histogram encodes both the appearance and the spatial relations of facial areas. Let - ( ) Sobel LBP I H R mean the histogram of the Sobel-LBP designs separated from the sub-district (1, ,) I R I ◎ ◎ N . The spatial histogram of the face picture is addressed as

$$SH(I) = \{H_{sobel-LBP}\ (R_i) | i = 1, \ldots\ldots, N\}$$

Note the sub-areas can be of various shapes other than square shapes, of various sizes, or mostly covering.

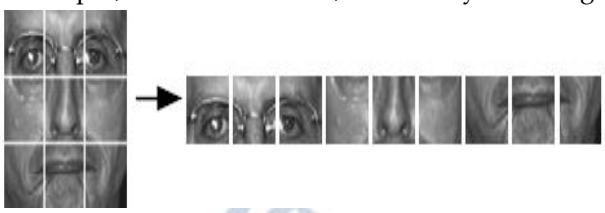

Fig 1.9 A face image divided into 3×3 sub-regions.

There are numerous similitude measures for histogram 1coordinating. In this paper, histogram convergence is used to think about two spatial histograms SH1 and SH2:

$$S_{HI}(SH^1, SH^2) = \sum_{i,j} \min\ (SH^1_{i,j}\ \ , SH^2_{i,j}\ )$$

Where lists I and j allude to jth receptacle in histogram comparing to the ith sub-area. This action has a natural inspiration in that it ascertains the normal pieces of two histograms. Since it requires just basic tasks, its computational intricacy is low.

8. ELLIPTICAL LBP

Eyes and mouth are major facial features in recognizing face. Eyes and mouth can be represented in the form of ellipses. So the efficiency in recognizing face using eyes and mouth can be obtained by using the horizontal ellipse. If r1 is equal to r2 then LBP is performed, if r1 is less than r2 then we will have a horizontal ellipse and if r1 is greater than r2 then we will have a vertical ellipse. Where r1 is the major axis radius of an ellipse and r2 is the minor axis radius of an ellipse. Encoding of micro facial features is performed in both directions as their combination extracts the information from the face and gives the best recognition performance. Horizontal features of face using ellipse can be calculated as follows:

$$hor = (c[0][1] * r2 * math.cos(0) * 1 + c[1][0] * r3 * math.cos(45) * 2 + c[2][0] * r1 * math.cos(90) * 4 + c[3][0] * r3 * math.cos(135) * 8 + c[4][1] * r2 * math.cos(180) * 16 + c[3][2] * r3 * math.cos(225) * 32 + c[2][2] * r1 * math.cos(270) * 64 + c[1][2] * r3 * math.cos(315) * 128)$$

Vertical features of face using ellipse can be calculated as follows:

$$ver = (c[1][0] * r2 * math.cos(0) * 1 + c[0][1] * r3 * math.cos(45) * 2 + c[0][2] * r1 * math.cos(90) * 4 + c[0][3] * r3 * math.cos(135) * 8 + c[1][2] * r2 * math.cos(180) * 16 + c[2][3] * r3 * math.cos(225) * 32 + c[2][2] * r1 * math.cos(270) * 64 + c[2][1] * r3 * math.cos(315) * 128)$$

Fig: 2.0 Face recognition using Elliptical LBP

9. EXTENDED LBP

The Extended LBP is a technique to improve critical competency of LBP. The Extended LBP operator performs comparison between center and neighboring pixels and codes exact value differences using additional binary numbers. The ELBP techniques contain several LBP codes at various layers which codes the gray value difference between the center pixel and its neighboring pixels. The original LBP code coding the sign of gray value difference is the first layer. The succeeding layers of ELBP then codes the complete value of gray value difference. Each complete gray value difference is first coded in its binary format, and then all the binary values at a given layer gives other local binary pattern. For example, the first layer is the original LBP code that codes the sign of gray value difference which gives a decimal number of 211 from its binary form (11010011)2. The complete values of gray value difference ,i.e. 1,5,3,2,1,2,3,0, are first converted into their binary numbers: (001)2, (101)2, (011)2, (010)2,…,etc. using a same weight code of the equivalent layer can be generated. For example second layer is composed of (01000000)2 and its decimal number is 64, similarly the other two layers are composed. As a result, when describing similar local textures, although the first layer LBP is not critical, the information coded in the other layers can be used to distinguish them. Its drawback is it greatly rises the feature dimensionality. It also includes the sign and gray level differences between center pixel and neighboring pixels to improve the discriminative power. Extended LBP is calculated as follows:

$$Im\,[i,j] = (x + a + b + c + d + e + f + g + h)/9$$

Fig: 2.1 Face recognition using Extended LBP

10. LAYERED LBP

Layered LBP consists of three steps. It uses the difference and high order derivative information. It takes the benefit of layering of pixel values and labelling the code that is obtained. Layered LBP contains one layer of LDP, two layers of LBP and one layer of difference.

LBP and the difference is considered as the 1st-order derivative pattern and LDP is considered as 2nd-order derivative pattern. In this method two different radii with two LBP are considered with the same center. Eight specific directions are chosen i.e. 0, 45, 90, 135, 180, 225, 270, and 315 for better refinement. There are three pixels p, C1 (i), C2 (i) which forms relations at each direction and here i represents the orientation angle. The difference between the two is used as 1st-order derivative information which is a simple and unique information. The difference values are converted into 0s and 1s like as LBP. For computational convenience the eight binary codes at each layer are converted to decimal number. The four layers contains all the required information from the labelled decimal number. The two LBP operators for layering is as follows:

$$LBP\ (R1) = P - C1(i)$$

$$LBP\ (R2)\ = P - C2(i)$$

In (4) and (5) where R1, R2 represents the radius of layer1 and Layer2, P represents the center pixel, C1, C2 represents the first layer and second layer pixels which varies on changing the angles. The difference information is calculated as follows:

$$Difference\ =\ C1(i) - C2(i)$$

To get the second order derivative all these three are added and then labelled.

Fig: 2.2 Face recognition using Layered LBP

11.Facial expression recognition with LBPEHMM

In [24] It can be divided to 3 steps: face detection, LBP expression feature extraction and EHMM training or recognition. Firstly, we must identify the face region from the input image. Here we use a classifier trained by the cascading boost [26] algorithm. It can detect face from the image quickly. To get an accurate facial image feature extraction, which is crucial for high-precision facial expression recognition, it should normalize the face region before sending it to the LBP feature extraction step. There are two issues involved. One is about the face alignment, which will get accurate location of facial feature. Active Shape Model (ASM) is commonly used in face alignment. But it is difficult to train a good ASM model for multi-expression. It is necessary to train one model for each facial expression. When searching the image, we place these ASM models in the center of the face region and do a coarse-to-fine searching; another is to convert all the face regions to the same size, mean gray and variance. Then we use LBP to extract the facial expression feature. Set suitable widow size and moving step, extract the LBP histogram using the method described in the Section 3 and then use PCA to reduce the data dimension. Finally, we can get an observation sequence for every image. The final step is to train EHMM model or use the trained EHMM model to recognize the new image's expression. The training method has been described in the Section 2 and we can get one model for each facial expression. The recognition step is to calculate the likelihood between the observation sequence and each facial expression EHMM model, and the highest is the recognition result.

12. THE LBP AND SLPP COMBINED METHOD

In [25], we propose the LBP and SLPP combined method for 3D facial expression recognition. In order to get more features of the facial expressions, an image is cut into small pieces to extract the features. Then the features are connected to describe the image. LBP is a widely used texture features extraction method. It extracts the local texture features of an image by comparing the surrounding pixels with the central one. The value of the central point is replaced with the binary codes of the surrounding points. After that, a histogram is got to present the features. In this paper, we use the depth images of the 3D faces to do the research. As we can see, depth images are not as colorful as 2D face images. So the LBP features of the depth images are much simpler than 2D face images. As is shown in the below Figure 2.3and Figure 2.4 below:

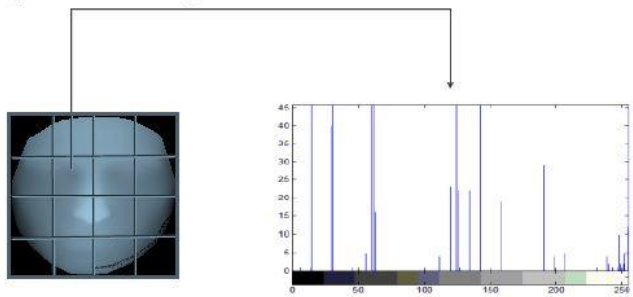

Fig: 2.3 The process of LBP with depth image

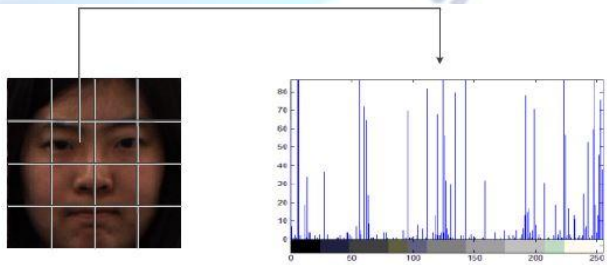

Fig: 2.4 the process of LBP with 2D face image

In this way, LBP method get a better glance of some face components like eyes, nose and mouth, which are of great importance in facial expression recognition.

Consider is the histogram of one small piece of the image. After LBP texture features extraction, we

normalize the features by dividing the histogram with the Euclidean distance. The formula is shown below.

$$hst_i = \frac{h_i}{\sqrt{\sum_{j=1}^{256} h_j^{\,2} + e}}$$

$$hst_i = \frac{h}{\sqrt{\sum_{j=1}^{256} h_j^2 + e}}$$

$$\sum_{j=1}^{256} h_j^2 + e$$

Where is used to prevent the denominator being zero.

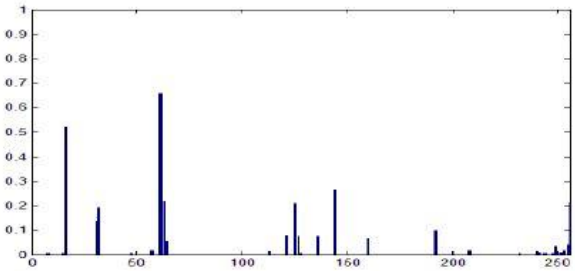

Fig 2.5: The result of normalization

The result of the feature normalization is shown in Figure2.5 After that, the normalization result of each piece is connected and we get the features of the image. These features are used as the presentation of one image. SLPP is used for the dimension-reduction of these features and for further feature-extraction. After SLPP, we get the features of the LBP and SLPP combined method, as is shown in Figure 2.6 below.

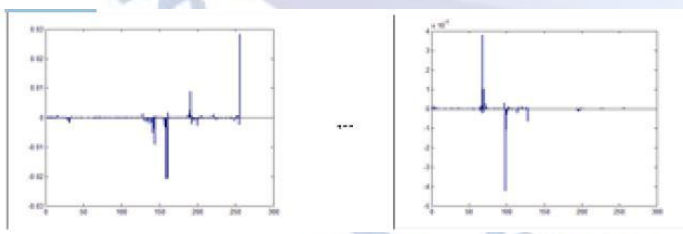

Fig 2.6: The Eigenvector of LBP and SLPP Combined Method

13. CONCLUDE AND FUTURE WORK

The technology of face detection has made some amazing progress over the most recent twenty years. Nowadays, to make secure transactions, for security tasks and surveillance and to enable controlled access to buildings machines adopted automatic classification technology. With such applications, maintaining accuracy and reliability is not so easy task in constrained or controlled environments. Significant exploration still needs to be done in making the most suitable, reliable, and adoptable methods in face recognition technology. Machine Learning or Deep Learning based automatic and high scalable face recognition models are the need of the hour.

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