# Local Binary Pattern on Hexagonal Structure for Face Matching

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**Abstract** - *Principal Components Analysis (PCA), Independent Component Analysis (ICA) and Linear Discriminant Analysis (LDA), have been widely used for 2D face recognition. Local Binary Pattern (LBP), however, provides a simpler and more effective way to represent faces. With LBP, face image is divided into small regions from which LBP histograms are extracted and concatenated into a single and global feature histogram representing the face image. The recognition is performed using Chi square and other commonly used dissimilarity measures. In this paper, we construct LBP codes together with three dissimilarity measures on hexagonal structure. We show that LBPs defined on hexagonal structure will lead to a faster and more accurate scheme for face recognition.*

**Keywords:** Hexagonal structure, face recognition, local binary patterns, chi square measure.

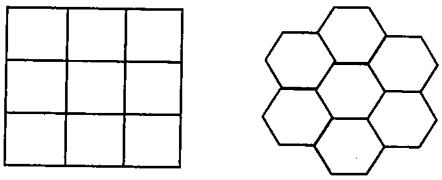
## 1 Introduction

Face recognition has many applications in law enforcement, crowd surveillance, security access control and human computer interaction. Most efforts for face recognition have been made using typical intensity images (referred to as 2D images) of the face [1]. Given images of a fixed size of $n$ columns and $m$ rows, each 2D face image is typically represented as a high-dimensional vector of size $n \times m$. Three face classifiers, namely *Principal Components Analysis* (PCA) [2], *Independent Component Analysis* (ICA) [3] and *Linear Discriminant Analysis* (LDA) [4], have been widely used for 2D face recognition. Corresponding to each classifier, a vector face space with dimensions much lower than $n \times m$ is constructed based on a specifically statistical viewpoint. Each classifier first projects images onto the face space. Then the projection coefficients (called *weights*) for each image are used as the feature representation of the image. The identification of a probe image is done by locating the image in the gallery whose weights are the closest to the weights of the probe image.

Local Binary Pattern (LBP) provides a simple and effective way to represent faces [5]. With LBP, face image is divided into small blocks and LBP features are extracted for individual blocks to represent the texture of a face locally and globally. *Weighted Chi Square Distance* of these LBP histograms is used as a dissimilarity measure for comparing two images. Research works done in [6] and [7] have shown that LBP based methods can produce good results for face recognition in 2D images [5]. Through its recent extensions, the LBP operator has been made into a really powerful measure of image texture, showing excellent results in terms of accuracy and computational complexity in many empirical studies. The LBP operator can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis.

In this paper, we construct LBP based on a hexagonal image structure and define a Weighted Chi Hexagonal Distance accordingly. We will show that LBP based face recognition on the hexagonal structure will be more efficient than LBP based methods on square structure.

The arrangement of a hexagonal grid is different from a rectangular grid as seen in Figure 1. The advantages of using a hexagonal grid to represent digit images have been investigated for more than thirty years. The importance of the hexagonal representation is that it possesses special computational features that are pertinent to the vision process. Its computational power for intelligent vision pushes forward the image processing field. Dozens of reports describing the advantages of using such a grid type have been found in the literature. The hexagonal image structure has features of higher degree of circular symmetry, uniform connectivity, greater angular resolution, and a reduced need of storage and computation in image processing operations [8].



*(a) Rectangular* *(b) Hexagonal*

**Figure 1. Vision unit in two different image architectures**

The rest of this paper is organized as follows. In Section 2, we present LBP coding methods on traditional square structure. LBP coding on hexagonal structure is presented in Section 3. Weighted Chi Square Distance is demonstrated in Section 4. Preliminary experimental results are demonstrated in Section 5. We conclude in Section 6.

## 2 LBP on Square Structure

LBP was originally introduced by Ojala et al. in [9] as texture description. LBP features have performed very well in various applications including texture classification and segmentation [5]. The basic form of an LBP operator on square image structure labels the pixels of an image by thresholding the 3×3 neighborhood of each pixel by the grey value of the pixel (the centre). An illustration of the basic LBP operator is shown in Figure 2. Note that the binary LBP code is circular. The basic LBP consists of 8 binary bits representing an integer from 0 to 255.

The major limitation of the basic LBP operator is that the 8 neighboring pixels are not exactly on a circle because of the unequal distances between the reference pixel and its neighbors. Grey values found in the 8 neighbors may not be equally dominant to the reference pixel. Therefore, Ahonen et al. extended the basic LBP to use neighborhoods of different sizes [6]. Using circular neighborhoods and bilinearly interpolating the pixel values allow any radius and number of pixels in the neighborhood. For neighborhoods, if we use $(P, R)$ to represent $P$ sampling points on a circle of radius of $R$, an example of the circular (8,2) neighborhood is shown in Figure 3 [6].

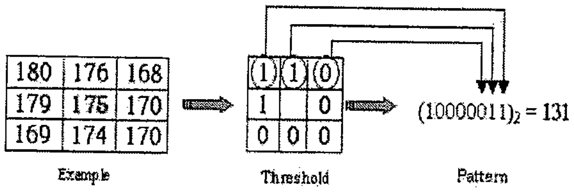



**Figure 2. Calculation of LBP code from 3×3 neighborhood [7]**

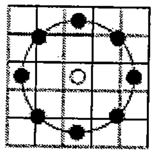


**Figure 3. The circular (8,2) neigbourhood. The pixel values are bilinearly interpolated whenever the sampling point is not in the center of a pixel**

Another extension is to use so called uniform LBP that contains at most two bit wise 0-1 or 1-0 transitions [5]. For example, 00000000, 00001000, 11000111 are uniform patterns. With this extension, there are 58 uniform LBP code patterns for 8 bit basic LBP code, and 256-58=198 non-uniform LBP code patterns. In order to understand better about the uniform LBP codes, we define as shown in [10] that

$$LBP^{ri} = \min\{ROR(LBP,i) \mid i = 0,1,\cdots,7\},$$

where $ROR(x, i)$ performs a right shift by 1 bit $i$ times on the 8-bit number $x$. Then, it is easy to derive that, if a *LBP* is uniform, its corresponding $LBP^{ri}$ is 00000000, 00000001, 00000011, 00000111, 00001111, 00011111, 00111111, 01111111 or 11111111. We call these nine uniform LBP codes basic uniform LBPs. These nine LBP codes and other uniform LBP codes function as templates for microstructure such as bright spot (00000000), flat area or dark spot (11111111), and edges of varying positive and negative curvatures (others) [10].

# 3 LBP on Hexagonal Structure

Similar to the construction of basic LBP on square structure, we now construct basic LBP on hexagonal structure as shown in Figure 4.

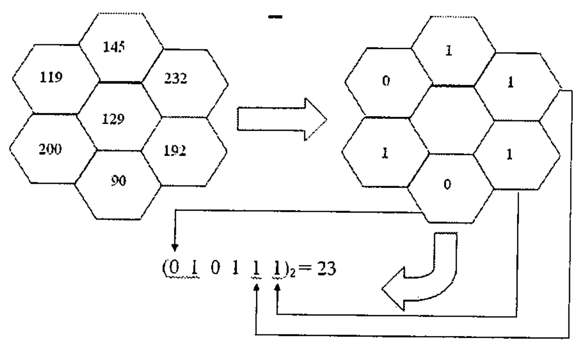



**Figure 4. Calculation of basic LBP code on hexagonal structure**

By defining the basic LBP codes on hexagonal structure, the number of different patterns has been reduced from $2^8 = 256$ on square to $2^6 = 64$ on hexagonal structure. More importantly, because all neighboring pixels of a reference pixel have the same distance to it, the grey values of the neighboring pixels have the same contributions to the reference pixel on hexagonal. Furthermore, because all six neighboring pixels are exactly on a circle with radius 1 (assuming the distance between neighboring hexagonal pixels is 1) and centre at the reference pixel, unlike on square structure, there is no longer need to perform an interpolation process before computing the LBP codes on hexagonal structure.

If we define a uniform LBP on hexagonal structure in the same way as on square such that each uniform LBP contains only two 1-0 or 0-1 transitions, then the number of uniform LBP codes is reduced from 58 on square structure to 32 on hexagonal structure. Moreover, the total seven basic uniform LBP codes are 000000, 000001, 000011, 000111, 001111, 011111 and 111111. Like uniform LBPs on square structure, uniform LBPs on hexagonal structure function as bright spot (000000), flat area or dark spot (111111), and edges of varying positive and negative curvatures (others).

Because of smaller number of basic LBPs and uniform LBPs compared with those on square structure and more even contribution of neighboring pixels to their reference pixel, one can expect that image recognition based on hexagonal structure using LBPs not only improves the recognition accuracy but also significantly increases the recognition speed. These two features are further enhanced when neighborhoods of different sizes are considered. Figure 5 below displays a collection of 49 hexagonal pixels that shows a more even distribution of pixels around a centre (the pixel with number 0) compared to the distribution of the same number of pixels on square structure around their central pixel as shown in Figure 6.

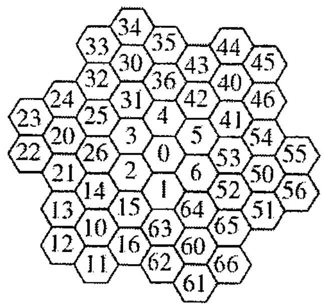



**Figure 5. A collection of 49 hexagonal pixels labeled with numbers of base 7**

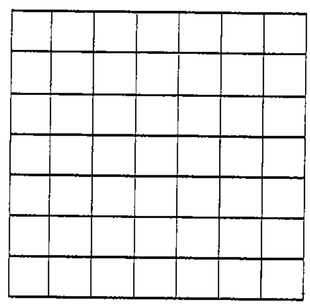


**Figure 6. A collection of 49 square pixels**

# 4 Histograms of LBPs

LBP histograms over local regions provide more reliable description when the pattern is subject to alignment errors. As shown in [10] that uniform patterns accounted about 90% of all patterns in the experiments with texture images on square structure, it is expected that this percentage will be a lot higher on hexagonal structure because the proportion of uniform LBPs to total LBPs (which is ½) is more than twice larger on hexagonal than on square structure (which is 29/128). Like the work done in [5, 6], we consider only the 32 uniform LBP code patterns as 32 LBP types plus one single type that consists of all non-uniform LBP codes. For each pixel $p$, let $LBP(p)$ denote the $LBP$ type at $p$. Then,

$$LBP(p) \in L, L = \{0,1,\cdots,32\},$$

for given $p$. Let $S(p)$ denote an image block centred at $p$, and $H_p(i)$ ($i$ = 0, 1, ..., 32) denote the local LBP histogram over $S(p)$ corresponding to bin value $i$, i.e.,

$$H_p(i) = \sum_{p' \in S(p)} I\{LBP(p') = i\},$$

where

$$I\{A\} = \begin{cases} 1, & A = true, \\ 0, & A \neq true. \end{cases}$$

We can now define the local LBP histogram $H_p$ over $S(p)$ by

$$H_p = (H_p(0), H_p(1), \cdots, H_p(32)).$$

The histogram $H_p$ contains information about the distribution of the local micro-patterns, such as edges, spots and flat areas, over the image block $S(p)$.

If an face image $I$ is divided into $M$ blocks of equal sizes centred at $p_j$ ($j$=0, 1, ..., $M$ - 1) respectively, then the LBP histogram of $I$ denoted by $H^I$ is defined by

$$H^I = \{H^I_{ji}\}_{M\times 33},$$

where

$$H^I_{ji} = H_{p_j}(i), i = 0,1,\cdots,32, j = 0,1,\cdots,M-1.$$

In this histogram, we effectively have a description of the face on three different levels of locality. The first level is described by the labels (LBP types) for the histogram containing information about the patterns on a pixel level. The second level is the LBP histograms on divided blocks that produce information on a block (region) level. The regional histograms are then concatenated to build a LBP histogram matrix that gives a global description of the face.

If we now denote a given probe face image by $P$ and a gallery face image by $G$, and also denote their LBP histograms by $H^P$ and $H^G$ respectively, then we can use the following dissimilarity measures to compare two histograms [6].

**Histogram intersection:**

$$D(H^P, H^G) = \sum_{i,j} \min(H^P_{ji}, H^G_{ji}).$$

**Log-likelihood statistic:**

$$L(H^P, H^G) = -\sum_{i,j} H^P_{ji} \log H^G_{ji}.$$

**Chi square statistic:**

$$\chi^2 = \sum_{i,j} \frac{(H^P_{ji} - H^G_{ji})^2}{H^P_{ji} + H^G_{ji}}.$$

As described in [6], when face images have been divided into regions, it can be expected that some of the regions contain more useful information than some others in terms of distinguishing between people. For example, eyes seem to be an important cue in face recognition. To take advantage of this, a weight can be set for each region based on the importance of the information it contains. For example, the weighted Chi-square statistic with weight $w_j$ for region $S(p_j)$ ($j$=0,1,2,...$M$-1) then becomes

$$\chi^2_w = \sum_{i,j} w_j \frac{(H^P_{ji} - H^G_{ji})^2}{H^P_{ji} + H^G_{ji}}.$$

## 5 Experimental Results

We use the Lena image as shown in Figure 7 to demonstrate that LBPs defined on the hexagonal structure contain higher percentage of uniform LBPs.

**Figure 7. Original Lena image**

The LBP maps on a square structure and a hexagonal structure are represented in Figure 8 and Figure 9 respectively.

**Figure 8. LBP map of Lena image on a square structure**

**Figure 9. LBP map of Lena image on a hexagonal structure**

It is easy to see that Figure 9 has clearer edges with less isolated points. Hence, it is expected that there is a higher percentage of uniform LBPs on hexagonal structure than on square structure. This is confirmed by our experimental results that show that there are 51828 uniform LBPs out of total 56865 LBPs on the hexagonal structure. The percentage of uniform LBPs is 91.14%. On the square structure, the total number of uniform LBPs is 50648 and the total number of LBPs is 64516. Hence the percentage of uniform LBPs on the square structure is 78.50%.

## 6 Conclusions and Discussion

In this paper, we have presented LBPs on hexagonal structure for face recognition. Compared to LBPs defined on square structure, LBPs on hexagonal structure provide more accurate description of faces in all of pixel, region and global levels. Because the number of LBP types and their uniform subset have been greatly reduced on hexagonal structure than on square structure, face recognition using LBPs on hexagonal structure is expected to be much more efficient.

We have also derived three commonly used dissimilarity measures based on the LBP histograms defined. The formulae for weighted measurements have also been given.

In [6], the authors divided face image into 49 20×15 blocks before applying the weighted measures for face recognition. On hexagonal structure, dividing an image into 49 hexagonal regions can be easily performed and the locations of the 49 regions can be determined using a very efficient Addition operation defined on hexagonal structure as shown in [11]. This is another advantage of using LBPs defined on hexagonal structure for face recognition.

This paper is a preliminary work for face recognition on hexagonal structure. We leave more detailed implementation of LBPs on hexagonal structure for face matching into the future research stages. In order to further enhance the recognition accuracy and increase the recognition speed, an AdaBoost learning method as shown in [12] will also be applied for 2D+3D face recognition.

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