

Multidirectional Binary Pattern for Face Recognition

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1. Introduction

During the past three decades, extensive research has been conducted on automatically recognising the identity of individuals from their facial images. In spite of the existence of alternative technologies such as fingerprint and iris recognition, human face remains one of the most popular cues for identity recognition in biometrics. Face recognition possesses the non-intrusive nature and are often effective without the participant's cooperation or knowledge. It makes a good compromise between performance reliability and social acceptance and well balances security and privacy. Other biometric methods do not possess these advantages. For instance, fingerprint recognition methods require the subjects to cooperate in making explicit physical contact with the sensor surface (Maltoni et al., 2003). Similarly, iris recognition methods require the subjects to cooperate in placing their eyes carefully relative to the camera. Nowadays, automatic face recognition has become one of the most active research topics in computer vision and pattern recognition, and received much attention from both scientific and engineering communities.

The immediate motivation for this growing interest stems from various commercial applications relating to security and surveillance, such as bankcard identification, access control, airport monitoring and law enforcement. The availability of public large-scale datasets of face images, e.g. (Bailly-Bailli re et al., 2003; Mart nez & Benavente, 1998; Messer et al., 1999; Phillips et al., 2005; Phillips et al., 1998; Sim et al., 2003), and evaluation protocols for assessing the performance of different techniques, e.g. (Bailly-Bailli re et al., 2003; Beveridge et al., 2005; Gao et al., 2008; Messer et al., 1999; Phillips et al., 2005; Phillips et al., 2000), further advances the development of face recognition algorithms. Possibly, understanding of our human selves also forms a motivating factor of face recognition (Mart nez et al., 2003). In fact, researchers have investigated various issues related to face recognition by humans and machines. Many studies in psychophysics and neuroscience have direct relevance to engineers working on designing algorithms or systems for face recognition (Zhao et al., 2003).

The purpose of face recognition is to visually identify or verify one or more persons from input still or video images. This task is performed by matching the input images (also known as the *probe*) against the model images (also known as the *gallery*), which are the faces of known people in a database. A typical face recognition system contains four major

steps: 1) face detection, in which the presence of one or more faces in an input image is detected and the rough positions of these faces are located; 2) face localisation, in which the accurate positions and sizes of faces are decided; 3) feature extraction, in which discriminative features are extracted from each face region to represent identity information. A prior face normalisation procedure may be involved in this step; and 4) feature classification, in which discriminative features are fed into the classification algorithm for identification or verification. After more than 30 years of research, the state-of-the-art face recognition techniques have demonstrated a certain level of maturity on large databases in well-controlled environments (Li & Jain, 2005; Matas et al., 2000; Messer et al., 2004a; Messer et al., 2004b; Messer et al., 2003; Phillips et al., 2003; Phillips et al., 2000; Zhao et al., 2003). Nevertheless, face recognition in uncontrolled conditions is still challenging and far from adequate to deal with most general purpose tasks (Li & Jain, 2005; Phillips et al., 2006; Phillips et al., 2003; Phillips et al., 2007; Zhao et al., 2003). A wide range of variations are inevitable when face images are acquired in an uncontrolled and uncooperative scenario. These variations, such as pose variation, illumination variation and facial expression variation, can cause serious performance degradation, and thus form important challenges to be solved in the research community.

Existing technologies for face recognition can be roughly classified into holistic approaches and analytic approaches. Using information derived from the whole face image, holistic approaches, such as Eigenface (Turk & Pentland, 1991) and Fisherface (Belhumeur et al., 1997), are conceptually simple and easy to implement, but their performance is affected by facial expression, pose and illumination changes in practice. On the other hand, analytic approaches, such as Elastic Bunch Graph Matching (EBGM) (Lades et al., 1993; Wiskott et al., 1997), Line Edge Map (LEM) (Gao & Leung, 2002) and Directional Corner Point (DCP) (Gao & Qi, 2005), extract local information from salient facial features to distinguish faces. Represented by a set of low dimensional local feature vectors, these methods have the advantage of robustness to environmental variations. Recently, the Local Binary Pattern (LBP) approach (Ahonen et al., 2004; Ahonen et al., 2006) has proven to be a quite successful achievement for face recognition, providing a new way of investigation into face analysis. As a non-parametric local descriptor, LBP was originally designed for texture description (Ojala et al., 1996; Ojala et al., 2002; Ojala et al., 2001), but later extended to face recognition and outperformed existing methods such as PCA, Bayesian and EBGM methods (Ahonen et al., 2006). Two most important properties of the LBP operator in real-world applications are its computational efficiency and robustness against monotonic gray-level changes. The first property makes it possible to analyse images in challenging real-time settings. LBP has also been applied to facial expression analysis (Zhao & Pietikäinen, 2007) and background modelling (Heikkilä & Pietikäinen, 2006).

The basic principle of LBP is that a face can be seen as a composition of micropatterns generated by the concatenation of the circular binary gradients. The statistical distribution (histogram) of these illumination invariant micropatterns is used as a discriminative feature for identification. The LBP operator is, by design, suitable for modelling repetitive texture patches, and is sensitive to random and quantisation noise in uniform image areas. Due to the fact that a holistic LBP histogramming retains only the frequencies of micropatterns and discards all information about their spatial layout, Ahonen et al. (2006) employed a spatially enhanced histogram for face recognition, which is extracted from evenly divided subregions of a face, followed by a histogram concatenation. This arbitrary spatial partition is not in

accordance with local facial morphology, and thus inevitably leads to loss of discriminative power.

In this chapter, we propose to extract micropatterns from the neighbourhoods of a sparse set of shape-driven points which are detected from edge map with rich information content on a face image. Both the number and the locations of the points vary with different individuals such that diverse facial characteristics of these individuals can be represented. To enhance the discriminative power of micropatterns, we also propose a Multidirectional Binary Pattern (MBP) to reflect binary patterns spanning multiple directions. The new representation is capable of describing both global structure and local texture, and also significantly reduces the high dimensionality of LBP histogram description. It inherits most of the other advantages of LBP such as computational efficiency and exemption from training. Besides, the proposed method can effectively alleviate the problem of sensitivity to random noise in uniform image areas, because MBP features are only extracted from the neighbourhoods of the sparse points, which are generally non-uniform areas. Using a new MBP measurement, we performed an investigation and evaluation of the proposed method for establishing point correspondence on the publicly available AR face database (Martínez & Benavente, 1998). A higher recognition accuracy than that of the Directional Corner Point (DCP) method (Gao & Qi, 2005) was obtained in our experiments, demonstrating the validity of this method on face recognition.

The remainder of this chapter is organised as follows. Section 2 presents the details of the proposed MBP representation, which is derived from a detection algorithm of sparse points and an illumination-insensitive pattern descriptor attached on each point. Section 3 describes using the specially designed MBP measurement to establish the correspondence among sparse points. In Section 4, the proposed method is experimentally evaluated through comparative experiments on the AR database. The last section summarises this chapter.

2. Representation

In this section, we first present a brief introduction of Local Binary Pattern (LBP), and then propose a new Multidirectional Binary Pattern (MBP). MBP is extracted from a sparse set of shape-driven points. This is different from most LBP approaches that cluster LBP occurrences from local image patches and thus can better represent both global structure and local texture for coding a face.

2.1 Local Binary Pattern

Initially derived from texture analysis community, the LBP operator was created as a gray-level invariant texture measure to model texture images (Ojala et al., 1996; Ojala et al., 2002; Ojala et al., 2001). Later, it demonstrated excellent performance in many other research fields in terms of both speed and discrimination capability (Ahonen et al., 2006; Heikkilä & Pietikäinen, 2006; Zhao & Pietikäinen, 2007).

Specifically, the LBP operator marks each pixel I_c of an image as a decimal number $LBP_{p,R}(I_c)$, which is formed by thresholding the P equally spaced neighbour pixels $I_{p,R}$ ($p = 0, \dots, P-1$) on a circle of radius R with the centre pixel I_c and concatenating the results binomially with factor 2^p :

$$LBP_{P,R} = \sum_{p=0}^{P-1} T(I_{p,R} - I_c) 2^p \quad (1)$$

where the thresholding function $T(x)$ is defined as

$$T(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (2)$$

If the coordinate of I_c is $(0, 0)$, the coordinates of $I_{p,R}$ are given by $(-R \sin(2\pi p/P), R \cos(2\pi p/P))$. The gray-level values of neighbours $I_{p,R}$ not falling exactly in the centre of pixels are estimated by interpolation (Ojala et al., 2002). Fig. 1 illustrates an example of obtaining a LBP micropattern $LBP_{8,1}$ with the parameters $P = 8$ and $R = 1$.

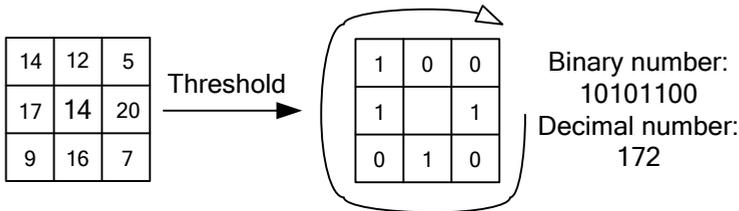


Fig. 1. The LBP operator.

2.2 Sparse points detection

The edges in an image reflect large local intensity changes that are caused by the geometric structure of the object, the characteristics of the surface reflectance of the object and the viewing direction (Gao & Leung, 2002). Containing spatial information, a sparse set of points is detected at positions which have rich edge information in a face image. In contrast to traditional methods where feature points are often predefined as the locations of eyes, nose, mouth, etc., we do not fix either the number or the locations of the sparse points. The number of the sparse points and their locations can vary in order to better represent diverse facial characteristics of different persons, such as dimples, moles, etc. These diverse features are also important cues that humans might use for recognising faces.

In order to ensure less demand on storage space and less sensitivity to illumination changes, the sparse points should be placed on the significant edge curves with high curvatures. While any general edge detection method can be used to detect the sparse points, we use an edge detector from (Nevatia & Babu, 1980), followed by the Dynamic Two-Strip algorithm (Dyn2S) (Leung & Yang, 1990) to obtain these points. After the edge map of a face image is detected, a strip is fitted to the left and right of each point on an edge curve, and the points inside each strip are approximated as a straight line. The orientation and width of the strip are adjusted automatically. Longer and narrower strips are favoured. In addition, the curvature and a measure of merit of each point can be calculated. Sparse points are selected in a three-step procedure:

- 1) Points with a small merit compared to their neighbours are eliminated.
- 2) A number of points, chosen from any points that are not covered by one of the strips selected in the first step, are reinstated to avoid over-elimination.

- 3) Points that align approximately on a straight line are deleted except for the two endpoints on the curve.

The remaining points after these steps are the detected sparse points. Fig. 2 illustrates two examples of sparse points superimposed on the original face image from the AR database.

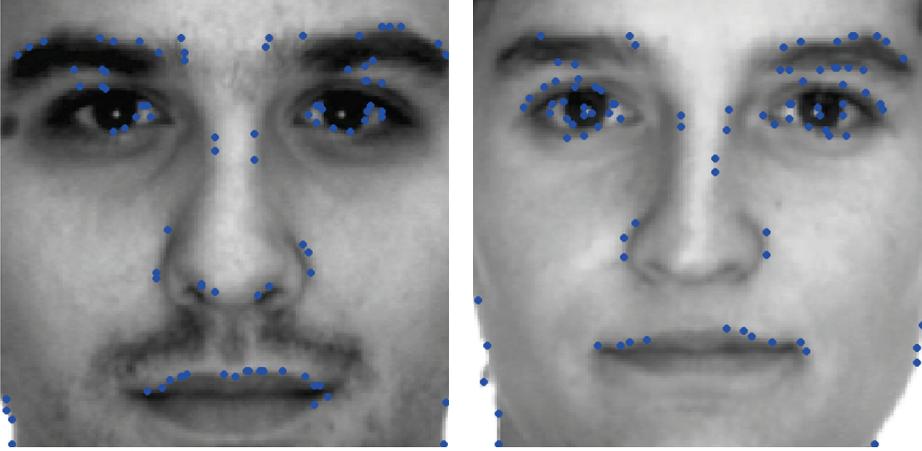


Fig. 2. Detected sparse points.

2.3 Multidirectional Binary Pattern

After the sparse points are detected, MBPs are extracted from these point positions. A MBP is defined as a pattern set which consists of four bunches of directional binary patterns: Horizontal Binary Patterns (HBPs), Vertical Binary Patterns (VBPs), Ascending Binary Patterns (ABPs) and Descending Binary Patterns (DBPs). In other words, MBP is composed of binary pattern bunches collected from four different directions. Fig. 3 visually illustrates the positions covered by these four pattern bunches. Similar to LBP, the pixels in the neighbourhoods are thresholded with the value of the centre pixel, and then linearly concatenated into four directional binary patterns as a local descriptor. One difference between MBP and LBP is that MBP is kept as original *binary patterns*, without being transformed into decimal figures for histogramming as in LBP. It should be noted that although the four bunches of directional binary patterns may be derived from the same pixels, the pattern-level features they represent are different. This is demonstrated from the example in Fig. 4. Mathematically, a MBP set takes the form

$$MBP = \{HBP_{L,N}, VBP_{L,N}, ABP_{L,N}, DBP_{L,N}\} \quad (3)$$

where HBP , VBP , ABP , and DBP refer to the four bunches of directional binary patterns respectively, with each bunch containing N binary patterns of the length L . For instance, the bunch of HBPs can be represented as

$$HBP_{L,N} = \{HBP_{L,1}, HBP_{L,2}, \dots, HBP_{L,N}\} \quad (4)$$

where each HBP is composed of concatenated L binary values:

$$HBP_{L,n} = [T(I_{H(1,n)} - I_c), T(I_{H(2,n)} - I_c), \dots, T(I_{H(L,n)} - I_c)]. \quad 1 \leq n \leq N \quad (5)$$

Here $I_{H(l,n)}$ ($1 \leq l \leq L$, $1 \leq n \leq N$) represent the horizontally spaced pixels located at $L \times N$ positions in the neighbourhood of the centre pixel I_c (see Fig. 3a). Similar representations are applied to the remaining three bunches of directional binary patterns. Fig. 4 provides an example of obtaining two bunches of directional binary patterns $HBP_{3,3}$ and $VBP_{3,3}$ with the parameters $L = 3$ and $N = 3$.

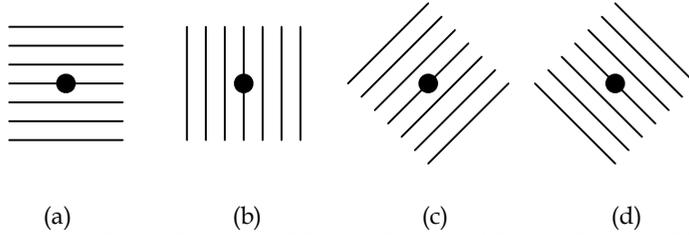


Fig. 3. Multidirectional Binary Pattern (MBP). (a) Horizontal Binary Patterns (HBPs). (b) Vertical Binary Patterns (VBPs). (c) Ascending Binary Patterns (ABPs). (d) Descending Binary Patterns (DBPs). The black dot stands for the centre pixel.

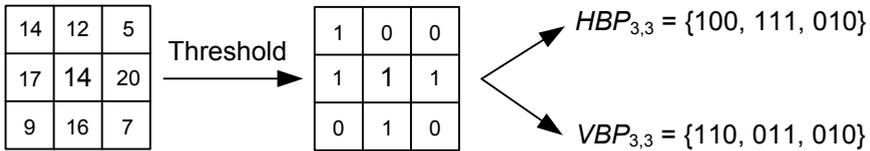


Fig. 4. An illustration of obtaining $HBP_{3,3}$ and $VBP_{3,3}$.

Based on this description, a face is represented by a sparse set of shape-driven points with MBP attached on each point as local texture. The MBP representation is extracted from sparse points rather than from histogramming all the pixels, and thus reduces the storage demand of an image. It also inherits LBP's advantage of insensitivity to illumination changes. Because the sparse points are derived from low-level edge map with rich feature information, they circumvent uniform areas where LBP suffers from random and quantisation noise. Meanwhile, the four-bunch MBP provides enhanced discriminative power for representation in order to improve the recognition accuracy.

3. Measurement

In practical applications, face images of a same individual generally suffer from intra-class variations such as illumination, expression and ageing. Finding correspondence of MBP pairs between two images is therefore very important to reveal the substantial similarity/difference of two faces. In this section, we first propose a new Binary Pattern Distance (BPD) to measure binary patterns, and then integrate it into a compound cost function to establish MBP correspondence for face recognition. The cost function is

motivated by the Hausdorff distance concept (Dubuisson & Jain, 1994). Hausdorff distance has been widely utilised as shape comparison metrics on binary images.

3.1 Binary Pattern Distance

As a preliminary step, two distances are proposed to take measurement of two binary patterns (a model binary pattern BP^M and a test binary pattern BP^T): *pattern distance* and *shifting distance*. Representing the pattern-level disparity between two binary patterns, the pattern distance d_p is measured by examining the Hamming distances (the accumulated sum of the disagreeing bits in between) of the model pattern and the test pattern with several bit-wise shifts. The minimal value of these distances is selected as d_p . The shifting distance d_s is defined as the number of shifting bits at which the pattern distance reaches the minimum. Fig. 5 provides examples of the proposed two distances. It is possible to assume that the pattern-level disparity originates from inter-class variation and the bit-wise shifting comes from intra-class variation. Therefore, d_p and d_s have the ability to reveal the local feature's inter-class and intra-class variations respectively.

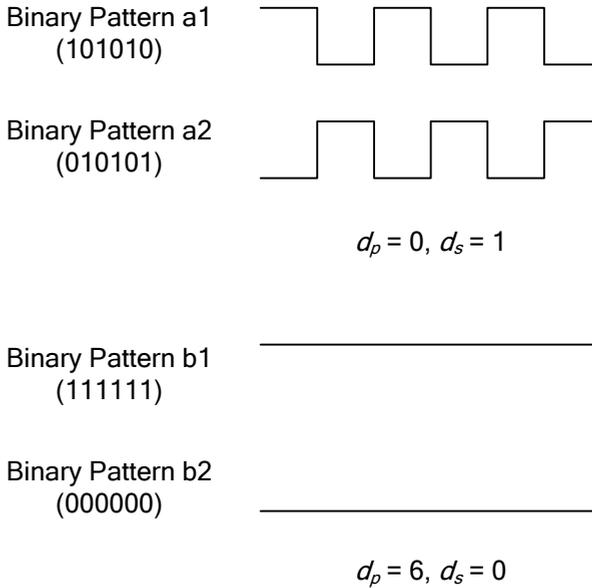


Fig. 5. The pattern distance (d_p) and the shifting distance (d_s).

Following the definitions of d_p and d_s , the BPD of binary patterns BP^M and BP^T is represented as:

$$BPD(BP^M, BP^T) = \sqrt{d_p^2 + \rho d_s^2} \quad (6)$$

where

$$\begin{cases} d_p = \min_{-K \leq k \leq K} \{HD(BP^M, SH(BP^T, k))\} \\ d_s = |\arg \min_{-K \leq k \leq K} \{HD(BP^M, SH(BP^T, k))\}| \end{cases} \quad (7)$$

Here ρ is used to balance the contributions of d_p and d_s . HD stands for the Hamming distance. The operation $SH(BP^T, k)$ performs a bit-wise directional shifting on BP^T for k ($k = -K, \dots, 0, \dots, K$) times. A positive k stands for a forward-shifting; a negative k stands for a backward-shifting; and when k equals 0, no shifting operation is performed. K ($K \geq 0$) is the bit-wise shifting limit.

3.2 MBP distance

For two MBPs (MBP^M and MBP^T) composed of four bunches of binary patterns respectively, the average BPD in each directional bunch is calculated, and then the minimal mean of four bunches is selected and defined as the MBP distance:

$$\begin{aligned} d(MBP^M, MBP^T) = \min \left\{ \frac{1}{N} \sum_{n=1}^N BPD(HBP_{L,n}^M, HBP_{L,n}^T), \right. \\ \frac{1}{N} \sum_{n=1}^N BPD(VBP_{L,n}^M, VBP_{L,n}^T), \\ \frac{1}{N} \sum_{n=1}^N BPD(ABP_{L,n}^M, ABP_{L,n}^T), \\ \left. \frac{1}{N} \sum_{n=1}^N BPD(DBP_{L,n}^M, DBP_{L,n}^T) \right\}. \end{aligned} \quad (8)$$

This measurement involves bit-wise shifting of local patterns in four different directions (see Fig. 6). By using a small balancing factor ρ , it can provide robustness to small local feature distortion caused by intra-class variation.

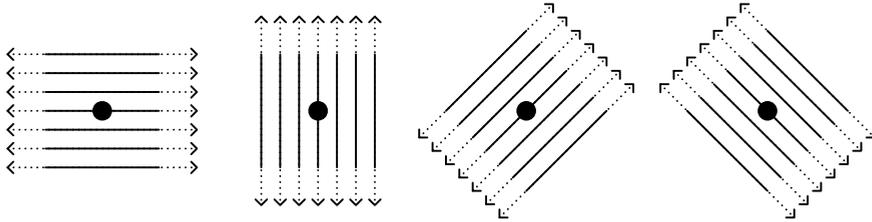


Fig. 6. The bit-wise directional shifting of MBP.

3.3 Compound cost function

A cost function is defined to find correspondence of MBP pairs between two face images. Given two finite MBP sets $M = \{MBP_1^M, MBP_2^M, \dots, MBP_p^M\}$ representing a model face in the database and $T = \{MBP_1^T, MBP_2^T, \dots, MBP_q^T\}$ representing a test face from input, where P and Q are the numbers of MBPs in M and T respectively. The cost function takes the form:

$$D(M, T) = \max \{dirD(M, T), dirD(T, M)\} \quad (9)$$

where the function $dirD(M, T)$ is the directed cost function from set M to T . Since the point position (x, y) where each MBP is extracted has been recorded, the directed MBP cost function can be defined as

$$dirD(M, T) = \frac{1}{P} \sum_{p=1}^P \min_{1 \leq q \leq Q} \sqrt{(x_p^M - x_q^T)^2 + (y_p^M - y_q^T)^2} + \lambda d^2(MBP_p^M, MBP_q^T) \quad (10)$$

This is a compound measurement composed of both spatial information and MBP features. The weight λ is used to balance the contributions of Euclidean distance and MBP distance. The cost function $D(M, T)$ evaluates the degree of mismatch between two MBP sets by measuring the distance of the MBP of M that has the largest distance from any MBP of T , and vice versa.

4. Experimental results

The proposed method was assessed on the public available AR face database (Martínez & Benavente, 1998), which contains over 4000 colour images from 126 peoples (70 men and 56 women). The database covers frontal view faces under controlled condition, different facial expressions and different illumination conditions. There are 26 different images per person, recorded in two different sessions with a two-week time interval, and each session consists of 13 images. Because images in some sessions were missing, we eventually obtained 120 complete set of images (65 men and 55 women). All the images were normalised (in scale and rotation) and cropped to 160×160 pixels based on the manually labelled positions of two eyes. We fixed the MBP size as $L = 8$, $N = 8$, the bit-wise shifting limit as $K = 4$ and the balancing factor as $\rho = 0.1$ in our experiments.

4.1 Determination of parameters

The weight λ In Equation (10) balances the contributions of spatial and MBP measurements. In this subsection, a set of experiments was performed to determine λ using all the neutral expression faces in the AR database. The model set is the neutral faces in the first session, and the test set is those in the second session. The top-one recognition accuracy against the weight λ is displayed in Fig. 7. The recognition accuracy reached and remained maximum when λ ranged from 120 to 300. The weight $\lambda = 160$ was selected and used in the rest of the experiments.

In the following, the MBP method was compared with the Directional Corner Point (DCP) method (Gao & Qi, 2005) under various situations, using the neutral faces in normal condition taken in the first session as the model set.

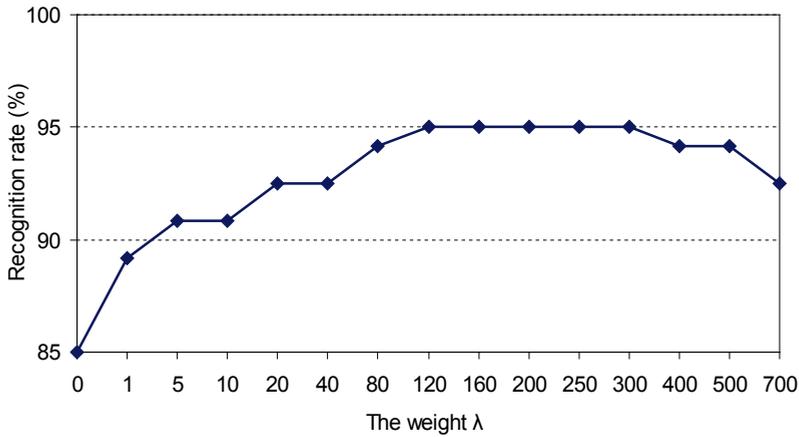


Fig. 7. Recognition accuracy against the weight.

4.2 Face recognition results

The face images under controlled condition in the second session were first used to evaluate the proposed method. The comparative recognition accuracy is illustrated in Fig. 8. Although the number of subjects used in this study (120) was more than that in DCP (112), the proposed MBP method still outperformed the DCP method.

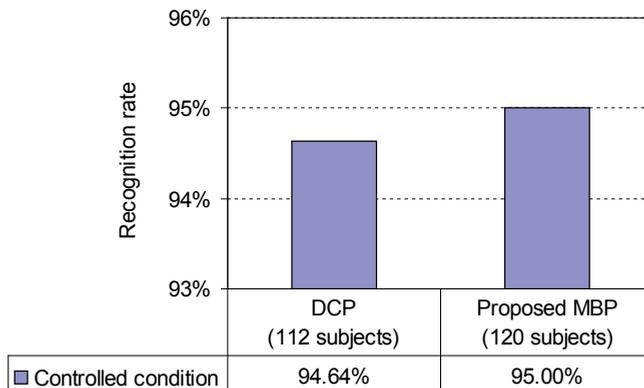


Fig. 8. Comparative recognition accuracy under controlled condition.

To compare the recognition accuracy with expression variations, the experiment was also performed on three different sets of images with smiling, angry and screaming expressions in the first session. The results are listed in Fig. 9. It can be seen from the figure that the performance of the proposed method is much better than the DCP method under all three expression variations, especially under the screaming condition, where the improvement is over 20%. This can be explained by the robustness of MBP against local feature distortion. It

indicates that the locations of feature points might be subject to significant change from screaming, but the pattern-level disparity of their neighbourhoods is comparably stable.

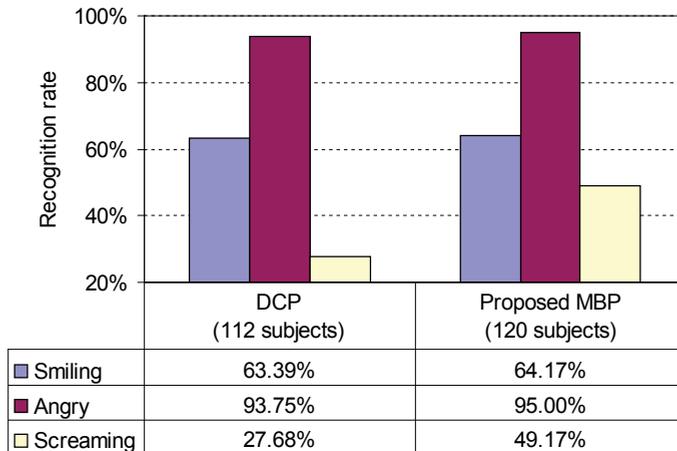


Fig. 9. Comparative recognition accuracy under different expressions.

We finally performed the experiment under the condition of illumination changes. The AR database contains three different lighting conditions: left light, right light and both lights on. Fig. 10 displays these experimental results. The recognition accuracy of the proposed method is noticeably above 90% when either left or right light on. This demonstrates that MBP is very tolerant to lighting changes. However, it is still sensitive to extreme lighting, which causes strong specular reflectance on the face skin and thus could erase some sparse points.

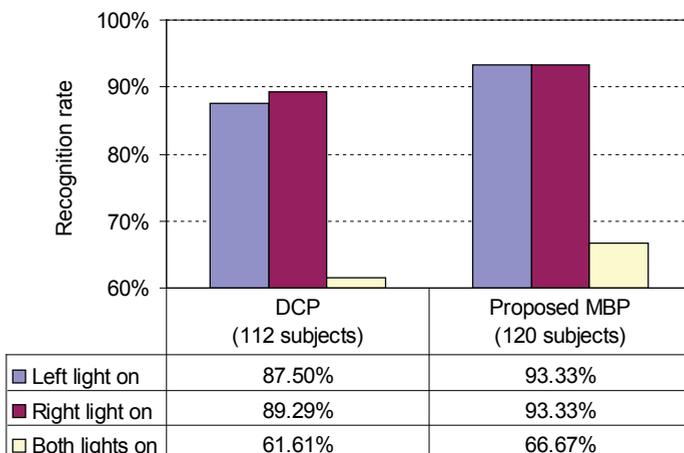


Fig. 10. Comparative recognition accuracy under different illuminations.

5. Conclusions

Local Binary Pattern (LBP) has proved to be a powerful descriptor for both texture and facial images, demonstrating excellent performance in computer vision community. This chapter proposed a more discriminative Multidirectional Binary Pattern (MBP) for face representation. Faces are modelled as a sparse set of shape-driven points with MBP attached on each point. The main contributions of the proposed method are: 1) Binary pattern bunches from multiple directions are collected to enhance the discriminative power of local features. 2) In stead of histogramming all the pixels of an image, local features are extracted from sparse points to reduce the storage demand. 3) A specially designed MBP measurement is proposed to evaluate binary patterns and establish point correspondence. The experiments on face recognition demonstrated the effectiveness of the proposed method against different environmental variations. This study reveals that the proposed MBP method provides a new solution towards robust face recognition.

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