On the Recent Use of Local Binary Patterns for Face Authentication

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Abstract

This paper presents a survey on the recent use of Local Binary Patterns (LBPs) for face recognition. LBP is becoming a popular technique for face representation. It is a non-parametric kernel which summarizes the local spacial structure of an image and it is invariant to monotonic gray-scale transformations. This is a very interesting property in face recognition. In this paper, we describe the LBP technique and different approaches proposed in the literature to represent and to recognize faces. The most representatives are considered for experimental comparison on a common face authentication task. For that purpose, the XM2VTS and BANCA databases are used according to their respective experimental protocols.

Index Terms

Face Recognition, Face Authentication, Local Binary Patterns.

I. Introduction

Local Binary Pattern (LBP) is becoming a popular technique for face representation as well as for image representation in general. Recently, LBP has been applied to the specific problem of face recognition [29], [1], [10], [31], [32], [22], [9]. The LBP is a non-parametric kernel which summarizes the local spacial structure of an image. Moreover, it is invariant to monotonic gray-scale transformations, hence the LBP representation may be less sensitive to changes in illumination. This is a very interesting property in face recognition. Indeed, one of the major problem in face recognition systems is to deal with variations in illumination. In a realistic scenario, it is very likely that the lighting conditions of the probe image does not correspond to those of the gallery image, hence there is a need to handle such variations. This probably explains the recent success of Local Binary Patterns in the face recognition community. In this paper, we will thus address only the problem of lighting variations both in artificial and realistic conditions. The reader should note that one of the database we are using, includes slight facial expression and pose variations. Moreover, in an authentication scenario, the claimant is supposed to cooperate with the system and thus we do not consider database with large facial expression and head pose changes.

We propose in this paper an overview of different LBP techniques proposed for face recognition in general and we experimentally compare the most representative ones on the face authentication task. *Face authentication* (or *verification*) involves confirming or denying the identity claimed by a person (one-to-one matching). In contrast, *face identification* (or *recognition*) attempts to establish the identity of a given person out of a closed pool of N people (one-to-N matching). Both mode are generally grouped under the generic *face recognition* term. Authentication and identification share the same preprocessing and feature extraction steps and a large part of the classifier design. However, both modes target distinct applications. In authentication mode, people are supposed to cooperate with the system (the claimant wants to be accepted). The main applications are access control systems, such as computer or mobile devices log-in, building gate control, digital multimedia access. On the other hand, in identification mode, people are generally not concerned by the system and often even do not want to be identified. Potential applications includes video surveillance (public places, restricted areas) and information retrieval (police databases, video or photo album annotation/identification).

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The problem of face authentication has been addressed by different researchers using various approaches. Thus, the performance of face authentication systems has steadily improved over the last few years. For a comparison of different approaches see [30]. These approaches can be divided mainly into *discriminant* approaches and *generative* approaches. A *discriminant* approach takes a binary decision (whether or not the input face is a client) and therefore has to be trained explicitly on both client data and impostor data. A *generative* approach computes the likelihood of an observation or a set of observations given a client model and compares it to the corresponding likelihood given a generic model (referred as world model). Examples of discriminant classifiers are Multi-Layer Perceptrons (MLPs) and Support Vector Machines (SVMs) [13]. Examples of generative methods are Gaussian Mixture Models (GMMs) [5], Hidden Markov Models (HMMs) [19], [4] or simply a metric [15], [14]. Both *discriminant* and *generative* approaches can use *local* features (local observations of particular facial features) or *holistic* features (the whole face is considered as an input). Examples of holistic features are gray-scale face images or their projections onto a Principal Component subspace (referred to as PCA or Eigenfaces [26]) or a Linear Discriminant subspace (referred to as LDA or Fisherfaces [3], [6]). Examples of local features are blocks extracted from an image or transforms of these blocks such as Discrete Cosine Transform (DCT) or others. Finally, the decision to accept or reject a claim depends on a score (distance measure, MLP output or Likelihood ratio) which could be either above (accept) or under (reject) a given threshold.

This paper is organized as follows. First, we introduce Local Binary Patterns and several variants or extensions. Then, we describe the main different approaches for the recognition of faces with LBP. Finally, we present experimental results, we draw conclusions and we discuss future research directions.

II. Local Binary Patterns

In this section, we introduce the original LBP operator as well as several extensions (multi-scale LBP, uniform LBP, improved LBP) and variants (Extended LBP and Census Transforms).

A. The Original LBP

The Local Binary Pattern (LBP) operator is a non-parametric 3x3 kernel which summarizes the local spacial structure of an image. It was first introduced by Ojala et al. [20] who showed the high discriminative power of this operator for texture classification. At a given pixel position (x_c, y_c), LBP is defined as an ordered set of binary comparisons of pixel intensities between the center pixel and its eight surrounding pixels (Figure 1).

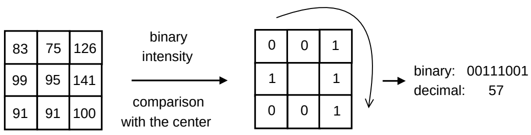

Fig. 1. Calculating the original LBP code

The decimal form of the resulting 8-bit word (LBP code) can be expressed as follows:

$$LBP(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c)2^n \tag{1}$$

where i_c corresponds to the grey value of the center pixel (x_c, y_c), i_n to the grey values of the 8 surrounding pixels, and function $s(x)$ is defined as:

$$s(x) = \begin{cases} 1 & \text{if} \quad x \geq 0 \\ 0 & \text{if} \quad x < 0 \ . \end{cases} \tag{2}$$

Note that each bit of the LBP code has the same significance level and that two successive bit values may have a totally different meaning. Actually, The LBP code may be interpreted as a kernel structure index. By definition, the LBP operator is unaffected by any monotonic gray-scale transformation which preserves the pixel intensity order in a local neighborhood (Figure 2).

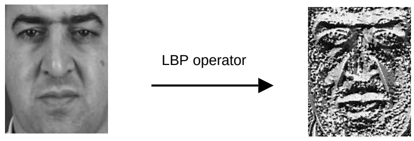

Fig. 2. Original image (left) processed by the LBP operator (right).

Due to its texture discriminative property and its very low computational cost, LBP is becoming very popular in pattern recognition. Recently, LBP has been applied for instance to face detection [12], face localization [11], face recognition [29], [1], [10], [31], [32], image retrieval [25], motion detection [8] or visual inspection [27][1].

B. The Multi-Scale LBP

Later, Ojala et al. [21] extended their original LBP operator to a circular neighborhood of different radius size. Their $LBP_{P,R}$ notation refers to P equally spaced pixels on a circle of radius R. For instance, the $LBP_{8,2}$ operator is illustrated in Figure 3.

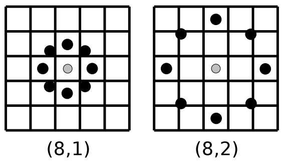

Fig. 3. Examples of extended LBP operators

C. The Uniform LBP

In [21], they also noticed that most of the texture information was contained in a small subset of LBP patterns. These patterns, called uniform patterns, contain at most two bitwise 0 to 1 or 1 to 0 transitions (circular binary code). 11111111, 00000110 or 10000111 are for instance uniform patterns. They mainly represent primitive micro-features such as lines, edges, corners. $LBP^{u2}_{P,R}$ denotes the extended LBP operator ($u2$ for only uniform patterns, labelling all remaining patterns with a single label).

D. The Improved LBP

Recently, new extensions of LBP have appeared. For instance, Jin et al. [12] remarked that LBP features miss the local structure under some certain circumstance, and thus they introduced the *Improved* Local Binary Pattern (ILBP). The main difference between ILBP and LBP lies in the comparison of all the pixels (including the center pixel) with the mean of all the pixels in the kernel (Figure 4).

The decimal form of the resulting 9-bit word (ILBP code) can be expressed as follows:

$$ILBP(x_c, y_c) = \sum_{n=0}^{8} s(i_n - i_m)2^n \tag{3}$$

where i_m corresponds to the mean grey value of all the pixels, and function $s(x)$ is defined as in Equation 2.

[1]a more exhaustive list of applications can be found on Oulu University web site at: http://www.ee.oulu.fi/research/imag/texture/lbp/lbp.php

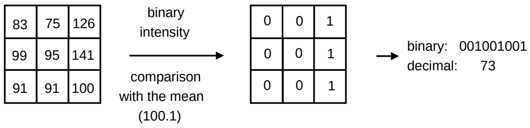

Fig. 4. Calculating the ILBP code

E. The Extended LBP

Huang et al. [11] pointed out that LBP can only reflect the first derivation information of images, but could not represent the velocity of local variation. To solve this problem, they proposed an *Extended* version of Local Binary Patterns (ELBP) that encodes the gradient magnitude image in addition to the original image. For that purpose, they simply applied kernels $LBP^{u2}_{8,1}, LBP^{u2}_{8,2}$ and $LBP^{u2}_{8,3}$ both to the original image and the gradient image. As a consequence, this method can't be considered as an extension of the LBP operator.

F. Census Transforms

We finally point out that, approximately in the same time the original LBP operator was introduced by Ojala [20], Zabih and Woodfill [28] proposed a very similar local structure feature. This feature, called *Census Transform*, also maps the local neighborhood surrounding a pixel to a bit string. With respect to LBP, the *Census Transform* only differs by the order of the bit string. Later, the *Census Transform* has been extended to become the *Modified Census Transform* (MCT) [7]. Again, one can point out the same similarity between ILBP and MCT (also published at the same time).

III. Face Recognition Systems using Local Binary Patterns

In this section, we present the most representative face recognition systems using LBP (Ahonen [1], Zhang [29], LBP/JSBoost [10], LBP/MAP [22], INORM LBP [9]).

A. Ahonen System

In [1], Ahonen proposed a face recognition system based on a LBP representation of the face. The individual sample image is divided into R small non-overlapping blocks (or regions) of same size. Histograms of LBP codes H^r, with $r \in \{1, 2, \ldots, R\}$ are calculated over each block and then concatenated into a single histogram representing the face image. A block histogram can be defined as:

$$H^r(i) = \sum_{x,y \in block_r} I(f(x,y) = i), \; i = 1, ..., N, \tag{4}$$

where N is the number of bins (number of different labels produced by the LBP operator), $f(x,y)$ the LBP label [2] at pixel (x,y) and I the indicator function.

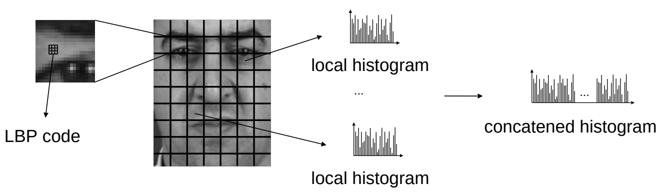

Fig. 5. LBP description of the face.

[2]Note that $LBP(x,y)$, the LBP operator value, may not be equal to $f(x,y)$ which is the label assigned to the LBP operator value. With the $LBP^{u2}_{P,R}$ operator, for instance, all non-uniform patterns are labelled with a single label.

This model contains information on three different levels (Figure 5): (1) LBP code labels for the local histograms (pixel level), (2) local histograms (region level) and (3) a concatenated histogram which builds a global description of the face image (image level). Because some regions are supposed to contain more information (such as eyes), Ahonen propose an empirical method to assign weights to each region. For classification, a nearest-neighbor classifier is used with Chi square (χ^2) dissimilarity measure, defined as follows:

$$\chi^2(\mathbf{S},\mathbf{M}) = \sum_{r,i} \frac{(S^r(i) - M^r(i))^2}{S^r(i) + M^r(i)}, \tag{5}$$

where $\mathbf{S}$ and $\mathbf{M}$ correspond to the sample and the model histograms. Ahonen investigated several variants of LBP including $LBP_{P,R}$ (varying the radius parameter) and LBP^{u2}. However, he reported best results with $LBP^{u2}_{8,2}$.

B. Zhang System

Following the work of Ahonen, Zhang et al. [29] underlined some limitations. First, the size and position of each region are fixed which limits the size of the available feature space. Second, the weighting region method is not optimal. To overcome these limitations, they propose to shift and scale a scanning window over pairs of images, extract the local LBP histograms and compute a dissimilarity measure between the corresponding local histograms. If both images are from the same identity, the dissimilarity measure are labelled as positive features, otherwise as negative features. Classification is performed with AdaBoost learning, which solves the feature selection and classifier design problem. Optimal position/size, weight and selection of the regions are then chosen by the boosting procedure. Comparative study with Ahonen's method showed similar results. Zhang et al.'s system uses however much less features (local LBP histograms).

C. Huang System

More recently, Huang et al. [10] proposed an improved version of Zhang et al. system. Their method is based on a modified version of the boosting procedure called *JSBoost* which incorporates Jensen-Shannon (JS) divergence into AdaBoost learning. This JS divergence provides a more appropriate dissimilarity measure between two classes than previous proposed measures. More stable and effective weak classifiers are learnt by *JSBoost*. This improved feature selection leads to slightly better recognition results with a significantly smaller number of features.

D. Rodriguez-Marcel System

In [22], Rodriguez et al. proposed to use a generative approach. This method, called LBP/MAP, considers local histograms as probability distributions and computes a log-likelihood ratio instead of a Chi square similarity. A generic face model is represented by collection of LBP-histograms. Then, a client-specific model is obtained by an adaptation technique (Figure 6) from this generic model under a probabilistic framework.

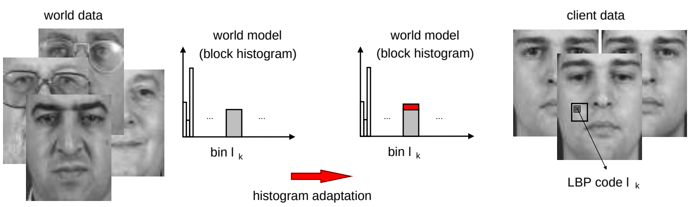

Fig. 6. Illustration of the adaptation of LBP histograms.

E. System using LBP as an Image Preprocessing

A completely different approach has been also proposed. Heusch et al. [9] suggested to use the LBP (more precisely $LBP_{8,2}$) directly as an illumination normalization technique (Figure 7). This method, called INORM LBP, applies the LBP operator on every pixel of the image and computes the LBP code. Each LBP code becomes a pixel in the INORM LBP image. Then, standard face recognition techniques such as LDA/NC [15] or DCT/HMM [4] can be used to solve the verification task.

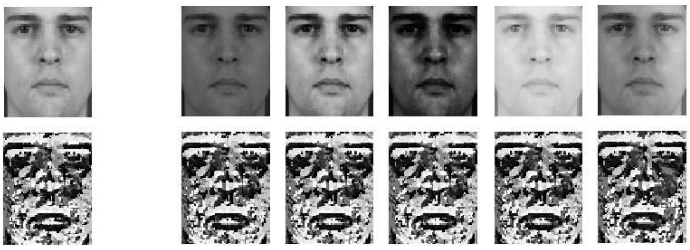

Fig. 7. Robustness to illumination changes.

IV. Experiments and Results

In this section, we provide comparative experiments with several systems introduced in Section III on two face authentication benchmark databases, namely XM2VTS and BANCA, which we briefly describe in this section. All algorithms have been developed using the Torchvision library (`torch3vision.idiap.ch`) and experiments have been performed using the pyVerif (`pyverif.idiap.ch`) biometric verification toolkit. We implemented the systems of Ahonen [1] and Zhang [29], but also LBP/MAP [22] as well as two standard state-of-the-art methods combined with two different image preprocessing techniques: histogram equalization (HEQ) and LBP (INORM LBP) [9]. The first system is a combination of Linear Discriminant Analysis with a Normalized Correlation (LDA/NC) based on a holistic representation of the face [23]. The second one is a generative approach based on the Discrete Cosine Transform and Hidden Markov Models (DCT/HMM) with a local description of the face [4]. We didn't implemented LBP/JSBoost, the system of Huang et al. [10], as the authors are claiming that LBP/JSBoost is an improvement of Zhang et al. system.

A. Databases

The XM2VTS database [17] contains synchronized video and speech data from 295 subjects, recorded during four sessions taken at one month intervals. The subjects were divided into a set of 200 training clients, 25 evaluation impostors and 70 test impostors. Recordings were acquired over a period of five months under controlled conditions (blue background, artificial illumination) for the standard set. The darkened set contains four images of each subject acquired with side lighting. Figure 8 shows images coming from both sets of the database. We performed the experiments following the *Lausanne Protocol Configuration I*. Concerning darkened set experiments, the protocol is the same but for the testing phase: it is done on the darkened images.

The BANCA database [2] was designed to test multi-modal identity verification with various acquisition devices under several scenarios (controlled, degraded and adverse). In the experiments described here we used the face images from the English corpora, containing 52 subjects, equally divided into two groups $g1$ and $g2$ used for development and evaluation alternatively. Each subject participated in 12 recording sessions. Each of these sessions contains two video recordings: one true client access and one impostor attack. Image acquisition was performed with two different cameras: a cheap analogue web-cam, and a high-quality digital camera, under several realistic scenarios: controlled (high-quality camera, uniform background, controlled lighting), degraded (web-cam, non-uniform background) and adverse (high-quality camera, arbitrary conditions). See Figure 8 for example images of each scenario.

(a) XM2VTS: standard and darkened

(b) BANCA: uncontrolled conditions

Fig. 8. Comparison of XM2VTS (a) and BANCA (b) image conditions. Whereas XM2VTS database contains face images in controlled conditions, BANCA is a much more challenging database with face images recorded in uncontrolled environment (complex background, difficult lightning conditions).

In the BANCA protocol, seven distinct configurations for the training and testing policy have been defined. In our experiments, the configurations referred as Match Controlled (Mc), Unmatched Adverse (Ua), Unmatched Degraded (Ud), Pooled Test (P) and Grand Test (G) are used. All of the of listed configurations, except protocol G, use the same training conditions: each client is trained using images from the first recording session of the controlled scenario. Testing is then performed on images taken from the controlled scenario (Mc), adverse scenario (Ua), degraded scenario (Ud), while (P) does the test for each of the previously described configurations. The protocol G uses training images from the first recording sessions of scenarios controlled, degraded and adverse.

B. Experimental Setup

1) Feature Extraction: For both XM2VTS and BANCA databases, face images are extracted to a common size of 80×64 (rows $\times$ columns), according to the provided ground-truth eye positions. We used this representation for all the methods we implemented. For LBP methods, face images are decomposed in 8×8 blocks ($R = 80$ blocks) and histograms of LBP codes are then computed over each block r.

2) Performance Measure: To assess authentication performance, the Half Total Error Rate (HTER) is generally used:

$$\mathrm{HTER}(\theta) = \frac{\mathrm{FAR}(\theta) + \mathrm{FRR}(\theta)}{2} . \tag{6}$$

where FAR if the false alarm rate, FRR the false rejection rate and θ the decision threshold. To correspond to a realistic situation, θ is chosen *a priori* on the validation set at Equal Error Rate (EER).

For experiments on XM2VTS database, we use all available training client images to build the generic model. For BANCA experiments, the generic model was trained with the additional set of images provided with the database, referred to as *world data* (independent of the subjects in the client database).

C. Results and Discussion

Table I reports comparative results for Ahonen, Zhang and LBP/MAP systems, as well as for state-of-the-art methods LDA/NC and DCT/HMM both using HEQ and INORM LBP image preprocessing. We also report the only result from LBP/JSBoost [10] obtained on BANCA (protocol G only).

From the results on XM2VTS (standard set), we first remark that several LBP methods obtain state-of-the-art results. Secondly, we notice that compared to the two other methods which use a LBP representation of the face, LBP/MAP performs clearly better on both databases and all protocols. On protocol G, where more client training data is available, LBP/MAP clearly outperforms the improved version of Zhang system (LBP/JSBoost). We also notice that LBP-based generative methods (INORM LBP + DCT/HMM and LBP/MAP) perform better that the two other LBP-based methods for all conditions. However, it must be noted that these methods (Ahonen and Zhang) have been originally designed for the face identification problem. We finally point out that as reported in [29] for identification, Ahonen and Zhang methods give similar results at least on the XM2VTS standard set.

TABLE I

HTER PERFORMANCE COMPARISON FOR TWO STATE-OF-THE-ART METHODS (LDA/NC AND DCT/HMM) AND LBP SYSTEMS, FOR THE XM2VTS DATABASE AND BANCA DATABASE.

Models	XM2VTS		BANCA				
	Std	Dark	Mc	Ud	Ua	P	G
HEQ + LDA/NC	3.2	10.6	4.8	13.8	20.8	15.2	7.1
HEQ + DCT/HMM	2.0	37.3	4.1	22.5	18.9	18.0	4.6
INORM LBP + LDA/NC	5.6	9.7	6.2	13.3	20.5	15.3	7.4
INORM LBP + DCT/HMM	**1.4**	**9.6**	**2.1**	**9.2**	**16.1**	**12.6**	**1.2**
LBP Ahonen	3.4	22.6	8.3	14.3	23.1	20.8	10.4
LBP Zhang	3.9	35.6	9.7	26.4	23.6	25.3	9.3
LBP/MAP	**1.4**	12.9	7.3	10.7	22.6	19.2	5.0
LBP/JSBoost [10]	-	-	-	-	-	-	10.7

More importantly, it should be noticed the degradation of all systems when tested on the darkened set of XM2VTS and on unmatched conditions of BANCA. However, once again LBP-based generative methods are the most robust to these illumination changes and the mismatch.

Finally, according to the results the best system is INORM LBP + DCT/HMM, that is when LBP is used as a preprocessing step and when an additional face recognition technique is used. Indeed, all LBP-based face recognition techniques perform histogram comparison. Therefore, we believe there might be a large potential for performance improvement by using more appropriate generative models of Local Binary Patterns.

V. CONCLUSION AND FUTURE WORK

In this paper, we presented a survey on some recent use of Local Binary Patterns (LBPs) for face recognition. We described the LBP technique as well as several different approaches proposed in the literature to represent and to recognize faces. We selected the most representatives to perform an experimental comparison on a face authentication task. The XM2VTS and BANCA databases were used according to their respective experimental protocols.

Results have shown that LBP based methods obtained state-of-the-art results and than some of them were even outperforming the state-of-the-art. Another interesting conclusion from the results suggested to combine Local Binary Patterns and generative models. We believe this might be a novel research direction to investigate.

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