Feature to Feature Matching for LBP Based Face Recognition

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Abstract. This paper presents a novel face recognition method called Local Binary Patterns with Feature to Feature Matching (LBP-FF). Contrary to other LBP approaches, we do not focus on the operator itself, however we would like to improve the matching procedure. The current LBP based approaches concatenate all feature vectors into one vector and then compare these large vectors. By contrast, our method compares the features separately. A sophisticated distance measure composed from two parts is used for face comparison. Chi square distance and histogram intersection metrics are utilized for vector distance computation. The proposed approach is evaluated on four face corpora: AT&T, FERET, AR and ČTK database. We experimentally show that our method significantly outperforms all compared state-of-the-art methods on all the databases. It is also worth of noting that the ČTK corpus is a novel face dataset composed of the images taken in real-world conditions and is freely available for research purposes at http://ufi.kiv.zcu.cz or upon request to the authors.

Keywords: Automatic Face Recognition, Czech News Agency, LBP with Feature to Feature Matching, LBP-FF, Local Binary Patterns

1 Introduction

Face recognition became one of the most popular biometric identification methods. It has a very broad spectrum of applications: access control, surveillance of people, automatic annotation of photographs and so on. The most of currently emerging approaches can be categorized as feature based because these methods proved to be more accurate than the holistic ones especially in case of images with significant variations in pose, lighting, etc.

One of the most popular methods for feature extraction are Local Binary Patterns (LBP). It was originally proposed for texture classification in [1]. Lately, it is frequently used also for other tasks such as facial expression recognition, content based image retrieval, face recognition or medical applications. The first method utilizing LBP for face recognition was proposed by Ahonen in [2]. The image is divided into a set of non-overlapping rectangular regions and a histogram of LBP values is computed in each one. One feature corresponds to one region. All features are finally concatenated and treated as one large vector that represents the face.

The LBP algorithm inspired many other, more sophisticated, image descriptors but the principle of creating the face representation remains usually the same. Histograms are created from the values obtained from the particular algorithm and are concatenated to one vector that creates the face representation. In our work, we concentrate rather on the comparison procedure than the descriptor itself.

We use the features individually and compare them one to another. A similar method was already presented in [3]. It showed significantly better performance than the method that uses one concatenated vector.

The main goal of this work is to improve the matching scheme and to show its impact on several face corpora. We use features equally distributed on a grid as in the original method to allow a direct comparison. For the face matching step we propose a novel method that combines two distance measures.

The rest of the paper is organized as follows. Section 2 describes the fundamental face recognition methods based on LBP. Section 3 describes the LBP algorithm and the proposed face recognition method. Section 4 first describes the databases we used for evaluation and then presents the results of experiments performed on these datasets. In the last section, we discuss the results and propose some ideas for future research.

2 Related Work

As already stated, the first method using LBP for face recognition was proposed by Ahonen in [2]. The authors also proposed a weighted LBP modification which gives more importance to the regions around central parts of the face.

An important idea proposed already by Ojala in [1] are Uniform Local Binary Patterns. The pattern is called uniform if it contains at most two transitions from 0 to 1 or from 1 to 0. The histogram is then shortened from 256 intervals (bins) to 59.

Li et al. propose in [4] Dynamic Threshold Local Binary Pattern (DTLBP). They consider the mean value of the neighbouring pixels and also the maximum contrast between the neighbouring points. The authors claim that this variation is less sensitive to the noise than the original LBP method.

Another LBP extension are Local Ternary Patterns (LTP) [5]. LTP uses three states to capture the differences between the central pixel and the neighbouring ones. Similarly to the DTLBP this method is less sensitive to the noise.

Local Derivative Patterns (LDP) are proposed in [6]. The difference from the original LBP is that it uses features of higher order. It thus can represent more information than the original approach.

Local Tetra Patterns (LTrPs) are proposed in [7]. The standard LBP and LTP encode the relationship between the reference pixel and its surrounding neighbours by computing gray-level difference. The proposed method encodes the relationship between the reference pixel and its neighbours by the directions calculated using the first-order derivatives in vertical and horizontal directions. The results on several benchmark datasets show that the performance of this method is better than the LBP, LTP and LDP.

Yang et al. propose in [8] an interesting method which uses uniform patterns. The authors state that the histogram bin containing non-uniform patterns dominates among the other bins and gives thus too much importance to this bin. Therefore they propose to assign such patterns to the closest uniform pattern.

A novel LBP based approach, patch based descriptor is proposed in [9]. The authors show that this approach improves the accuracy of the original LBP method in both multi-option identification and same/not-same classification on the LFW corpus [10]. Three-patch LBP (TPLBP) and Four-patch LBP (FPLBP) are proposed.

Zhang et al. propose in [11] Multiblock LBP (MB-LBP) which captures not only the microstructures but also the macrostructures. The main difference of this method from the original LBP is that it compares average intensities of neighbouring subregions instead of comparing individual pixels.

Mawloud et al. propose in [12] a novel alternative to the original LBP, Modied Local Binary Pattern (MLBP). This method exploits the sparsity of the representative set of MLBPs for recognition of different faces. Compressive sensing theory was employed to construct a so-called sparse representation classifier. Experimental results on three popular face databases show the superiority of the proposed method over other state-of-the-art techniques.

He et al. present in [13] a modified LBP operator with a pyramid model. In this approach, a separate output label for each uniform pattern and all non-uniform patterns is reclassified. The experiments on the AT&T and Honda/UCSD video databases show that this novel approach outperforms other related methods.

Davarzani et al. propose in [14] a weighted and adaptive LBP-based texture descriptor. This approach successfully handles some issues in the previously proposed LBP-based approaches such as invariance to scaling, rotation, viewpoint variations and non-rigid deformations. In this method, both the radius of the circular neighbourhood and the orientation of sampling in LBP descriptor are defined in adaptive manner. The authors experimentally show that this approach achieves significantly better results over other LBP-based methods.

Local Gabor Binary Pattern Histogram (LGBPH) [15, 16] combines Gabor wavelets with LBP. It first filters the image with a set of Gabor filters and obtains a set of magnitude images. Then the LBP operator is applied to each of the magnitude images.

For additional information about the LBP based methods, please see the surveys [17, 18].

It is worth of mentioning that in all above described LBP methods, the images are divided into rectangular regions and histograms are computed in each region. All histograms from one image are then concatenated to create the face representation.

A method that differs from the above described ones is proposed in [3]. The features are not placed on a rectangular grid. The method instead detects the feature points automatically using the Gabor wavelets. The points thus differ for each image. The dynamically determined points proved to be more suitable for images with higher amount of variations. One important part of the method is the matching scheme that compares the features individually. Chi square distance is used for vector comparison.

3 LBP with Feature to Feature Matching (LBP-FF)

Our method extends the LBP based face recognition method proposed by Ahonen [2]. The first step in the face representation creation is applying the LBP operator to the facial image. We use the $LBP_{8,2}$ operator that proved to be superior in [3]. The resulting LBP image is then divided into a set of square cells lying on a regular grid. The feature vector is composed of two parts. The first one are the coordinates of the feature point and the second one is the histogram of LBP values computed in a given cell. The coordinates of the feature point are set to the center of the cell. The resulting feature vector is thus composed of $2 + 256$ values.

3.1 Local Binary Patterns

The original LBP operator uses a 3×3 square neighbourhood centred at the given pixel. The algorithm assigns either 0 or 1 value to the 8 neighbouring pixels by Equation 1.

$$N = \begin{cases} 0 \text{ if } g_N < g_C \\ 1 \text{ if } g_N \geq g_C \end{cases} \tag{1}$$

where N is the binary value assigned to the neighbouring pixel, g_N denotes the gray-level value of the neighbouring pixel and g_C is the gray-level value of the central pixel. The resulting values are then concatenated into an 8 bit binary number. Its decimal representation is used for further computation.

Currently, LBP is mostly used with a circular neighbourhood which is formed by a certain number of points P placed on a circle with a given diameter R. Values in the points that are not placed exactly in the centre of a pixel are interpolated from the values of neighbouring pixels. The points are compared to the central pixel in the same way as in the original descriptor. The operator is then denoted as $LBP_{P,R}$.

The value of the operator is computed by Equation 2.

$$LBP_{P,R} = \sum_{p=1}^{P-1} s(g_p - g_c)2^p, S(x) = \begin{cases} 0 \text{ if } x < 0 \\ 1 \text{ if } x \geq 0 \end{cases} \tag{2}$$

where g_p denotes the points on the circle and g_c is the central point. The computation is illustrated by Figure 1.

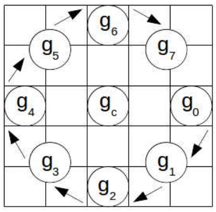

Fig. 1. Computation of LBP operator with a circular neighbourhood, P = 8, R = 2

3.2 Face Comparison

Face comparison is the main contribution of the proposed method. As stated previously, we compare the features individually instead of concatenating them into one large vector. Let T be a test image and G a gallery one. The distance of the two faces $dist_{T,G}$ is defined as:

$$dist_{T,G} = \alpha D_{T,G} + (1 - \alpha)V_G \tag{3}$$

where α is a weighting coefficient and its optimal value will be found experimentally. The first variable $D_{T,G}$ represents an average vector similarity in a given region and is defined as:

$$D_{T,G} = mean\,\{d(t, g), t \in T, g \in G(N_t)\} \tag{4}$$

where $G(N_t)$ is the neighbourhood of feature t defined by a distance threshold DT (see Eq. 5) and $d(t, g)$ is the (distance) metric used for histogram comparison. We evaluate two different metrics: Chi square distance and histogram intersection.

$$\sqrt{(x_t - x_g)^2 + (y_t - y_g)^2} \leq DT \tag{5}$$

The second variable V_G determines the face with the most similar vector to the test vector t as follows.

$$V_G = C_G/N_G \tag{6}$$

The variable C_G defines how many times the gallery face G was the closest to some of the vectors of the test face T and N_G is the number of features in the face G. Same as for the variable $D_{T,G}$, only the vectors within a neighbourhood defined by the distance threshold DT are considered.

The recognized face $\hat{G}$ is then defined as:

$$\hat{G} = \arg\min_{G}(dist(T, G)) \tag{7}$$

4 Experimental Setup

4.1 Corpora

This section briefly summarizes the face databases used for evaluation of our approach.

AT&T Database of Faces This database [19] was formerly known as the ORL database. It was created at the AT&T Laboratories[3]. The pictures were captured between years 1992 and 1994. The database contains the faces of 40 people, 10 pictures for each person are available. Each image contains one face with a black homogeneous background. They may vary due to the different time of acquisition, head size and pose and lighting conditions. The size of pictures is 92×112 pixels. We used these images without any modification of size.

FERET Dataset FERET dataset [20] contains 14,051 images of 1,199 individuals. The images were collected between December 1993 and August 1996. The resolution of the images is 256×384 pixels. The images are divided into the following categories according to the face pose: frontal, quarter-left, quarter-right, half-left, half-right, full-left and full-right, and they are stored in the *.tiff* format. The images are also grouped into several probe sets. The main probe sets of the frontal images are summarized in Table 1. Note that only one image per person/set is available. We used images cropped to 130×150 pixels in our experiments.

Table 1. Image numbers in the main frontal probe sets of the FERET dataset

Type	Images no.
fa	1,196
fb	1,195
fc	194
dup1	722
dup2	234

[3] http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html

AR Face Database AR Face Database[4] [21] was created at the Univerzitat Autonòma de Barcelona. This database contains more than 4,000 colour images of 126 individuals. The images are stored in a *raw* format and their size is 768×576 pixels. The individuals are captured under significantly different lighting conditions and with varying expressions. Another characteristic is a possible presence of glasses or scarf. In our experiments, we used images cropped to 120×165 pixels.

Czech News Agency (ČTK) Database This database was created automatically from real-world photographs owned by the Czech News Agency and contains gray-scale images of 638 people of the size 128×128 pixels. All images were taken over a long time period (20 years or more) and have significant variations in pose and lighting conditions. Up to 10 images for each person are available. The testing part contains one image for each person whereas the remaining part is used for training. Note that only the testing part was checked manually. No additional cropping was performed on these images.

Figure 2 shows three example images from this corpus. The corpus is available freely for research purposes at `http://ufi.kiv.zcu.cz` or upon request to the authors.

Fig. 2. Three example images from the ČTK face database

4.2 Experiments

The first series of experiments was realized on the AT&T database of faces.We used the scenario where only one image is used for training and the remaining 9 for testing. As baselines, we used the algorithm designed by Ahonen [2] and an approach based on automatically detected feature points [3]. The recognition accuracies of these two baseline approaches are 56.17% and 68.8% respectively. The experiments on this small dataset were performed in order to choose the best performing distance metric and to set up optimal values for the parameters of the method.

Distance Metric Determination In the first experiment, we compare the results when Chi square distance and histogram intersection are used as distance

[4] http://www2.ece.ohio-state.edu/ aleix/ARdatabase.html

metrics. The coefficient α is set to 0.5 and the distance threshold DT is set to 0 (only features at the same positions are compared) in this experiment. Table 2 shows the results of these two metrics for cell sizes set to 11, 13 and 15.

Table 2. Recognition accuracies in % of the Chi square distance and histogram intersection metrics on the AT&T database.

Distance	**Cell size**		
	11	**13**	**15**
Chi square	36.81	54.81	61.86
Histogram intersection	69.61	71.00	72.28

The table shows clearly that the histogram intersection outperforms the Chi square distance in all cases. Therefore, we use this metric in all following experiments.

Optimal Value of the α Coefficient Determination In the second experiment, we determine an optimal value of the coefficient α (see Equation 3). The results of this experiment are depicted in Figure 3. We also compare the results with the distance threshold DT set to 0 and with a value that allows comparison of neighbouring cells. AT&T database is utilized in this experiment.

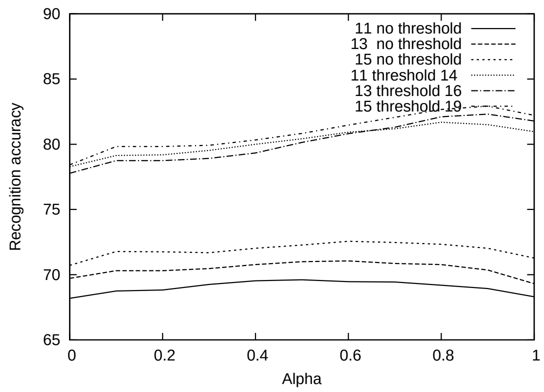

Fig. 3. Dependency of recognition accuracy on the coefficient α on the AT&T database. Histogram intersection distance is used and no distance threshold. Three values of cell size are tested.

Based on this experiment, we can conclude that:

- It is beneficial to use the distance threshold DT;
- The optimal value of the coefficient α is around 0.9.

The best obtained recognition accuracy in this experiment reached 82.92%.

Optimal Cell Size Determination The following experiment is realized in order to set an optimal value of the cell size. These tests are also done on the AT&T database. Figure 4 shows the dependency of recognition accuracy on the cell size. The results show that the suitable values of the cell size are $cellSize \in \langle 15; 18 \rangle$. The rapid changes at some values are caused by placing the grid on the image. In case of larger cell the cells may not correspond to the image features.

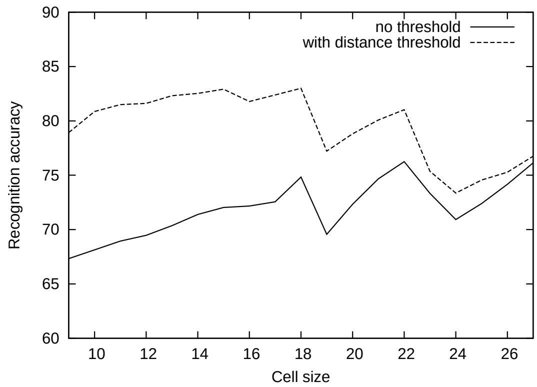

Fig. 4. Dependency of recognition accuracy on the cell size

Experimental Evaluation on Three Face Datasets In the last and the most important experiment, we would like to evaluate and compare our method with the other state-of-the-art (SoTa) approaches. We use two standard datasets: AR and FERET and our ČTK corpus. For the AR database, we use a scenario with 7 training and 7 testing examples for each person. The reported FERET experiments use fa set for training and fb set for testing. For the ČTK dataset, we use one image for testing and the remaining ones for training. According to the previous experiments was the cell size set to 18 in all cases.

This table shows that the proposed FBP-FF method outperforms the Ahonen's baseline in all cases. Moreover, the results on AR and FERET datasets are significantly better than the method reported in [3] as well as the other reported SoTa methods.

In the case of the ČTK dataset, the scores are slightly lower. This is probably caused by the real-world character of images in this dataset where it is more important to detect the most representative feature points. It must be also mentioned that the novel method has lower computational costs than the method method [3] which is an important factor for practical applications.

Table 3. Recognition accuracy in % on AR, FERET and ČTK datasets

Method	Database		
	AR	FERET	ČTK
Orig. LBP (Ahonen) [2]	87.71	93.89	39.81
DP-LBP (Lenc) [3]	97.00	98.24	59.10
Scale adaptive features [22]	92.78	98.16	-
Direct LGBPHS [15]	98.00	94.00	-
LBP + SRC [14]	96.00	-	-
LBP-FF (proposed)	99.57	99.16	57.37

5 Conclusions and Future Work

This paper proposes a novel face recognition method based on LBP features. Compared with other LBP-based method we concentrate mainly on the face comparison process. The main contribution is proposal of a novel face comparison algorithm that compares the features individually. The distance of two faces is computed as a weighted linear combination of two partial distance metrics. The proposed method was evaluated on four face databases: AT&T, AR, FERET and ČTK. We experimentally showed that our approach significantly outperforms other state of the art methods.

In this work, we used the $LBP_{8,2}$ operator. Therefore, the first perspective is to use a more sophisticated descriptor such as LDP, POEM or LQP together with our matching scheme. Another perspective consists in using other distance metrics or use weighting of the features according to its position in the face.

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