Novel Texture Descriptor Family for Face Recognition

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Abstract. This paper presents a novel image descriptor family. The shaped local binary patterns are an extension of the popular local binary patterns (LBPs). It takes into consideration larger neighbourhoods of the central pixel. The main novelty is that this descriptor allows using varying shapes of the neighbourhood instead of just one point. This property ensures better robustness and gives the opportunity to fine-tune the descriptor for a given task. We evaluate the descriptor on the face recognition task in the frame of an application for recognition of real-world face images. The results on two standard face corpora show improved performance over the basic LBP method.

Keywords: face recognition, FERET, image descriptor, local binary patterns, LBP, S-LBP, UFI

1 Introduction

Image descriptors are utilized for creation of image representations in many tasks such as object detection or recognition, image annotation, etc. The properties of the descriptors are crucial for the success of the classifiers that are based upon representations created this way. In this work we concentrate on the face recognition task where many successful descriptor based methods are used.

The descriptor usually captures certain properties of the processed image such as colour, shape or texture. The proposed *Shaped local binary patterns (S-LBP)* belongs to the family of texture descriptors and is based on local binary patterns (LBP) [1]. It was designed in order to better describe the local image patches and to ensure robustness to noise in the images. It allows to use several topologies (shapes) for which an average is computed and is used for comparison with the central pixel. The other parameters of the method are range and neighbours. These parameters define the radius of the circle and the number of neighbouring points respectively.

The descriptor is tested on two face recognition corpora, namely FERET and UFI. Both datasets possess different characteristics which allows a thorough evaluation of the method.

2 Related Work

The original LBP operator was proposed in [8]. It was used for texture classification and is basically a variant of the texture unit [13]. Its computation is based on a small local neighbourhood of a given pixel. The central pixel is compared with 8 neighbouring ones. The resulting code is a number in range 0 to 255. Ahonen et al. [1] [2] first found its usefulness for the face recognition task and achieved very good results on FERET dataset. These publications started a boom of local descriptors coming out of the LBP method.

A simple extension was proposed in [11]. It is called local ternary patterns (LTP) and utilizes a threshold and a three-level division for the resulting codes. It is then split into two binary codes and is treated as two separate LBP channels. It outperformed the results of LBP mainly on face corpora with challenging illumination conditions.

Another variant is dynamic threshold LBP (DTLBP) [6]. It takes into consideration the mean value of the neighbouring pixels and also the maximum contrast between the neighbouring points. It is stated there that this variation is less sensitive to noise than the original LBP method. The recognition rates reported on the Yale B database outperform both LBP and LTP.

Completed LBP (CLBP) [3] utilizes the sign of the difference between the central and the neighbouring pixels as well as its magnitude. It results in three codes that are fused to create the final representation. The approach proved better performance on the texture classification task then LBP.

Another type of descriptor was proposed in [16]. The local derivative patterns (LDP) construct features of higher order compared to the first order LBP. It showed better capabilities mainly on face recognition task with varying illumination.

Three- and Four-patch LBP variations were proposed in [14]. The codes are constructed by comparison of three or four patches respectively. The more sophisticated computation brings better robustness. The algorithm works very well on face recognition using the LFW dataset.

More information about texture descriptors is available in [7].

3 Face Recognition Using S-LBP

In this section we describe the methodology of using the S-LBP descriptor for face recognition.

3.1 Local Binary Patterns

Local binary patterns algorithm is used as a baseline for comparison with the proposed method. We briefly describe next the circular version of the LBP, because our methods extends this LBP variant and it also represents a stronger baseline compared to the original square LBP operator.

The operator is denoted as $LBP_{P,R}$ where P is the number of neighbouring points used for calculation and R is the radius of the circle on which the points lie. The values of points that are placed in the pixel centres are computed using a bilinear interpolation. The value of the operator is computed by Equation 1.

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

where g_p denotes the points on the circle and g_c is the central point. Figure 1 illustrates the computation of $LBP_{8,2}$ operator.

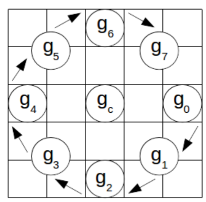

Fig. 1. Computation of $LBP_{8,2}$ operator.

3.2 Shaped Local Binary Patterns

The S-LBP operator is based on the LBP computation. It was developed to increase the robustness of the resulting descriptors by incorporating more pixels in the neighbourhood for the computation. This concept should ensure that more information about the local patch is preserved in the operator computed in the given central point. The main difference from the circular LBP is that S-LBP computes an average value of the pixels in the neighbourhood of the pixel lying on the circle. This value is then used for comparison with the central pixel.

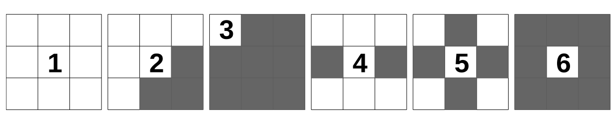

Fig. 2. Six different S-LBP shapes.

We propose 6 different shapes of the neighbourhood as depicted in Figure 2. The number placed in the central pixel denotes the specific S-LBP topology. The grey region is used for computation of the average value.

S-LBP descriptor is then defined as $S-LBP_{(N,r,S)}$, where N is the number of neighbours, r is the S-LBP range (radius of the circle) and S defines the shape topology $S \in [1;2;3;4;5;6]$. The shape number 1 represents the basic circular LBP where only one point is used for comparison.

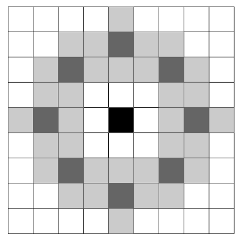

Fig. 3. $S-LBP_{(8,3,5)}$ computation.

Figure 3 shows an example of this operator in configuration $S-LBP_{(8,3,5)}$. In this case the neighbourhood contains 32 pixels that are used for computation of the S-LBP value. The black pixel is the central one. Grey pixels lie on the circle with radius 3 and the light grey ones are the pixels in the neighbourhood (defined by shape 5) that are used for averaging.

S-LBP as well as original LBP can use either all patterns or only so called uniform patterns. The uniformity is evaluated according to the binary notation of the code. The pattern is uniform if it contains at most two transitions from 0 to 1 or vice versa. In the case of methods with 8 points, the number of uniform patterns is 58. It thus reduces the space from 256 to 59 (the 59th pattern is used for all non-uniform patterns). It has been shown that the majority of patterns occurring in the images are uniform [2]. The reduction of the number of patterns thus causes only small information loss but can highly improve the speed of the algorithm.

3.3 Face Representation and Recognition

The representation is based on the operator values in all points of the image. The S-LBP values of the image pixels are thus computed first. The feature vectors are created as so called histogram sequences [17] as follows. The image is uniformly divided to non-overlapping square regions (*cells*) of a given size. The cell size is an important parameter of the whole approach. Then the histogram of S-LBP values is computed for each region. Resulting n histograms are then concatenated to one large vector which represents the image. The histogram sequence constructed this way ensures that parts of the image are compared to corresponding parts of the other image.

The classification is performed using the nearest neighbour (1-NN) classifier. It finds, using some distance function, the most similar image in the gallery (training) set. The label of the most similar image is then used for the classified image. We utilize the histogram intersection (HI) [10] metric in this work, because it proved the best performance in the preliminary experiments. The HI is computed according to Equation 2.

$$HI(H_1, H_2) = \sum_{i=1}^{n} H_1(i) - \min(H_1(i), H_2(i)) \tag{2}$$

H_1 and H_2 are the compared histograms and n is the size of the histograms.

4 Evaluation

4.1 Experimental Set-up and Corpora

UFI Dataset Unconstrained facial images (UFI) dataset [4] contains face images of 605 persons extracted from real photographs and is mainly dedicated to face recognition in real conditions. In this work, we use the cropped partition where faces are already extracted from the photographs. The resolution of the images is 128×128 pixels. Figure 4 shows three example images from this corpus.

Fig. 4. Three example images from UFI face database.

FERET Dataset FERET dataset [9] contains 14,051 images of 1,199 individuals. In this paper, we use *fa* set as the gallery (training) set while *fb* is used for testing. Only one image per person is available in each set. For the following experiments, the faces are cropped according to the eye positions and resized to 130×150 pixels. Figure 5 shows three example images from FERET database.

Fig. 5. Three example images from FERET face database.

4.2 Analysis of the Algorithm Parameters

The proposed algorithm has several important parameters that influence the final classification result. The following sections are thus dedicated to the analysis of these parameters in order to identify the optimal configuration for the automatic face recognition task on both corpora.

Cell Size Cell size is a crucial parameter for the face representation stage while it determines the size and properties of the resulting feature vector. However, its value does not influence the S-LBP operator itself. We assume that it should be more or less independent on the used operator and depends mainly on the image resolution and character. Therefore, we first set this value experimentally using the standard $LBP_{8,1}$ operator. Figure 6 shows the influence of cell value on the classification accuracy on FERET (left) and UFI datasets.

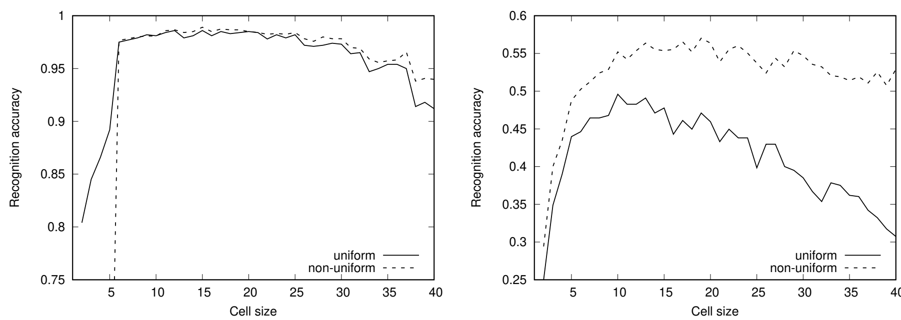

Fig. 6. Impact of the cell size on the classification accuracy tested with $LBP_{8,1}$ operator on FERET (left) and UFI datasets.

This figure shows that the proposed algorithm is relatively robust to this parameter and the range of suitable values for FERET is rather wide. The results on UFI show that the appropriate choice of this parameter is crucial for a sufficient recognition score. Optimal value of this parameter using UFI dataset lies within the interval $[10; 15]$.

In the following experiment (see Figure 7), we would like to confirm our assumption that this parameter is rather independent on the operator used. Therefore, we analyze the impact of the cell size with the novel S-LBP[3] operator on the UFI corpus. This experiment shows that the optimal value of this parameter is also, as in the previous case, in interval $[10; 15]$ points. Therefore, we confirm our assumption that this parameter is rather independent on the operator used. This experiment also shows that the influence of the cell size on the recognition score is much larger in unconstrained settings where the images vary significantly.

[3] We used $S-LBP_{8,5,6}$ configuration.

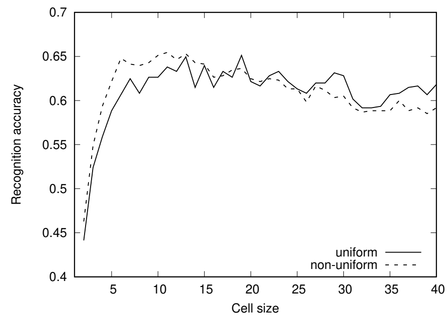

Fig. 7. Impact of the cell size on the classification accuracy tested with $SLBP_{8,5,6}$ operator on UFI dataset.

Based on the above experiments, we propose to use the cell size of 13 pixels in the following experiments while it brings a good recognition score in all cases. This value guarantees large enough cells to handle small shifts and rotations in the image while preserving sufficient amount of details with reasonable computational costs.

S-LBP Range and Shape The S-LBP range specifies the radius of the circle on which the points are considered. It means that this value influences mainly the size of the features that are captured by the operator. This experiment demonstrates the dependence of classification accuracy on this parameter. The number of neighbours is fixed and set to 8 in all cases. We used both UFI and FERET datasets for this experiment.

Figure 8 illustrates this dependence for all proposed S-LBP shapes (shape 1 is equivalent to basic circular LBP) on both FERET (left) and UFI corpora. The best results on FERET are obtained using the shape number 6 combined with the range size of 2. The best performing combination for UFI is also shape 6 but with range 7. This difference can be explained by higher variations among images in the UFI dataset. The results indicate that the behaviour of this parameter is very consistent for all shapes. Moreover, all of them outperform the basic LBP operator. We can conclude that larger range values are suitable mainly for more challenging real-world datasets.

Based on this experiment, we suggest using the shape 6 which gives the best results for both datasets and the range 5 which is a compromise between the two best performing values (7 and 2). This configuration will be used for the following experiments. This choice was done to show the robustness of our operator.

Number of Neighbours The last important parameter of the S-LBP method is the number of neighbours. Therefore, we analyze the dependence of the recognition rate on the number of neighbours on both corpora.

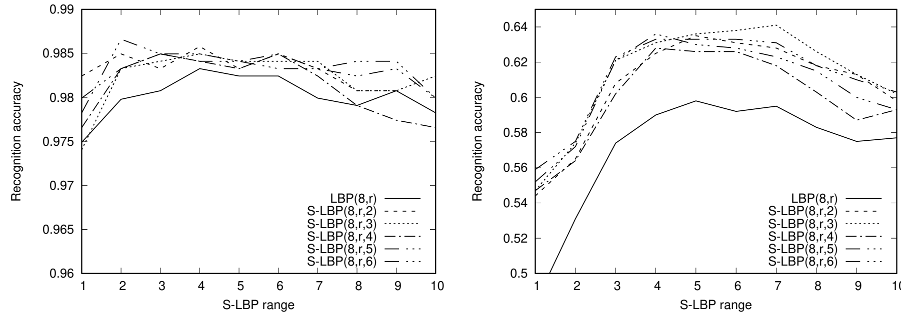

Fig. 8. Performance of the proposed S-LBP shapes depending on the S-LBP range using FERET (left) and UFI corpora.

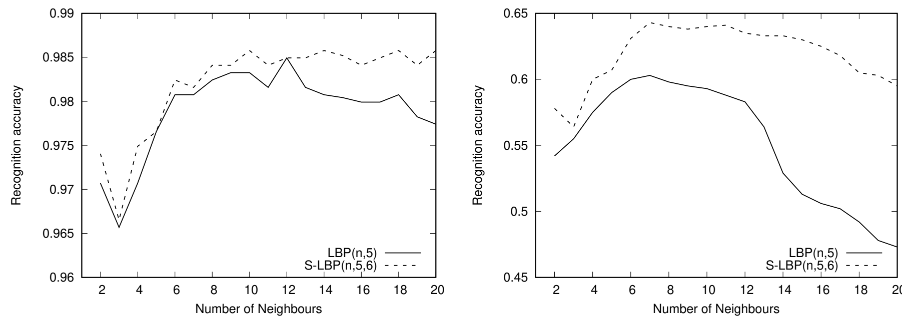

Fig. 9. Performance of the proposed S-LBP method depending on the number of neighbours using FERET (left) and UFI corpora; tested with shape 6 and range 5. Compared with results for LBP with radius 5.

The results of this experiment are shown in Figure 9. The depicted curves have analogical behaviour for both datasets. We can observe that the numbers of neighbours in intervals $[8; 13]$ and $[7; 12]$ are sufficient for reaching a good accuracy on FERET and UFI datasets respectively. Further increasing of this value leads to very long feature vectors and slows down the computation. Based on this results, we propose to use the average value of 10 neighbours.

4.3 Comparison of Uniform and Non-uniform Versions

The uniform variant of the proposed operators can bring better results with a decrease of computation costs. Therefore, we further analyze the differences in the behaviour of non-uniform and uniform patterns (see Table 1).

This table shows that in both cases the non-uniform operators outperform the uniform variant. This is particularly evident in the case of the standard S-$\mathrm{LBP}_{8,1}$ operator. For the proposed S-$\mathrm{LBP}_{10,5,6}$, the decrease of accuracy is only very small. We also show the times needed for the evaluation on the UFI corpus.

The results show that the computation time is roughly one order higher for the non-uniform patterns. These results show a clear advantage of the proposed method over the basic LBP.

Approach	Recognition rate [%]	Time [s]
$LBP_{8,1}$ uniform	49.10	153
$LBP_{8,1}$ non-uniform	56.36	549
S-$LBP_{10,5,6}$ uniform	64.79	458
S-$LBP_{10,5,6}$ non-uniform	**65.62**	3332

Table 1. Comparison of $LBP_{8,1}$ and S-$LBP_{10,5,6}$ descriptors with uniform and non-uniform patterns on UFI dataset.

4.4 Final Results

Table 2 summarizes the results obtained on both UFI and FERET corpora. It allows comparison of the proposed method with several other approaches.

Approach	Recognition rate [%] UFI	FERET
SRC (Wagner et al. [12])	-	95.20
LGBPH (Yao et al. [15])	-	97.00
LBP (ahonen et al. [1])	55.04	93.89
$LBP_{8,2}$	59.83	97.99
LDP (Lenc et al. [4])	50.25	97.4
FS-LBP (Lenc et al. [5])	63.31	**98.91**
S-$LBP_{10,5,6}$ (proposed)	**65.62**	98.4

Table 2. Final results of the proposed approach on the UFI and FERET databases in comparison with several state-of-the-art methods.

This table shows that the proposed S-LBP operator outperforms all methods on the UFI dataset. The best achieved result on FERET is competitive with the best reported accuracy. It must be noted that the previous best reported result on UFI uses a more complicated feature extraction method which is much slower than the proposed method. The results also indicate that the newly developed descriptor is particularly suitable for the challenging real-word images present in the UFI dataset where the performance gains are more noticeable.

5 Conclusions and Future Work

This paper described a novel local descriptor family called S-LBP. It allows using more points creating different shapes for comparison with the central pixel. The computation ensures better robustness and has the ability to hold more information in the resulting representation.

The descriptor has been tested on the face recognition task utilizing two standard corpora. It achieved a new state-of-the art result on the UFI dataset and significantly outperformed basic LBP variants. A competitive result was obtained on the fb partition of the standard FERET dataset. The best obtained accuracies are 65.6% and 98.4% on UFI and FERET respectively.

The method has been tested on the face recognition task, however it may be used also in other tasks such as image annotation, etc. The possible future work is thus evaluation of this descriptor on other tasks.

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