Local Salient Patterns - A Novel Local Descriptor For Face Recognition

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Abstract

Feature extraction is critical to the success of a face recognition system. Local Binary Patterns (LBP), with its different extensions, is one of the most popular texture descriptors, because of its demonstrated accuracy and efficiency. A LBP code is jointly determined by a number of local comparisons between a central pixel and its surrounding pixels. Therefore even a single flipping of any comparison results will dramatically change the resulting LBP code. This paper proposes a novel feature descriptor, named Local Salient Patterns (LSP), which aims to only encode the most robust local comparisons, with the largest positive or negative contrast magnitude in LBP feature representation. Therefore LSP is expected to be more robust than the conventional LBP descriptor. In addition, LSP can be further extended to high order cases which explore more local relationships among multiple pixels. Extensive experimental results demonstrate that LSP outperforms the uniform LBP in most cases, when encoding using different radii and number of sampling points. LSP also achieves better performance than some advanced variants of LBP descriptors such as Local Ternary Patterns (LTP). We show that multi-order LSP achieves state-of-the art face recognition performance.

1. Introduction

Face recognition has received much attention in the past two decades due to its wide applications such as access control, human computer interaction and teleconference [3]. One of the most important steps in face recognition systems is feature extraction. There are mainly two kinds of methods for face feature extraction: holistic based methods and local feature based methods. Most past works show that local feature based methods outperform global ones, being more robust to different kinds of noise. Gabor wavelets are one of the most discriminative and robust local features for face recognition [9]. It is a common practice that five scales and eight orientations of Gabor features are used [12, 13], which involves eighty convolutions for each face image. Thus both the time complexity and the space complexity, are very high. On the other hand, Local Binary Patterns (LBP) [8], another successful local descriptor, can be computed very fast and at the same time has very low memory cost.

The original LBP operator [6] first computes the differences between a pixel and its neighbor pixels. The differential values are then thresholded by zero to be binary codes. Finally all binary codes are concatenated together and converted to a decimal. The flowchart of the original LBP operator, with a radius of 1 pixel and 8 sampling points, is represented at the upper part of Figure 1. In some cases, if the face image is affected by noise, even only one of the comparison results changes, the code will not be consistent. One example is illustrated at the lower part of Figure 1.

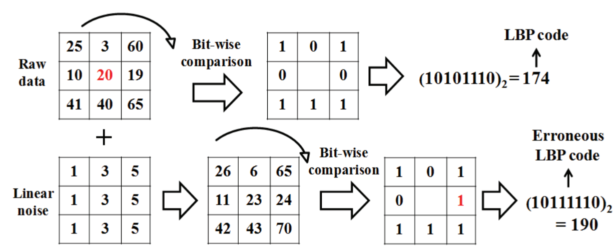

Figure 1. Illustration of the sensitivity of local binary patterns to noise.

In order to obtain more robust descriptors, much improvement on the original LBP has been made recently [8]. For example, uniform LBP (uLBP) [1] is proposed to use the 58 most frequent patterns from the 256 possible codes. All the remaining codes are then combined to be just one pattern, in order to reduce the risk of being erroneously coded [6]. Multi-scale Block LBP (MBLBP) [4] uses the block information in place of single pixel to get more robust comparison results. Another derivative of LBP aiming at getting a more robust descriptor is Local Ternary Patterns

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(LTP) [10]. LTP is proposed to use an extra parameter t as a threshold for the eight comparisons and uses ternary encoding instead of binary encoding, which makes the code more robust. In this paper, we aim to obtain a more robust descriptor using a novel strategy. We consider that the absolute differential values without being encoded to 1 or 0 can be more discriminative if used properly. The proposed method, called Local Salient Patterns (LSP), aims at exploring the absolute differential values directly. We have been inspired by the phenomenon that it is very easy for us to find the two dummies annotated with the star in Figure 2, because they have more obvious differences from the reference dummy than the rest. This kind of salient information, if encoded properly, could be useful for face recognition task. Thus in our case, we define the most significant values from the comparison results as the salient ones. Then different from LBP, only the two salient comparison results are used to encode. Finally, spatial histograms are estimated on each of the divided face blocks and all the histograms are concatenated together as the final feature of a face image.

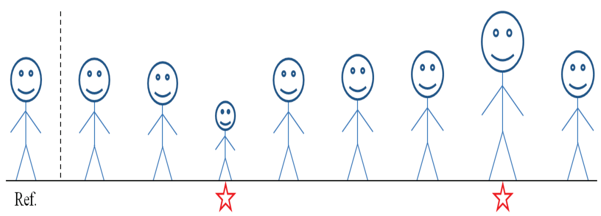

Figure 2. Salient information in our real life.

The remainder of this paper is organized as follows: in Section 2, the details of the proposed LSP method are introduced; in Section 3, extensive experimental results are presented; finally conclusions are drawn and discussions are shown in Section 4.

2. Face image description based on Local Salient Patterns

There are mainly three steps to calculate the Local Salient Patterns for a normalized face image: 1) to make local comparisons and find salient ones, 2) to encode the salient information and 3) to obtain the spatial histograms of the computed patterns. Each of the steps will be given in details in the following.

2.1. Salient comparisons

The original LBP consists on encoding each local comparison into a binary number, as is shown at the upper part of Figure 3. This brings some robustness to some extent, but at the expense of losing some discriminative information by such kind of coarse quantification. Hence we try to explore the differential information directly, and we propose to encode using the salient comparisons only, i.e. the most significant differences. We believe this will reduce the risk of being erroneously encoded. There are mainly two steps for getting the salient comparisons, which are illustrated in Figure 3: 1) compute the local comparisons at a given order; 2) find the corresponding extrema of local absolute differences, which is defined as salient comparison pair and represented as (maximum,minimum).

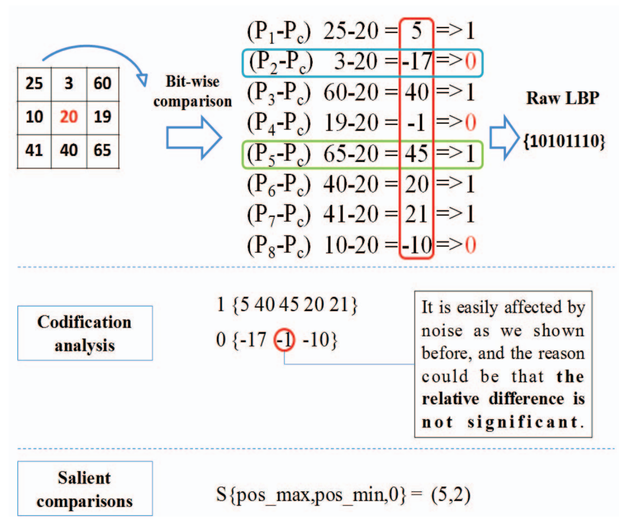

Figure 3. Analysis of the difference between the salient comparisons and the original local comparisons in LBP.

The 0-order local comparisons have the similar formula defined in computing LBP, which can be written as follows:

$$V_{0,i} = P_i - P_c, \tag{1}$$

where P_i is the intensity value of the i-th sampling point, and P_c is the intensity value of the center pixel. The only difference is that we keep the original differential values (red rectangle in Figure 3), while LBP operator will quantify them with a threshold function. Then, the salient comparison pair centered at P_i can be defined as a dual tuple $(pos\_\max, pos\_\min) = S\{\mathrm{V}_{0,1},\mathrm{V}_{0,2},...,\mathrm{V}_{0,n}|0\}$, where the function S has two returned values: $pos\_\max$ and $pos\_\min$, which are the positions of the maximum and minimum values of the set $\{\mathrm{V}_{0,1},\mathrm{V}_{0,2},...,\mathrm{V}_{0,n}\}$, 0 stands for 0 order and n is the number of sampling points. Examples of salient (maximum and minimum) comparisons are highlighted in blue and green boxes in Figure 3. We consider that extreme values are usually the most stable ones, so here we use only the positions of the two more salient comparisons for encoding. Before going to the details of our salient coding function, we want to illustrate the importance of the salient information. Considering the example in Figure 3 (middle part), it can be appreciated that in the original LBP operator, even though five of the comparison results are codified as "1", the source differential values are ranged from

5 to 45. Similarly, the three values codified as “0” vary from -17 to -1. Hence, discriminative information of face structure may be neglected, which means that in LBP even though the positions of some pixels (all of them encoded as ”1”) are exchanged, the coding result will be the same, but in this case the appearance will be different. However our salient comparison does not have such kind of ambiguity.

0-order local comparisons

$V_{0,1} = (P_1 - P_c)$
$V_{0,2} = (P_2 - P_c)$
$V_{0,3} = (P_3 - P_c)$
$V_{0,4} = (P_4 - P_c)$
$V_{0,5} = (P_5 - P_c)$
$V_{0,6} = (P_6 - P_c)$
$V_{0,7} = (P_7 - P_c)$
$V_{0,8} = (P_8 - P_c)$

1-order local comparisons

$V_{1,1} = (V_{0,1} - V_{0,2}) = P_1 - P_2$
$V_{1,2} = (V_{0,2} - V_{0,3}) = P_2 - P_3$
$V_{1,3} = (V_{0,3} - V_{0,4}) = P_3 - P_4$
$V_{1,4} = (V_{0,4} - V_{0,5}) = P_4 - P_5$
$V_{1,5} = (V_{0,5} - V_{0,6}) = P_5 - P_6$
$V_{1,6} = (V_{0,6} - V_{0,7}) = P_6 - P_7$
$V_{1,7} = (V_{0,7} - V_{0,8}) = P_7 - P_8$
$V_{1,8} = (V_{0,8} - V_{0,1}) = P_8 - P_1$

2-order local comparisons

$V_{2,1} = (V_{1,1} - V_{1,2}) = P_1 + P_3 - 2*P_2$
$V_{2,2} = (V_{1,2} - V_{1,3}) = P_2 + P_4 - 2*P_3$
$V_{2,3} = (V_{1,3} - V_{1,4}) = P_3 + P_5 - 2*P_4$
$V_{2,4} = (V_{1,4} - V_{1,5}) = P_4 + P_6 - 2*P_5$
$V_{2,5} = (V_{1,5} - V_{1,6}) = P_5 + P_7 - 2*P_6$
$V_{2,6} = (V_{1,6} - V_{1,7}) = P_6 + P_8 - 2*P_7$
$V_{2,7} = (V_{1,7} - V_{1,8}) = P_7 + P_1 - 2*P_8$
$V_{2,8} = (V_{1,8} - V_{1,1}) = P_8 + P_2 - 2*P_1$

Figure 4. 0-order, 1-order and 2-order local comparisons.

We believe that different orders of local comparisons may have some complementary properties with each other. So here for simplicity we only show the extension of the 0-order local comparisons to 1-order case, and give results of the 2-order local comparisons directly. The 1-order local comparisons can be defined as $V_{_{1,i}} = V_{_{0,i}} - V_{0,(i+1)\%n}$, where $V_{_{0,i}}$ stands for the 0-order local comparison result of the i-th sampling point, n is the total number of sampling points and % is the module function. The 0-order, the resulted 1-order and 2-order local comparisons can be expressed as shown in Figure 4.

To be more general, the k-order local comparisons (if $k \geq 1$) can be represented by (k-1)-order local comparison results, which can be written as:

$$V_{_{k,i}} = V_{_{k-1,i}} - V_{_{k-1,(i+1)\%n}}, \qquad (2)$$

where i represents the i-th sampling point, n is the total number of the sampling points and % is the module function. The higher order case can be deduced using the same Equation (2). The way to get the salient comparison pair for high order case is the same as the 0-order, which can also be written as a dual tuple $(pos\_\max, pos\_\min) = S\{\mathrm{V}_{k,1}, \mathrm{V}_{k,2}, ..., \mathrm{V}_{k,n}|k\}$.

2.2. Salient Coding Function

As we calculate the two salient comparisons in the first step, then we use the order pair of the salient comparisons to encode. The first element in the order pair is the position of the maximum differential value (5th in Figure 5), considering the top-left value as the first one, and the other element in the order pair is the position of the minimum differential value (2nd in Figure 5).

In the proposed encoding, if the number of sampling points is 8, then there are 57 (A(8,2) + 1) patterns in all, where A is the number of possible permutations between all comparisons. The former 56 patterns exist when the orders of the two salient comparisons are different, and the 57th pattern means all comparison results are the same. The details for salient code map and also some notice are shown in Figure 5 and Figure 6. It is easy to find that when the number of sampling points grows to 16, there will be 241 (A(16,2) + 1) patterns in all. Thus we can find that LSP encoding complexity does not grows exponentially with the number of sampling points. Besides, LSP can be extracted very fast using a predefined look-up-table (LUT). Even compared with the uniform LBP which has 59 and 243 patterns with sampling points 8 and 16, our LSP still has a little lower feature dimensions without the necessity of considering only the uniform cases.

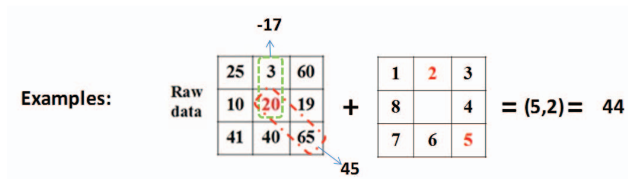

Figure 5. Salient codification process.

Order encoding map

(1,2) = 1; (1,3) = 2; (1,4) = 3
(1,5) = 4; (1,6) = 5; (1,7) = 6
(1,8) = 7; (2,1) = 8; (2,3) = 9
(2,4) = 10; ... ... ; (5,2) = 44
(5,3) = 45; ... ... ; (7,8) = 56
(x,x) = 57 (x = {1,2,3,4,5,6,7,8})

Notice

1) (1,2) and (2,1) are two different codes

2) Code 57 happens only when the eight comparison results are the same

Figure 6. Salient codification and notice.

2.3. LSP Histograms

After the salient patterns of a face image are obtained, local histograms are computed within each of the spatially divided face regions at each order. This process for computing histogram in the block n for the order k can be formulated as follows:

$$H_{n,k} = \sum_{z \in R_n} \delta\{\mathrm{LSP}(z,k), l\}, l = 0, 1, ..., m \qquad (3)$$

where z represents one pixel in the block n of a face image; l is the l-th LSP code in the salient code map; m is the total kinds of LSP labels and δ is the Kronecker delta:

$$\delta(i,j) = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases} \tag{4}$$

Finally, the histograms computed from non-overlapping blocks of the face image, can be concatenated together into a higher dimensional histogram to form the final descriptor of the face image. The histogram dissimilarity between two face images at a given order can be measured using χ^2 distance, which can be written as:

$$\chi^2(H1, H2) = \sum_{l=1}^{L} \frac{(H1_l - H2_l)^2}{(H1_l + H2_l)} \tag{5}$$

where $H1$ and $H2$ are the histograms of two images under comparison and L is the number of LSP patterns for the given order.

3. Experimental Evaluation

The FERET database [7] and the AR database [5] were used in order to evaluate the performance of the proposed LSP method.

The FERET database contains face images with large variations in expression, lighting and aging. It has a gallery set (Fa), with frontal images of 1,196 subjects and four evaluation sets with different kinds of variations. Fb subset contains 1,195 face images with variations of expression. Fc subset has 194 images with variations of lighting. Dup I is composed by 722 face images taken with an elapsed time with respect to the images in the gallery set. Finally Dup II, is a subset of Dup I, containing 234 images in which the elapsed time is at least one year. Sample images are shown in Figure 7.

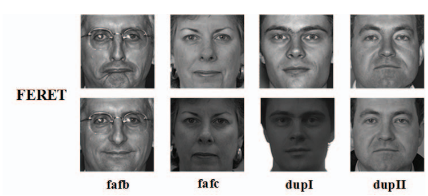

Figure 7. FERET database sample images. The first row shows images in the gallery set and the second row shows some sample images in each one of the other subsets.

On the other hand, the AR database contains more than 3,200 face images of 126 subjects captured on two different sessions. Each person has up to 13 images per session with different expressions, illuminations and occlusions (Figure 8). Similar to previous works, 100 different subjects were randomly selected (50 males and 50 females). The two neutral expression images of each person from both sessions were used as gallery and the rest of them (24 images) with different expressions,lighting and occlusions were used for testing.

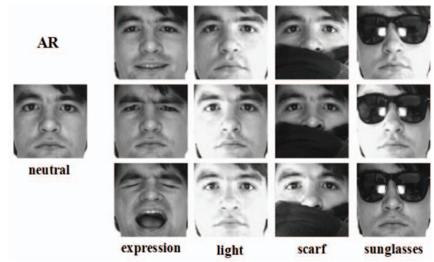

Figure 8. AR database sample images for one subject in one session. Columns show the images in each subset.

Images in both databases were geometrically normalized to be 116x116 of size. For all experiments, all faces were photometrically normalized with the Preprocessing Sequence (PS) method proposed in [10]. They were then divided into 6x6 non-overlapping blocks from which the corresponding spatial histograms were computed. Besides the proposed LSP descriptor, spatial histograms of the uniform LBP and of one of its extensions LTP, were obtained for comparisons. We have not compare with too many LBP variants, however we think other LBP variants such as MBLBP and ILBP can also be benefit with our encoding strategy by tuning their parameters in a proper way. What is more, in order to have a fair comparison, we keep all the conditions the same and only the simplest Nearest-neighbor classifier with the χ^2 similarity measure is used. The extracted histogram feature is used directly without any post-processing like feature reduction or feature selection in order to test the performance of the pure descriptors only.

3.1. Experimental results on FERET database

Experimental results with different radii and number of sampling points on FERET database are drawn on Table 1.

Table 1. Top rank recognition rates on the FERET database.

Method	Fb	Fc	DupI	DupII
LBP-r_1-s_8	92.13	93.29	63.57	56.41
LTP-r_1-s_8	91.88	92.78	63.29	54.70
LSP-r_1-s_8-o_0	93.47	92.26	64.95	**61.11**
LSP-r_1-s_8-o_1	93.97	92.78	64.95	56.41
LSP-r_1-s_8-o_2	**95.39**	**97.93**	**66.89**	60.25
LBP-r_2-s_8	95.48	95.87	69.39	61.96
LTP-r_2-s_8	95.56	95.87	69.66	62.39
LSP-r_2-s_8-o_0	97.23	95.36	71.32	68.80
LSP-r_2-s_8-o_1	95.56	95.87	72.57	66.23
LSP-r_2-s_8-o_2	**97.23**	**95.87**	**74.09**	**69.23**
LBP-r_2-s_{16}	96.31	97.42	72.71	65.38
LTP-r_2-s_{16}	96.31	97.42	72.99	66.29
LSP-r_2-s_{16}-o_0	97.99	97.93	74.51	71.36
LSP-r_2-s_{16}-o_1	97.15	97.42	**78.53**	**72.22**
LSP-r_2-s_{16}-o_2	**98.32**	**99.48**	76.03	71.79

In the used notation (descriptor $-r_n$ $-s_p$ $-o_q$), n stands for the radius, p for the number of sampling points used to compute the local descriptor and q is the order of local comparisons.

We find from the table that by encoding the salient comparison pair, the resulted LSP is also discriminative for face recognition. The LSP descriptor, with the listed several different orders, outperforms both LBP and LTP almost in all cases. For a better analysis, we have plotted in Figure 9 the results of LSP (radius 2, sampling points 16) for different orders of local comparisons. As can be appreciated the performance is different for different kinds of variations. The 1-order LSP performs the best on dup1 and dup2, but performs the worst on fafb and fafc. Hence, we believe LSP with different orders of local comparisons can be complementary to each other. Thus we fuse them in score level. The experimental results of the fused feature are listed on Table 2 in comparison with some state-of-the-art descriptors.

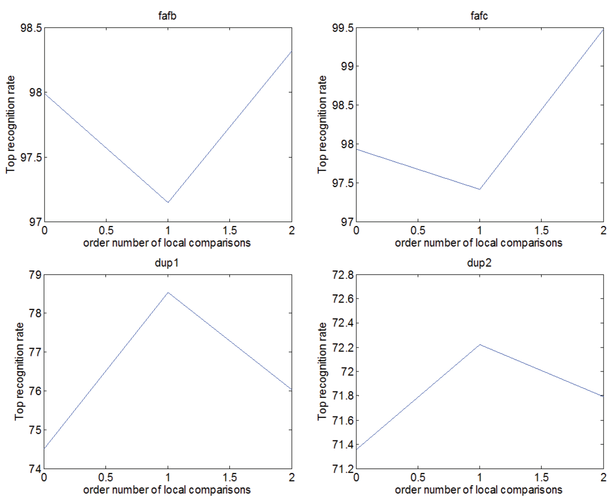

Figure 9. Top recognition rates on each subset of the FERET database with different orders of local comparisons.

The table shows that by using the combined orders of LSP, the performance of the LSP descriptor is improved. Regarding the speed of feature extraction, our proposal is comparable with the state of the art HOG-based method Patterns of Oriented Edge Magnitudes (POEM); but in performance, our fused LSP still wins by a little. Compared to other state-of-the-art Gabor based methods, such as the Local Gabor Binary Patterns Histograms (LGBPHS) [13], Histogram of Gabor Phase Patterns (HGPP) [12], Histogram of Gabor Ordinal Measures (HOGOM) [2], our LSP can be extracted much faster, and the recognition rate is higher than LGBPHS and HGPP, and just slightly worse than HOGOM.

Table 2. Top rank recognition rates on the FERET database with fused features.

Method	**Fb**	**Fc**	**DupI**	**DupII**
LSP-r_1-s_8-o_{01}	94.47	94.32	66.34	61.53
LSP-r_2-s_8-o_{01}	95.56	95.87	72.57	66.23
LSP-r_2-s_{16}-o_{01}	97.74	98.96	78.94	75.64
LSP-r_1-s_8-o_{012}	95.48	95.36	68.83	65.38
LSP-r_2-s_8-o_{012}	97.57	96.90	76.03	71.79
LSP-r_2-s_{16}-o_{012}	**98.07**	98.96	**79.22**	76.49
LGBPHS [13]	94.00	97.00	68.00	53.00
HGPP [12]	97.60	98.90	77.70	76.10
HOGOM [2]	98.00	**99.50**	76.80	**78.20**
POEM [11]	97.60	96.00	77.80	76.50

3.2. Experimental results on AR database

In order to show the effectiveness of LSP in front of more kinds of face variations, we also test it on the AR database. The results obtained on each subset of AR database are listed on Table 3. It can be seen that using different configurations for obtaining the local patterns, i.e. different radii, different number of sampling points and different orders of local patterns, the proposed descriptor outperforms the uniform LBP and the LTP in all cases for those variations present on this database. Specially significant improvements are achieved for the two occlusion sets, indicating that LSP descriptor is much more discriminative for this case. The top recognition rate with different orders of local comparisons are drawn in Figure 10. It can be found that the complementary attribute in terms of recognition rate of LSP with different orders of local comparisons is more obvious on this database.

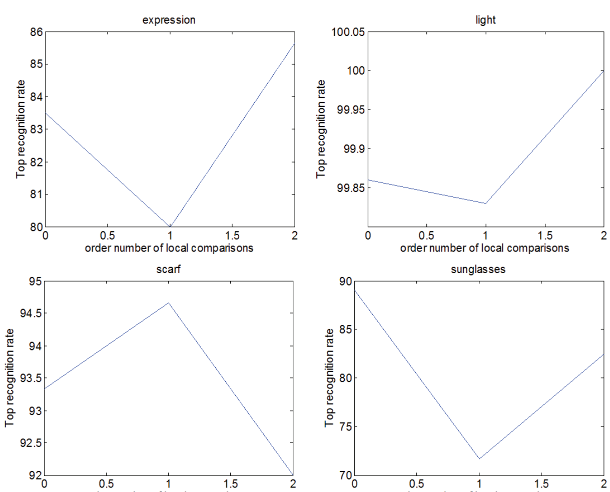

Figure 10. Top recognition rates on each subset of the AR database with different orders of local comparisons.

Table 3. Top rank recognition rates on AR database.

Method	Expression	Light	Scarf	Sunglasses
LBP-r_1-s_8	73.66	98.50	61.83	44.33
LTP-r_1-s_8	73.66	98.50	62.66	45.00
LSP-r_1-s_8-o_0	78.50	98.50	70.83	56.50
LSP-r_1-s_8-o_1	72.66	99.00	69.16	44.83
LSP-r_1-s_8-o_2	**82.00**	**99.50**	**80.00**	**76.66**
LBP-r_2-s_8	76.00	99.33	81.66	63.33
LTP-r_2-s_8	76.00	99.00	82.66	63.00
LSP-r_2-s_8-o_0	80.00	**99.50**	89.83	**81.00**
LSP-r_2-s_8-o_1	77.33	99.50	87.16	58.33
LSP-r_2-s_8-o_2	**84.16**	99.33	**91.33**	78.16
LBP-r_2-s_{16}	77.33	99.33	90.16	68.83
LTP-r_2-s_{16}	77.83	99.50	90.83	71.50
LSP-r_2-s_{16}-o_0	83.50	99.83	93.33	**89.00**
LSP-r_2-s_{16}-o_1	80.00	99.83	**94.66**	71.66
LSP-r_2-s_{16}-o_2	**85.66**	**100**	92.00	82.50
LSP-r_1-s_8-o_{01}	76.66	99.66	73.33	53.83
LSP-r_2-s_8-o_{01}	79.16	99.66	91.00	74.50
LSP-r_2-s_{16}-o_{01}	81.00	99.83	96.00	89.16
LSP-r_1-s_8-o_{012}	79.66	99.66	78.83	63.83
LSP-r_2-s_8-o_{012}	81.16	99.66	92.83	80.66
LSP-r_2-s_{16}-o_{012}	**83.83**	**100**	**96.33**	**89.83**

4. Conclusions and future work

We propose a novel descriptor for face recognition called Local Salient Patterns (LSP). First, different orders of local comparisons are computed. Then by using the salient (maximum and minimum) information of the local comparison results instead of the traditional threshold function used in LBP and most of its variants, fewer comparisons will be involved for encoding. Even when the number of sampling points grows, the complexity of LSP encoding does not increase exponentially.

What is more, experimental results show that in most cases, LSP can outperform uniform LBP and LTP, demonstrating to be a more discriminative descriptor. On the other hand, the speed for LSP feature extraction is much faster than the state-of-the-art Gabor based methods, while the performance is comparable with each other.

Similar to other descriptors and LBP variants, the LSP can be further combined with some weighing strategy and sophisticated classifiers in order to achieve even better results. Moreover, we believe that both the salient operator and the order pair encoding are not perfectly defined, and there are still some potential to be further improved.

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