LIGHT FIELD LOCAL BINARY PATTERNS DESCRIPTION FOR FACE RECOGNITION

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ABSTRACT

Light field cameras are emerging as powerful sensor devices to capture the full spatio-angular visual information in a viewing range. As more information should allow better analysis performance, this paper proposes a simple, yet effective descriptor, named Light Field Local Binary Patterns (LFLBP), able to exploit the richer information available in light field images for face recognition. The LFLBP descriptor combines two main components, the spatial, local LBP and the angular LBP, to capture not only the usual spatial information but also the light field angular information associated to the set of sub-aperture images, corresponding to different viewpoints. Experiments were conducted with the novel IST-EURECOM light field face database. When compared with competing methods, the proposed descriptor has shown superior face recognition performance under varied and challenging acquisition conditions. Moreover, the proposed light field angular LBP descriptor can be flexibly combined with any available spatial descriptor to derive combined descriptors for enhanced light field based face recognition performance.

Index Terms— Face Recognition, Light Field, Local Binary Patterns, Local Descriptors, Spatio-angular Information.

1. INTRODUCTION

As one of the most acceptable, collectable and universal biometric modalities, face recognition has received significant attention in multiple legal and commercial applications [1], [2]. The recent availability of richer imaging sensors is opening a new range of possibilities for many face recognition systems [3]. Among them, light field imaging technologies have recently come into prominence as they capture not only the intensity of light on a specific 2D plane position but also the intensity of the light rays for any direction in space. Thus, light field cameras can provide richer scene representations for recognition tasks, e.g. by allowing depth map computation and exploitation, *a posteriori* refocusing, disparity exploitation and slightly changing the viewpoint around the central one [4], [5]. Preliminary works [6], [7], [8], [9] have explored the added value of light field imaging in terms of 2D face recognition at distance, achieving improved accuracy when compared with conventional images, notably by performing post-capture refocusing and upsampling approaches. This paper takes a different approach as the proposed descriptor exploits the whole light field during feature extraction. Given the captured light field image, it is possible to select specific viewpoints around the central one to explore the richer spatio-angular information available. As a light field allows rendering a set of 2D sub-aperture images, each one corresponding to a specific viewpoint, disparity information is newly available.

Local Binary Patterns (LBP) [10] have emerged as one of the most widely studied types of descriptors for local texture description. Baseline LBP and its extensions [11] have been widely used for feature extraction in the context of face recognition systems [12]. The results have shown very good performance, both for LBP alone or in combination with other complementary features/descriptors.

This paper proposes an extended LBP descriptor, so-called *Light Field Local Binary Patterns* (LFLBP), which is able to exploit the richer information available in a light field image to increase the face recognition performance. LFLBP has two main components: (i) a conventional Spatial Local Binary Pattern (SLBP), corresponding to the LBP for the central rendered 2D sub-aperture image; and (ii) a novel Light Field Angular Local Binary Pattern (LFALBP), which represents the variations associated to the different directions of light captured in light field images. The proposed combination of the novel angular LBP with the conventional spatial LBP complement each other to improve the accuracy of a face recognition system. LFALBP may also be combined with other spatial descriptors within the LFLBP framework.

The rest of this paper is organized as follows: Section 2 briefly reviews related work. Section 3 describes the proposed combined descriptor and its components. Section 4 presents the experimental setup and assessment methodology. Results and analysis are presented in Section 5 and, finally, Section 6 concludes the paper.

2. RELATED WORK

A large number of LBP variations has been proposed for face recognition [11], [12]. The generic system architecture used to extract LBP features from an image is shown in Fig. 1. Different LBP variants correspond to different solutions for one or several modules of this architecture.

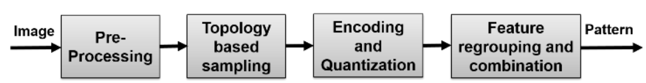

Figure 1: Generic architecture for LBP based descriptors.

The first module performs image pre-processing by applying methods such as Gabor filtering [13], [14] [15], gradient processing [16] or wavelet transformation [17]. Local patterns with different neighborhood topologies or scales are sampled in the second module. While baseline LBP considers pixels in a circular ring neighborhood, other examples include Local Line Binary Patterns [18], which use lines in vertical and horizontal directions to compute LBP features, and Hierarchical Multiscale LBP [19], which encodes LBP information at different scales. For sampling schemes such as Completed LBP [20], differences in the local region are decomposed into two complementary components, the signs and the magnitudes, to compute more discriminant features for face recognition. Local difference information, as proposed in [21] [22], measures not only the relation between the central position and its neighborhood, but also the intensity relationship in the neighboring pattern.

The encoding and quantization module of baseline LBP calculates the gray-level difference between the center pixel value and that of its neighbor pixels, encoding the result in binary format comparing the obtained difference with a threshold value of zero. In Improved

LBP [23], local means is used instead of the center pixel gray value. In [24], 3DLBP was proposed for 3D face recognition where geometrical features of the facial surfaces are used to quantize range data into different layers. Multi-scale Block LBP [25] employs a static or dynamic threshold to extract a single bit from each histogram bin. Adaptive Local Ternary Pattern [26] proposes an automatic strategy to select the threshold level.

In the last module, complementary features can be regrouped and combined to obtain more discriminative, robust and compact features. Uniform LBP [27] groups those patterns that occur more frequently while non-uniform patterns are associated to a single bin of the image histogram. Symmetry Uniform LBP [28] regroups the uniform LBPs to obtain lower feature dimensionality and higher discriminability than baseline uniform LBPs for face recognition. Hamming LBP [29] was designed to make better use of the non-uniform patterns, instead of discarding them. Sparse Representation-based Classification has been combined with baseline LBP in [6] and with Center-Symmetric LBP in [30] to cope with the dimensionality problem. As a final example, the combination of LBP and SIFT has been exploited in [31] for heterogeneous face recognition.

More recently, a few solutions have been proposed to exploit the richer light field images information by dealing with the high dimensionality signals in their native form. One such approach is the Multilinear Principal Component Analysis (MPCA) [32], which interprets the light field as a tensor. This and other similar methods [33] [34], can be used for light field based face recognition.

3. PROPOSED COMBINED DESCRIPTOR: LFLBP

When a user faces a camera in different occasions, the captured pose will never be exactly the same, even if the user is cooperating with the system. If one could capture images taken from slightly different angles, then the match between the face registered in the database and the newly acquired face images would be expected to improve. This is precisely the potential associated with light field cameras which is explored by the proposed Light Field Local Binary Patterns (LFLBP) descriptor, as described in detail in this section

3.1. Architecture and Walkthrough

The generic architecture of the proposed face recognition system is illustrated in Fig. 2. By exploiting the multiple views, the so-called sub-aperture images, available from a light field image, the proposed LFLBP descriptor is expected to improve the face recognition system performance.

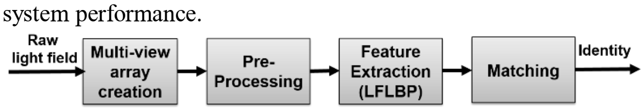

Figure 2: Architecture for the proposed face recognition system.

The proposed system includes the following main steps:

1. **Multi-view array creation:** Initially, a raw light field image, e.g. a Lytro LFR (light field raw) file, is acquired and demosaiced to the RGB color space, to create a light field image constituted by a number of so-called *micro-images*, each corresponding to a specific microlens. Then, sub-aperture images corresponding to different viewpoints can be extracted, forming a multi-view array, as illustrated in Fig.3-a. In this work, the Matlab Light Field Toolbox v0.4 [35] has been used to create the multi-view array, i.e. $L(u,v,x,y)$, where u and v identify the viewpoint, x and y the pixel position within a sub-aperture image [36]. For the camera used u and v take integer values in the range {-7, …, 7}, and the size of each sub-aperture is 625x434. The central sub-aperture image is the reference view position, denoted as $L(0,0,x,y)$, as highlighted in yellow in Fig.3-a.
   Each sub-aperture image can also be identified in polar coordinates using two parameters: 1) the radius, R, expressing the Euclidean distance to the reference view, and being related to the observed disparity; and 2) the angle, A, measured counter-clockwise from the positive part of the real axis. A third parameter, N, defines the number of sub-aperture images, or views, to consider. Fig. 3-b shows three examples of sub-aperture images, highlighted in red, for R=7, $A\in\{0°,45°\}$ and $N\in\{4,8\}$.

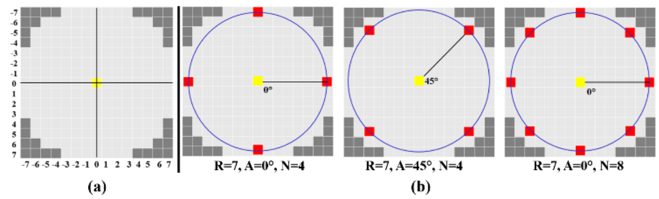

Figure 3: a) A multi-view array and its central reference view position (yellow). b) Examples of selected sub-aperture images (red). The sub-aperture images highlighted in dark grey do not contain usable image information due to the micro-lens shape.

2. **Pre-Processing:** Facial images undergo a geometrical normalization, aligning the face in all sub-aperture images, based on the eye location in the central view. Then, each face is cropped and resized to 128×128 pixels. Examples of pre-processed central sub-aperture images are shown in Fig. 4.
3. **Feature extraction:** The proposed LFLBP descriptor is extracted from the normalized multi-view array – see Section 3.2.
4. **Matching:** The LFLBP description vectors obtained in the previous step are matched using a nearest neighbor classifier, with L1 norm (city block) as the distance metric. A simple classifier is used since this paper focuses on evaluating the discriminative properties of the proposed descriptor.

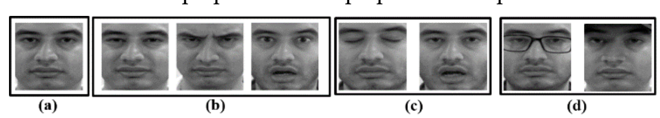

Figure 4: Sample central sub-aperture images from [37]: a) Neutral face; b) Emotions; c) Actions; and d) Occlusions.

3.2. LFLBP Combined Descriptor

The LFLBP combined descriptor is an extension of LBP, which is able to exploit the richer information available in light field images. Similarly to the original LBP [27], the novel LFLBP processes the gray level intensities of the captured light fields.

The proposed LFLBP descriptor combines two components: (i) the Spatial Local Binary Patterns (SLBP) descriptor, which corresponds to LBP applied to the central, reference view; and (ii) the novel Light Field Angular Local Binary Patterns (LFALBP) descriptor, which is simple to compute, while capturing the full power of the multi-view information available in the light field image.

1) Spatial Local Binary Pattern (SLBP): For a selected set of p samples in the spatial neighborhood, at distance r from the reference sample x,y, with starting angle a, SLBP is computed for each sample x,y in the reference view, $L_{0,0,x,y}$, as follows:

$$\mathrm{SLBP}_{r,a,p}(x,y) = \sum_{i=1}^{p} \mathrm{sign}\left(L_{0,0,(x+k),(y+l)} - L_{0,0,x,y}\right) \times 2^{i-1} \quad (1)$$

where

$$\begin{cases} k = \left\lceil r\,\sin\left(a + \frac{360°}{p} \times (i-1)\right)\right\rceil \\ l = \left\lceil r\,\cos\left(a + \frac{360°}{p} \times (i-1)\right)\right\rceil \end{cases} \quad (2)$$

and sign(x) is the sign function, defined as:

$$\text{sign}(x) = \begin{cases} 1, & if\ x \geq 0 \\ 0, & otherwise. \end{cases} \quad (3)$$

2) Light Field Angular Local Binary Pattern (LFALBP): The LFALBP descriptor is being proposed to explore the information corresponding to the variations observed for light rays travelling in different directions, as captured by light field images. For a set of sub-aperture 2D images selected at the desired distance from the reference view, expressed by radius R, LFALBP pattern value for each sample position x,y may be formalized as follows:

$$\text{LFALBP}_{R,A,N}(x,y) = \sum_{j=1}^{N} \text{sign}(L_{u,v,x,y} - L_{0,0,x,y}) \times 2^{j-1} \quad (4)$$

where

$$\begin{cases} u = \left\lfloor R\ \sin\left(A + \frac{360°}{N} \times (j-1)\right) \right\rceil \\ v = \left\lfloor R\ \cos\left(A + \frac{360°}{N} \times (j-1)\right) \right\rceil \end{cases} \quad (5)$$

As defined in Section 3.1, angle A indicates the starting angle for the first sub-aperture image to consider in the angular neighborhood, and N indicates the number of views to consider, as illustrated in Fig. 3-b. As in the conventional LBP descriptor, the binary thresholding result obtained by the s function is multiplied by the binomial factor, 2^{i-1}, and the resulting values are summed to get the LFALBP pattern value for each sample position x,y.

The computation of LFALBP for a sample pixel x_1,y_1, is illustrated in Fig. 5, considering parameter values R=3, A=0º and N=4. The LFALBP pattern value is obtained by taking the gray values of pixel x_1,y_1 from the reference view (central position) and from the other N views. The reference view value is used for thresholding; whenever the other view's value in position x_1,y_1 is below the threshold it takes value 0, otherwise it takes value 1, as illustrated in Fig. 5. Finally, the thresholded values are multiplied by the corresponding binomial weights and summed to obtain the LFALBP pattern value for pixel x_1,y_1 – value 13 in the example.

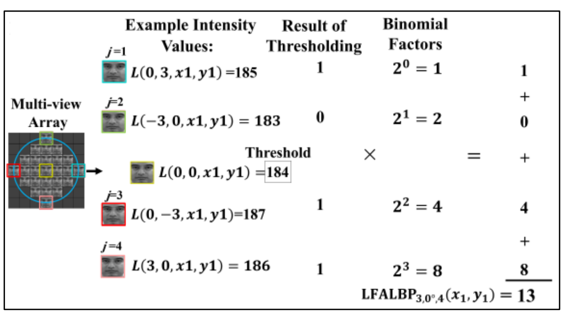

Figure 5: Example of angular sampling and encoding by LFALBP.

3) LFLBP – LFALBP and SLBP Combination: For performance assessment, this paper proposes a specific combination, the LFLBP descriptor, computed according to Eq. (6).

$$\text{LFLBP}_{r,a,p,R,A,N}(x,y) = \quad (6)$$

$$\left(\text{LFALBP}_{R,A,N}(x,y) \times 2^p\right) + \text{SLBP}_{r,a,p}(x,y)$$

where $\left(\text{LFALBP}_{R,A,N}(L_{0,0,x,y}) \times 2^p\right)$ means a binary left shift of p bits. Eq. (6) concatenates the spatial SLBP with the angular light field descriptors to form the combined LFLBP descriptor. The resulting descriptor has p + N bits for each sample, and the final feature vector is the histogram of LFLBP pattern values computed for all x, y samples.

LFALBP, which is the major contribution of this paper, may be combined with not only SLBP to build LFLBP, but also with any existing local descriptor, to derive enhanced descriptors for light field based face recognition. In fact, the combination of angular and spatial descriptors 'fuses' complementary information, thus improving the final face recognition performance. An alternative would be to combine LFALBP and SLBP to form joint histograms, thus producing different features. This combination flexibility is expressed by generic combination framework presented in Fig. 6 where any spatial descriptor can be used to replace SLBP while still benefiting from the complementary angular information captured by the novel LFALBP descriptor.

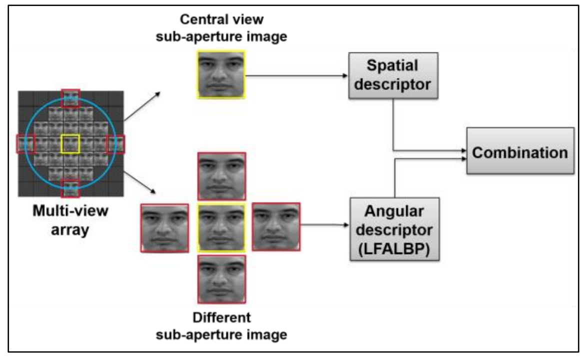

Figure 6: Proposed spatial and angular descriptors combination framework.

4. ASSESSMENT METHODOLOGY

This section presents the test material and experimental setup. It also discusses the metrics considered for performance evaluation.

The IST-EURECOM Light Field Face Database (LFFD) [37] consists of light field images captured by a Lytro ILLUM camera [38]. It is the first face database including raw light field images, along with sample 2D rendered images, corresponding depth maps, and a rich collection of metadata. The database includes 20 shots per person, per each of two separate acquisition sessions, capturing several facial variations including neutral, emotions, actions and occlusions – see examples in Fig. 4. In this paper, light field images from 50 subjects are used to test the proposed descriptor. Central rendered sub-aperture images are used for benchmark evaluation.

For the experimental assessment, the two neutral face light field images of each subject, in a total of 100 light field images, are used for feature extraction and registration in the database. Then, three recognition tasks with increasing complexity are considered by providing as input to the recognition system images in which the subjects' faces show different: 1) *Emotions*, including happy, angry and surprised faces; 2) *Actions*, including faces with closed eyes or open mouth; and 3) *Occlusions*, with faces occluded by glasses or a hat. There are 100 light field test images available per each face variation, two per subject.

Based on a trade-off between recognition performance and feature vector length, $\text{SLBP}_{4,0°,16}$ has been selected for extracting the features from the central sub-aperture image.

To evaluate the performance of the proposed solution, standard metrics, such as the *Recognition Rate at rank n* (RR_n) and *Cumulative Recognition Rate at rank n* (CRR_n) are used. RR_n can be calculated according to Eq. (7):

$$\text{RR}_n = \frac{C}{|T|} \quad (7)$$

where C is the number of correct rank n recognitions, and $|T|$ is the total number of test images. CRR_n can be computed using Eq. (8):

$$\text{CRR}_n = \sum_{i=1}^{n} \text{RR}_i \quad (8)$$

These metrics will be considered for the three recognition tasks mentioned above.

5. PERFORMANCE ASSESSMENT

The experimental evaluation was conducted as described above by comparing results for the proposed LFLBP descriptor with competing solutions. The experimental work started by analyzing the influence of the radius parameter, *R*. Once the optimal value of *R* is fixed, the impact of considering a different numbers of angular views (*N*) and of the starting angle (*A*) parameters, was investigated. Comprehensive comparisons for the proposed approach versus the competing methods are presented.

5.1. Parameter evaluation: View radius

As mentioned before, light field images allow the recognition technique to benefit from the captured disparity, therefore the amount of disparity to consider is the first aspect to be analyzed. For this purpose, the value of *R* is increased from 3 up to 7, with *A*=45º and *N*=4. The CRR_5 values for the emotion, action and occlusion tasks are illustrated in Fig. 7. The results show a clear increase on the recognition rate as the disparity increases. This is extremely useful as, even in controlled face recognition environments, where subjects are cooperative, the pose is never exactly the same. By considering a larger radius, more distinctive angular information is captured by the proposed LFALBP descriptor, and therefore the matching accuracy between the test face and those registered in the database is considerably improved.

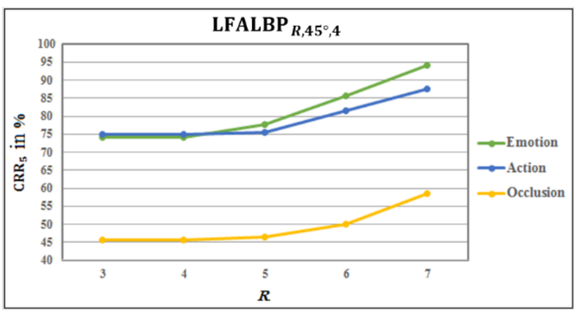

Figure 7: CRR_5 versus *R* for $LFALBP_{R,45°,4}$.

5.2. Parameter evaluation: Number of views and starting angle

After finding the optimal value of *R*, the second set of experiments aims to select the ideal starting angle (*A*) and number of angular views (*N*) to use. Table I shows RR_1 and CRR_5 (in percentage) for the proposed system with three different parameter settings for *A* and *N*. Table I shows results for *N* values of 4 and 8. Results show that considering 4 views allows to capture the essential angular variations, leading to the best recognition performance. Concerning parameter *A*, there is no significant difference between the results obtained when using 0° or 45°.

Table I: RR_1 and CRR_5 for LFLBP depending on *A* and *N*.

Method	Recognition Tasks							
	Emotion		*Action*		*Occlusion*		*Average*	
	RR_1	CRR_5	RR_1	CRR_5	RR_1	CRR_5	RR_1	CRR_5
$LFLBP_{4,0°,16,7,0°,4}$	97	98	93.5	97	86	96.5	92.1	97.1
$LFLBP_{4,0°,16,7,45°,4}$	96.6	97.3	93	97	86.5	96.5	92	96.9
$LFLBP_{4,0°,16,7,0°,8}$	86.3	94.3	84.5	95	80.5	91	83.7	93.4

5.3. Comparative evaluation

In addition to the proposed solution, eight alternative face recognition solutions have been tested for benchmarking purposes. The tested recognition solutions can be grouped into two categories in terms of feature extraction: 1) Global appearance based, including Principal Component Analysis (PCA) [39], Independent Component Analysis (ICA) [40], Generalized PCA (GPCA) [32], and Multilinear PCA (MPCA) [32]; 2) Local descriptor based, including Rotation Invariant LBP [41], Uniform LBP [27], Baseline LBP (SLBP) [10], and Local Phase Quantization (LPQ) [42].

Table II reports the obtained recognition results in terms of RR_1 and CRR_5 (in percentage). The sub-aperture images considered for the proposed LFLBP descriptor are also used for the tensor based MPCA solution [32], and for the solution combining LFALBP with LPQ. For the other experiments, the central sub-aperture 2D image is used as input.

Table II: RR_1 and CRR_5 for LFLBP and benchmarking solutions.

Method	Recognition Tasks							
	Emotion		*Action*		*Occlusion*		*Average*	
	RR_1	CRR_5	RR_1	CRR_5	RR_1	CRR_5	RR_1	CRR_5
PCA [39]	80	91.3	76	89	68	83.5	72.6	87.9
ICA [40]	80.6	91	73	89	74	89	75.8	89.6
GPCA [32]	83.5	92	81	95	79.5	91	81.3	92.6
MPCA [32]	85.6	94.3	83	92.5	80.5	92.5	83.3	93.1
Rot.Inv.$LBP_{4,0°,16}$[41]	24.3	54	24	55	19	39.5	22.4	49.5
Uni.$LBP_{4,0°,16}$ [27]	79.6	89	72.5	88.5	47	68	66.3	81.8
$SLBP_{4,0°,16}$ [10]	91	**98**	92.5	96	83	**96.5**	89.1	97
$LFALBP_{7,0°,4}$	72	93	73	87.5	25	58	56.6	79.5
$LFLBP_{4,0°,16,7,0°,4}$	**97**	**98**	**93.5**	**97**	**86**	**96.5**	**92.1**	**97.2**
LPQ_3 [42]	66	87.3	61	82.6	42.5	68	56.5	79.3
LPQ_3 + $LFALBP_{7,0°,4}$	92.3	96.3	87.5	93	54.5	82.6	78.1	90.6

Table II shows that the proposed LFLBP achieves the best recognition results in all recognition tasks. The good results obtained are, to a large extend, due to the consideration of the angular information as expressed by the proposed LFALBP descriptor, which provides complementary information and discriminative power to SLBP, as shown by the improved performance of LFLBP over SLBP.

Using the proposed descriptor combination framework, see Fig. 6, it is possible to combine the novel LFALBP angular descriptor not only as proposed for the LFLBP descriptor, but also with other existing 2D local face descriptors. The last line in Table II effectively shows this possibility by replacing SLBP with LPQ. Comparing the LPQ performance with and without combination with LFALBP, confirms that angular information considerably improves the baseline LPQ performance, showing the efficiency and flexibility of the proposed combination framework.

6. SUMMARY AND FUTURE WORK

This paper proposes a Light Field Local Binary Patterns (LFLBP) descriptor which explores the richer information available in light field images. LFLBP consists of two components, SLBP and LFALBP, to capture the spatial and angular information available in the set of sub-aperture images. A comprehensive set of experiments has been conducted with the IST-EURECOM light field face database to show that the proposed approach achieves superior recognition performance. Moreover, the proposed combination framework can easily combine LFALBP with different local descriptors, to derive enhanced features for light field based face recognition. In the future, the performance of LFALBP combined with other descriptors will be assessed with the expectation to obtain better performance if more advanced spatial descriptors are used.

7. ACKNOWLEDGMENT

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