An Efficient LBP-based Descriptor for Facial Depth Images applied to Gender Recognition using RGB-D Face Data

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Abstract. RGB-D is a powerful source of data providing the aligned depth information which has great potentials in improving the performance of various problems in image understanding, while Local Binary Patterns (LBP) have shown excellent results in representing faces. In this paper, we propose a novel efficient LBP-based descriptor, namely Gradient-LBP (G-LBP), specialized to encode the facial depth information inspired by 3DLBP, yet resolves its inherent drawbacks. The proposed descriptor is applied to gender recognition task and shows its superiority to 3DLBP in all the experimental setups on both Kinect and range scanner databases. Furthermore, a weighted combination scheme of the proposed descriptor for depth images and the state-of-the-art LBP^{U2} for grayscale images applied in gender recognition is proposed and evaluated. The result reinforces the effectiveness of the proposed descriptor in complementing the source of information from the luminous intensity. All the experiments are carried out on both the high quality 3D range scanner database - Texas 3DFR and images of lower quality obtained from Kinect - EURECOM Kinect Face Dataset to show the consistency of the performance on different sources of RGB-D data.

1 Introduction

Originally proposed by Ojala et al. [1] for texture analysis, Local Binary Patterns (LBP) has now shown its leading performance in a wide range of applications, especially in facial image processing. A large number of works demonstrating excellent results in applying LBP variants to various tasks ranging from face recognition [2], facial expression analysis [3] to age estimation [4], gender and ethnicity classification [5][6], etc. could be widely found in literature recently.

Due to its simplicity yet very powerful discriminative capability, many LBP variants have been developed since its first introduction. Most of them focus solely on luminous intensity [7][8]. Some other methods also extend the LBP approach to 3D data [9] or spatio-temporal signals [10]. However, there are very few efforts in customizing the technique for depth images and RGB-D data. Meanwhile, the explosive development of 3D content and devices recently has made the depth information widely available and successfully exploited in many applications. The access to the RGB-D source of information of home customers has never been as easy with the introduction of Kinect-like devices. Depth data is a special source of information that could characterize the object shape while being fully invariant to textures and lighting condition, which has been proved to be consistently improving the performance of various tasks in computer vision [11][12]. In [13], Huang et al. put a pioneering effort in developing an LBP-based descriptor, namely 3DLBP, specialized for facial depth images utilizing a special characteristics of the smoothness of facial depth images comparing to grayscale images. This work can be seen as the current state-of-the-art LBP-based feature specially developed for human facial depth images. However, the method suffers from some shortcomings as the feature length is much larger while the performance gain compared to LBP^{U2} is not significant. The encoding method is unstable when separating and encoding each digit of the binary form of the depth differences individually. Furthermore, the encoding scheme only uses the absolute value of the depth difference and ignores its true signed measure. These shortcomings should potentially reduce the performance of the approach.

With the above analysis, in this paper we introduce a novel efficient LBP-based descriptor, namely Gradient-LBP, for facial depth images which is proven to be superior to 3DLBP and resolves its inherent drawbacks. The proposed descriptor is applied to the gender recognition task and demonstrate its efficiency in outperforming 3DLBP in all the experimental setups on both the Kinect and range scanner images. Furthermore, we propose and evaluate a weighted combination scheme of the proposed descriptor for depth images and LBP^{U2} for grayscale images in gender recognition using different RGB-D sources of information. Experimental results reinforce the effectiveness of the proposed descriptor in complementing the result on grayscale images and confirm the efficiency of the combination of LBP-based approaches on RGB-D data for facial analysis.

In short, the contributions of the paper are as follow:

- Proposition of an efficient descriptor for facial depth images: the descriptor is much more compact and outperforms 3DLBP in all the experimental setups on both Kinect and range scanner images in gender recognition task.
- Proposition and analysis of a weighted combination scheme of the proposed descriptor for facial depth images and the state-of-the-art LBP^{U2} feature for grayscale images in gender recognition using different sources of RGB-D data: the experimentation is carried out on both high quality 3D range scanner database and images of lower quality from Kinect device. The experimental results reinforce the effectiveness of the proposed descriptor in complementing the information from grayscale images and confirm the efficiency of the combination of LBP-based approaches on RGB-D data.

The rest of the paper is organized as follows. Section 2 briefly reviews the related works in literature. The definition of LBP and 3DLBP is recapulated in section 3. Section 4 presents our proposed descriptor for human facial depth images. Section 5 introduces the proposed weighted combination scheme on RGB-D data. The experimental setups and results are given in section 6. Finally, the conclusion and future works are presented in section 7.

2 Related Work

LBP is originally proposed as a simple yet efficient operator that encodes the sign of the differences between the central pixel and its eight surrounding neighbors. Since then, the method has been continuously improved and now there are many variants applied in a vast domain of applications. In [14], Jin et al. proposed an improved LBP (ILBP) which compares all the pixels with the mean intensity of the patch to enhance its discriminative capability. Since LBP only encode the signs of the gray-value differences (GDs), Guo et al. proposed a complete LBP (CLBP) [7] to partly encode all the information from the sign, the GDs and also the gray values of the central pixels. Also to compensate the information of the gray values of neighboring pixels in the patch, Ylioinas et al. introduced the combination of LBP and the variance of the gray values of surrounding pixels in LBP/VAR [15] and showed consistent improvement. A complete survey of these methods could be found in [16].

Most of the variants are solely introduced for grayscale images. Some other efforts tried to extend the approach to 3D and spatio-temporal data. In [9], Fehr exploited the spherical harmonic transform to compute LBP for 3D volume data in frequency domain. Whereas Zhao and Pietikäinen successfully extended the approach to spatio-temporal data with the introduction of volumn LBP (VLBP) [10], in which it combines motion and appearance information in image sequences. However, very few variants are found in the domain of depth images and RGB-D data. In [13], Huang et al. made a pioneering attempt to extend the LBP approach to facial depth images with the introduction of 3DLBP. The method utilizes the special characteristics of the smoothness of the facial depth images comparing to grayscale images, where most of the depth differences (DDs) of neighboring pixels are very small. Therefore, 3DLBP uses a limited number of bits to represent the DDs and encodes them in an LBP-like way. This approach shows its efficiency when encoding most of the depth difference information into the feature, besides the original LBP. However, it suffers from some drawbacks as the feature length is large, the encoding scheme is unstable when transforming the DDs into the binary form and encoding each digit separately, breaking the integrity of the values, causing a very little change of the DDs would create a big difference in the coded values. Furthermore, the method only uses the absolute values of the DDs, ignoring their signed nature with positive and negative entities. These shortcomings should potentially affect the performance of the approach.

3 Face Representation Using LBP and 3DLBP

In this section, LBP and 3DLBP are reviewed as the background for the comprehension of our proposed approach in section 4.

3.1 LBP

LBP operator performs by thresholding the differences of the center value and the neighborhood in the 3x3 grid surrounding one pixel. The resulting values are then considered as an 8-bit binary number represented for that pixel (Fig. 1). The histogram of these binary numbers in the whole image can be used as a descriptor for the image.

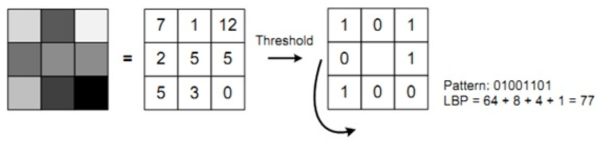

Fig. 1. An example of the original LBP operator [15].

The operator was then extended and generalized for any radius and number of points in the neighborhood. The notation (P, R) is used to indicate the use of P sample points in the neighborhood on the circle of radius R. The value of the LBP code at the pixel (x_c, y_c) is given by:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \tag{1}$$

where g_c is the gray value of the center pixel (x_c, y_c), g_p are the gray values of P pixels at the radius R, s defines the thresholding function as follow:

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

Another remarkable improvement of LBP is the so called uniform pattern [1]. LBP codes are not uniformly distributed, some codes appear much more frequently than the others. These frequent codes have at most two transitions from 0 to 1 or vice versa when the pattern is traversed circularly, and are called uniform patterns. When computing the histogram, every uniform pattern is labeled with one distinguished value while all the non-uniform patterns are group into one category. The uniform LBP is denoted as $LBP_{P,R}^{U2}$. The $LBP_{8,1}^{U2}$ has 59 bins and was proven as much more efficient than the original LBP.

3.2 3DLBP

LBP is a powerful approach to analyze and discriminate textures. However, it just considers the sign of differences and ignores the difference values, which can be an important source of information. By just keeping the sign of the differences, two different textures could be misclassified as the same by LBP.

In [13], Huang et al. extended the LBP approach to encode the extra information of the values of depth differences (DD) specialized for facial depth images.

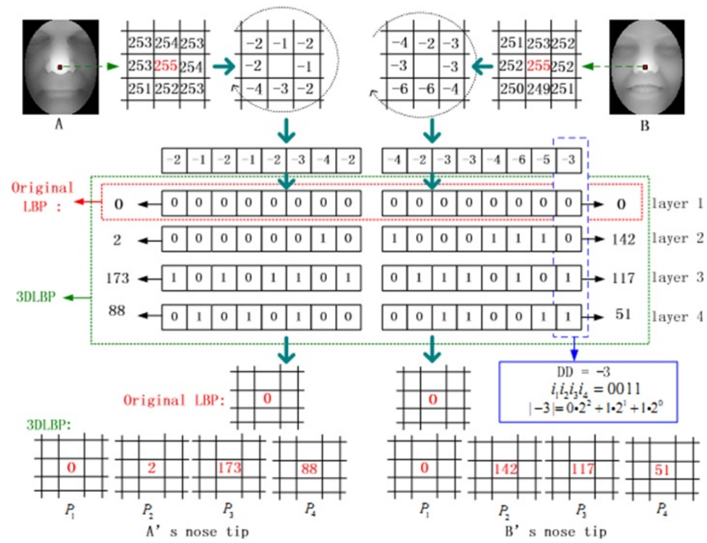

Fig. 2. An example of 3DLBP and its comparison to LBP [13].

From a statistical point of view, the authors observe that more than 93% of the DD between points in R = 2 are smaller than 7. This is due to the smoothness in depth transitions of human faces, which is not true for grayscale images in general, where the neighboring points could be arbitrarily different depending on the texture and environmental conditions. Hence, the authors then use just three bits to represent the DD. Three binary units can characterize the absolute value of DD from 0 to 7. All the $|DD| > 7$ are assigned to 7. The DD is then binarized. Therefore, combining with one bit representing the sign of the DD, for each pixel surrounding the center point, there are four bits representing that position $\{i_1 i_2 i_3 i_4\}$, where $i_2 i_3 i_4$ represents the absolute value of the DD and i_1 represents the sign (encoded as the original LBP). Formally speaking, we have:

$$i_1 = \begin{cases} 1 & \text{if DD} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

$$|DD| = i_2 * 2^2 + i_3 * 2^1 + i_4 * 2^0 \tag{4}$$

The four bits are then separated into four layers. Then, for each layer, the corresponding bits of all the DD from the surrounding pixels are concatenated and generate one LBP code. In total, there are four LBP codes {P1, P2, P3, P4}, where the first LBP code is the same as the original LBP. They are called 3D Local Binary Patterns (3DLBP) (see Fig. 2). For matching, the histogram of each LBP code is computed, then the four histograms are concatenated to form a unique descriptor for the image.

4 Gradient-LBP for Facial Depth Description

3DLBP is a good descriptor that incorporates depth differences into the feature besides the original LBP. This feature works especially well for depth images thanks to the smoothness of facial depth images, where most of the depth differences are smaller than 7 levels. However, this approach suffers from several limitations:

- The feature length is large. At each pixel, there are four LBP codes. For the creation of the descriptor, each LBP code will then contribute to a histogram. With the standard $LBP_{8,1}$, each histogram is of size 256 bins. Four histograms would correspond to a feature length of 256 x 4 = 1024.
- The encoding scheme is unstable. A very small change of the depth difference (DD) in a position could lead to a big difference in the coded values. For example, when the DD of 3 (binary representation 011) increases into 4 (binary representation 100), the whole three last LBP codes will change. This problem is caused by the unconventional way of transforming the DD into binary form and forcefully encoding each binary digit separately in an LBP-like way.
- The DD are encoded on the basic of their absolute values, losing the information of the full range DD including negative and positive entities. Although this is compensated by the inclusion of the LBP from the signs of DD in the first LBP code, the separate encoding of this information into an LBP code and transforming into the histogram loosens the intrinsic connection of the sign and the absolute value parts of the DD.

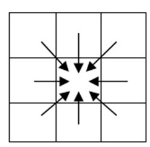

Fig. 3. The eight orientations in computing the standard $LBP_{8,1}$.

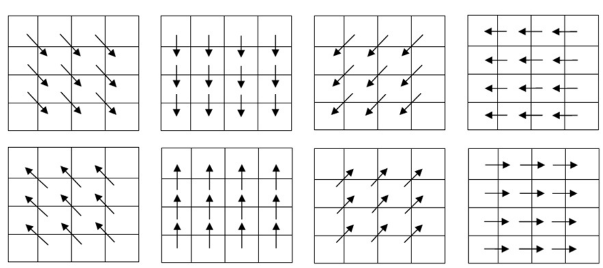

Fig. 4. The eight LBP8,1-based orientations of the depth differences. The example demonstrates the separated depth difference images in each orientation of the sample image patch of size 4x4.

With the above observations, we propose a novel efficient approach to incorporate the DD into the original LBP that overcomes all the mentioned shortcomings of 3DLBP. The proposed method has been proved to be superior to the 3DLBP approach in all the experimental setups carried out.

The proposed approach is based on a different orientation-based view towards the LBP operator. For the standard $LBP_{8,1}$, we can view the LBP operator under a different perspective where eight surrounding pixels are compared to the center value following eight orientations as shown in Fig. 3. The values of DD are indeed calculated through these eight orientations. As illustrated in Fig. 4, we consider each orientation in the computation of LBP separately for the whole image, which leads to the creation of eight depth difference images corresponding to eight orientations used by $LBP_{8,1}$ (Fig. 3). This notion of orientations and the oriented depth difference images can be generalized with the use of $LBP_{P,R}$ of any number of sample points and radius. P sample points used correspond to P orientations and would generate P oriented depth difference images, when we consider each orientation separately in the computing of DD of neighboring pixels. Each oriented depth difference image contains the DD values of neighboring pixels in one corresponding orientation. At each position (x_c, y_c) where the $LBP_{P,R}$ code is computed as in equation (1), the P oriented depth differences corresponding to that central pixel are provided as follow:

$$ODD^{P,R,p}_{p=0...P-1} = max(min(g_p - g_c, 7), -8) \tag{5}$$

where $ODD^{P,R,p}$ is the Oriented Depth Difference at pixel (x_c, y_c) in the depth difference image corresponding to the orientation p (the orientation formed by the point (x_p, y_p) and (x_c, y_c)), g_p is the depth value at position (x_p, y_p) on the circle of radius R surrounding the center pixel, g_c is the depth value at the center pixel, min(x,y) and max(x,y) are two functions that take the min and max value between two variables (x,y) respectively. This means that we clip the DD to be in the range -8 to 7, anything greater than 7 is set to be 7 and anything less than -8 is set to -8. The DD thus has sixteen possible values. This threshold is based on the statistical observation of 3DLBP that most of the DD of neighboring pixels are no more than 7. Notice that we use the true values of DD, not taking their absolute part.

After having P oriented depth difference images obtained as stated above, we can build the histogram of each depth difference image in each orientation, resulting in P histograms. Each histogram has 16 bins from -8 to 7. The information from P histograms is then combined by concatenation to form a unique oriented histogram of depth differences. For the creation of the image descriptor, the histogram of LBP^{U2} is also extracted from the original depth image. The descriptor is then the concatenation of the histogram of LBP^{U2} and the oriented histogram of depth differences. It should be noticed that, the P depth difference images corresponding to P orientations in computing LBP are pairwise symmetric (see Fig. 4), they are pairwise minus sign of the other. Thus, using all P depth difference images would be redundant. We propose to use only half of the P depth difference images in the computation of the final descriptor and call this Gradient-LBP (G-LBP). For the standard LBP of 8 sample points, the proposed descriptor has the length of 59 + 16*4 = 123 (the histogram of LBP^{U2} with 59 bins concatenated with four histograms of four oriented depth difference images, each has 16 bins) which is much more compact compared to 3DLBP.

5 Weighted Combination of LBP and Gradient-LBP on RGB-D Face Data for Gender Recognition

Although the problem of Gender Recognition has been explored extensively in the scope of grayscale face images [6][5], there are very few works on Depth or RGB-D source of information. In [11], Lu et al. experimented the combination of range and luminous intensity data in gender and ethnicity classification and showed the improvement by this approach. However, the authors just use the simple pixel-based feature and the basic averaging fusion of the depth and luminous intensity information and demonstrate moderate results. Furthermore, the experiments are carried out only on range scanner data. The analysis on lower quality RGB-D data obtained from other widely used devices such as Kinect has not been examined.

Here, we apply a weighted combination scheme based on our proposed descriptor for depth images and the state-of-the-art LBP^{U2} feature for grayscale images, since the contribution of each part is unbalanced, usually grayscale images are more discriminative than depth images. The method is then evaluated on both professional 3D range scanner images and a Kinect database to evaluate the behavior of the approach on different sources of RGB-D data. Support Vector Machines is chosen to perform the classification task due to its superior efficiency in demographic classification as has been proven in [17]. More specifically, the classification is first performed separately for grayscale and depth images using SVM, which returns the probabilities of belonging to classes of male or female for each subject. The combination scheme of the results on two sources of information is formulated as follow:

$$p(male|s) = \frac{w_g * p(male|s_{gray}) + w_d * p(male|s_{depth})}{w_g + w_d} \tag{6}$$

$$p(female|s) = \frac{w_g * p(female|s_{gray}) + w_d * p(female|s_{depth})}{w_g + w_d} \tag{7}$$

where s is the subject to be classified, $p(male|s)$ and $p(female|s)$ are the final probabilities that the subject belongs to male or female class respectively, $p(male|s_{gray})$ and $p(female|s_{gray})$ are the resulting posterior probabilities returned by SVM for grayscale images while $p(male|s_{depth})$ and $p(female|s_{depth})$ are the results from depth images, w_g and w_d are the weighting factor for the grayscale and depth information respectively, they are the free parameters and could be adjusted according to the contribution of each part to the final decision. In our experimentation, we propose to use these parameters as the resulting accuracy returned by SVM when using each source of information (grayscale or depth) separately for training and validating.

6 Experimental Analysis

6.1 Experimental Data

The EURECOM Kinect Face Dataset [19] and Texas 3DFR Dataset [18] are used for experimentation, both having color and depth images where the former is obtained using Kinect device while the latter is captured by range scanner.

The EURECOM Kinect Face dataset contains face images of 52 people (14 females, 38 males) taken in two sessions. In each session, the people are captured with nine states (neutral, smile, open mouth, left profile, right profile, occlusion eyes, occlusion mouth, occlusion paper, light on), besides the depth image, the raw depth level sensed by Kinect is also provided in a .txt file for better precision. The dataset also includes 6 manually located landmark points on the face (left eye, right eye, tip of the nose, left and right side of the mouth, the chin).

The Texas 3DFR dataset provides 1149 images (366 females, 783 males). The data includes both the raw images and the preprocessed data where the images underwent Gaussian smoothing, median filtering and hole filling steps. The 25 manually located anthropometric facial fiducial points are also provided.

6.2 Preprocessing

Based on the manual landmark points on the face, the images are first cropped into a square centered by the nose with the width and height two times the distance between the left and right eye centers.

Fig. 5. The sample preprocessed images from EURECOM Kinect Face Dataset.

For the depth information of EURECOM Kinect Face Dataset, we use raw depth levels in .txt files to have better representation. To fill holes, the closing operation is further applied to depth images. An illustration of the preprocessed images is shown in Fig. 5. For the Texas 3DFR dataset, we use the preprocessed images provided by the database. The cropped images in the EURECOM Kinect Face Dataset are then scaled to 96x96 pixels and the ones in Texas 3DFR dataset are scaled to 256x256 due to their higher resolution.

6.3 Settings

The images are divided into 8x8 blocks. The LBP^{U2}, 3DLBP and Gradient-LBP are extracted for each block and then concatenated to form a spatially enhanced feature for evaluation. Different configuration of (P,R) = (8,1) and (P,R) = (8,2) for all the three descriptors are experimented to obtain the in-depth evaluations.

For the classification task, we use SVM with non-linear RBF kernel as it has been proven to be a prominent technique in gender classification. We use 3 states in the EURECOM Kinect Face Dataset (Neutral, Smile and Light On) which cover different expressions and lighting conditions. For all the investigated methods, we carry out three experimental setups. In the first experiment (Kinect 1), we use the first session of EURECOM Kinect Face Dataset as the training set, the second session is the testing set. The second experiment (Kinect 2) is carried out by using first half number of males and females in both sessions of EURECOM Kinect Face Dataset as training set, the remaining are for testing. The third experiment (Range Scanner) is executed on the Texas 3DFR Dataset, where first half number of males and females are used as training and the remaining are used for testing, as in Kinect 2 setup.

6.4 Results and Analysis

Table 1. The detailed comparison of the accuracy (in %) of the three investigated descriptors on depth images.

	Kinect 1			Kinect 2			Range Scanner		
	Male	Female	Overall	Male	Female	Overal	Male	Female	Overal
$LBP^{U2}_{8,1}$	96.49	83.33	**92.95**	80.70	73.81	**78.85**	95.15	59.02	**83.65**
$LBP^{U2}_{8,2}$	98.25	78.57	**92.95**	83.33	71.43	**80.13**	96.17	59.19	**83.13**
$3DLBP_{8,1}$	95.61	90.48	**94.23**	83.33	83.33	**83.33**	95.66	60.11	**84.35**
$3DLBP_{8,2}$	96.49	88.10	**94.23**	84.21	90.48	**85.90**	97.96	63.39	**86.96**
Gradient-LBP$_{8,1}$	96.49	92.86	**95.51**	86.84	88.10	**87.18**	99.74	62.30	**87.83**
Gradient-LBP$_{8,2}$	96.49	92.86	**95.51**	85.09	88.10	**85.90**	100	68.31	**89.91**

Table 2. The accuracy (in %) of the combination scheme compared to using LBP-based descriptors on depth and grayscale images for the configuration of (P,R) = (8,1).

	Kinect 1			Kinect 2			Range Scanner		
	Male	Female	Overall	Male	Female	Overal	Male	Female	Overal
G-LBP$_{8,1}$ (Depth)	96.49	92.86	**95.51**	86.84	88.10	**87.18**	99.74	62.30	**87.83**
LBP$^{U2}_{8,1}$ (Gray)	98.25	97.62	**98.08**	94.74	69.05	**87.82**	95.15	92.90	**94.43**
Combination	99.12	100	**99.36**	95.61	76.19	**90.38**	98.98	91.80	**96.70**

To evaluate the performance of the proposed Gradient-LBP for depth images, the comparison between Gradient-LBP, 3DLBP and LBP^{U2} on depth images in three experimental setups as stated in section (6.3) are carried out. The detail results are shown in Table 1. From the experiments, we can draw two conclusions regarding the performance of the features specialized for depth images:

- LBP_{U2} alone is not a good descriptor for depth images, the extra depth difference information included in 3DLBP does improve the recognition performance for depth images.
- For the depth images, the Gradient-LBP outperforms the 3DLBP and LBP^{U2} approaches in all the experimental setups on both Kinect data and range scanner images, and for both radius of 1 and 2, this proves the consistent superiority of the proposed descriptor on facial depth data.

Table 3. The accuracy (in %) of the combination scheme compared to using LBP-based descriptors on depth and grayscale images for the configuration of (P,R) = (8,2).

	Kinect 1			Kinect 2			Range Scanner		
	Male	Female	Overall	Male	Female	Overal	Male	Female	Overal
G-LBP$_{8,2}$ (Depth)	96.49	92.86	**95.51**	85.09	88.10	**85.90**	100	68.31	**89.91**
LBP$^{U2}_{8,2}$ (Gray)	95.61	97.62	**96.15**	92.98	71.43	**87.18**	93.62	90.16	**92.52**
Combination	98.25	97.62	**98.08**	93.86	80.95	**90.38**	97.96	89.62	**95.30**

The evaluated effectiveness of the combination scheme of Gradient-LBP for depth images and LBP^{U2} for grayscale images comparing to the use of these methods alone on both Kinect and range scanner data are given in Table 2 and Table 3. The results demonstrate that, although LBP^{U2} is very robust and efficient in representing grayscale images in gender classification, the addition of Gradient-LBP source of information from depth images always improve the final performance. The results are very consistent in both the range scanner data and images of lower quality from home devices like Kinect. This result reinforces the effectiveness of the proposed feature for depth images in complementing the luminous intensity information and the efficiency of the combination of LBP-based approaches on RGB-D data.

It can also be noticed that, all the experimental results follow the same trend in which the experimental setup with the first session of the EURECOM Kinect Face Dataset used as training produces the highest accuracy, followed by the setup where half the images in Texas 3DFR are trained, the lowest result corresponds to using half the images in both sessions of the EURECOM Kinect Face Dataset as training. This can be explained since in Kinect 1 setup, all the people presented in the testing set also appear in the training set, which helps the classifier easily recognize the features. The result of the experimental setup Kinect 2 in overall is worse than Range Scanner because the resolution and quality of images in the Texas 3DFR database are better than Kinect data.

7 Conclusion and Future Works

In this paper, a novel feature descriptor specialized for facial depth images inspired by 3DLBP is introduced. The proposed descriptor is much more compact yet consistently outperforms 3DLBP in all the experimental setups carried out on both sets of images from Kinect device and range scanner. We further propose a weighted combination scheme and reinforce the effectiveness of the proposed descriptor by its efficient combination with the result from LBP^{U2} on grayscale images. Although LBP^{U2} is already an excellent descriptor for grayscale images, the combined scheme consistently shows the improvement across different experimental setups and RGB-D sources.

In the scope of this work, experimentations have been performed on a simple two-class problem, that is to say gender recognition, in order to validate the efficiency of the proposed approach. Next step would consist in extending our tests on multiple-class problems, e.g. age, ethnicity, identity classification.

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