3D Face Recognition Based on Histograms of Local Descriptors

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***Abstract*— Face recognition in an uncontrolled condition such as illumination and expression variations is a challenging task. Local descriptor is one of the most efficient methods used to deal with these problems. In this paper, we present an automatic 3D face recognition approach based on three local descriptors, local phase quantization (LPQ), Three-Patch Local Binary Patterns (TPLBP) and Four-Patch Local Binary Patterns (TPLBP). Facial images are passing through one of the three descriptors and divided into sub-regions or rectangular blocks. The histogram of each sub-region is extracted and concatenated into a single feature vector. PCA (Principal Component Analysis) and EFM (Enhanced Fisher linear discriminant Model) are used to reduce the dimensionality of the resulting feature vectors. Finally, these vectors are sent to the classification step, when we use two methods; SVM (Support Victor Machine) and similarity measures. CASIA 3D face database is introduced to experimental evaluation. The experimental results illustrate a high recognition performance of the proposed approach.**

***Keywords*—3D face recognition, Locale descriptors, Local Phase Quantization, TPLBP, FPLBP, Support Vector Machines.**

I. Introduction

Recently, face recognition is one of the most important and popular fields in the domain of computer vision and pattern recognition. There are several variations and challenges which have been weakened the effectiveness of Two-dimensional face recognition systems such as illumination, facial expression, pose obstacles… etc.

Currently, with the development of 3D imaging systems, 3D face recognition provides a solution to the previous problems challenges. In this work, we have used 3D scans like an input to our system in order to improve the accuracy and the robustness of 3D face recognition system in the presence of facial expression and illumination variations by the use of three different local descriptors.

The main idea about the use of the local descriptors in face recognition systems is the representation of the facial image by discriminative descriptors with their interesting characteristics in local regions, in order to address several problems and challenges such as expression and illumination variations, this is what we want to treat in this paper. The histograms of LBPs have become a popular technique for face recognition tasks due to their simplicity, computational efficiency, and robustness to change in illumination [1]. LBP is one of the excellent operators used the application of face recognition [2]. Also, TPLBP and FPLBP are a successful LBP variants proposed in [3]. We used these methods in order to improve the performance of our 3D face recognition system.

LPQ is another descriptor that evaluated in this work; the local phase quantization descriptor is based on quantizing the Fourier transform phase in local neighborhoods [3]. More details about these descriptors are given in this paper.

In this paper LPQ, TPLBP, and FPLBP are proposed to be use in order to improve the accuracy of 3D face recognition system. After the detection of face region and the preprocessing, facial images are passed through one of the three local descriptors mentioned above. Then, images are divided in sub-regions or blocks then the histogram of each region in the image is extracted. All the histograms are concatenated in a single feature vector, which is characterized by a high dimensionality. For that, PCA with EFM [4] are applied to reduce the size of feature vectors. Finally, these features are sent to the classification stage using two methods, SVM or similarity measure.

The results of our work presented in [5], motivate us to continue our research on local descriptors. Also, we are inspired by the work [3, 9] to develop our approach which based on the three local descriptors; LPQ, TPLBP and FPLBP. The flowchart of our proposed 3D face recognition is shown in Figure 1.

The structure of the paper is as follows. Related work is presented in section 2. In section 3 we introduce the preprocessing and detection methods. Section 4 presents the theory of local descriptors. In section 5 the histogram feature extraction is introduced. Section 6 contains the discussion of experimental results and the comparison with the state-of-art. Finally, conclusion and future work are given in Section 7.

II. Related Work

Local descriptors have been shown to be more robust against different challenges in different applications. Many works about local descriptors have been proposed in the literature; in the following we present some related works.

Wolf, et al. [3] studied and compared the performance of similarity learning methods to descriptor based methods in the task of multi-option face identification. TPLBP and FPLBP are a new patch based descriptors proposed by the authors. These descriptors are based on patch statistics, and its aims are to ameliorate the performance of LBP descriptor which is very effective in the applications of face recognition.

Chi Ho, et al. [6] Proposed multi scale blur-robust face descriptor based on multiscale LPQ (MLPQ) Histogram, which projected to the LDA (Linear Discriminant Analysis) space in order to increase the performance of face recognition system. MLPQ descriptor is calculated on small regions in face image, these features are combined using Kernel Discriminant Analysis (KDA) fusion.

Choi, et al. [7] explored the 3D shape information in order to present an automatic face recognition approach based on histogram features. PCA and curvature calculations were used to determinate the symmetry axis of faces after the nose tip detection. To exploit more detailed information concerning the local geometry, faces images are subdivides into N horizontal stripes, then features are extracted from the depth value in each stripe where the feature vector corresponds

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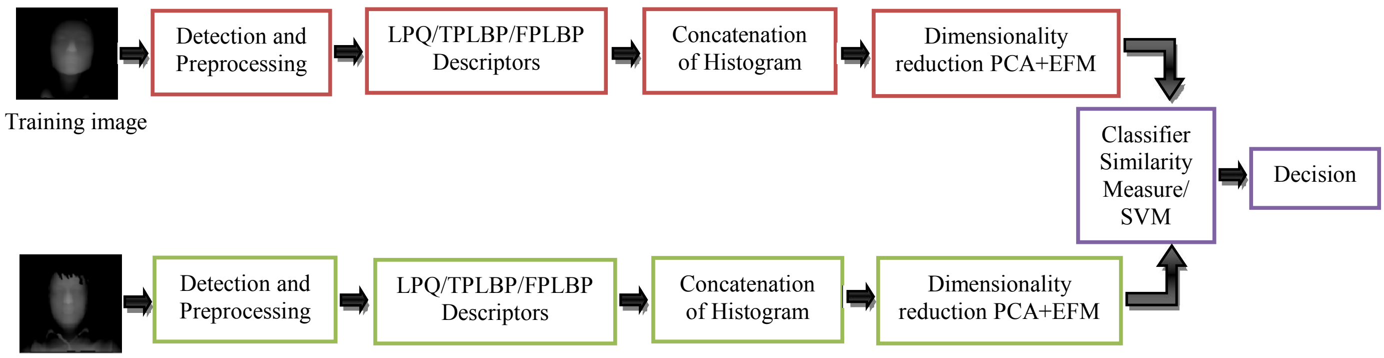

Fig. 1. The flowchart of the proposed 3D faces recognition system

to the histogram of each stripe. To compare the features, the authors used different metrics: city block, Euclidean distance and correlation indicate the similarity of the templates.

Liu, et al. [8] propose two the use of Local Histogram Specification (LHP) to solve the problem of High frequency illumination and low frequency face features. In the first step, a high-pass filter is applied to eliminate the low frequency illumination, after that, the authors used local histograms and local histograms statistics from natural illumination faces images. The combination of face descriptors (LBP, Gabor, MBC-O) are used in this paper, to improve the results, as well as fusing feature extraction methods KLDA and BFLD.

Lei, et al [9] proposed an efficient 3D face recognition method based on the fusion of novel local low-level features. Features were extracted, and a region-based histogram descriptor is computed from these features in order to represent a 3D face. Then, Support Vector Machine is used as a classifier based on the proposed histogram descriptors. In this paper, Feature-level and score-level fusion were tested to verify the effect of two important facial regions (eyes-forehead and nose). Among the significant results given in this work, that the fusion of the rigid and semi-rigid regions contains the most reliable discriminating features in the presence of the expressions variations.

Qian, et al. [10] presented an approach which used discriminative histograms of local dominant orientation (D-HLDO) for feature extraction. Singular value decomposition (SVD) is applied on the gradient matrix in the local patch around the pixel to calculate the local dominant orientation map and the corresponding relative energy map, in order to construct the concatenated histogram features. In the step of reduction of dimensionality, the authors used the Local Mean Based Nearest Neighbor Discriminate Analysis (LM-NNDA) and get low-dimensional information. This approach is tested on different biometric modalities (face, finger-knuckle-print and Palm).

Ahonen, et al. [11] worked on recognition of blurred faces, they proposed Local Phase Quantization (LPQ) operator. The histogram of LPQ is calculated with locale regions and used as a descriptor of face. The authors provides an important result in this paper, that LPQ descriptor is highly tolerant to blur but still very descriptive outperforming LBP both with blurred and sharp images. Almost, in the same idea of recognition of blurred faces in video based face recognition; Chi-Ho, et al. [12] proposed the use of Linear Discriminant Analysis (LDA) of (Multiscale) LPQ histogram. The histograms resulted from local regions of images after the applying of LPQ are projected into LDA space. The proposed approach is tested in BANCA video database, on standard still image FERET and BANCA face databases. This method has shown excellent results.

Baohua, et al. [13] proposed an approach that combined LPQ and LBP in order to obtain the most important information for the purpose of improving the performance of face recognition system. A feature vector used in this method is a concatenation of LBP operator (spatial domain) and LPQ operator (frequency domain). LPQ+LBP have given better results than using each method alone.

III. PREPROCESSING AND DETECTION

Preprocessing and face detection are very important in 3D face recognition systems. The aim the detection stage is to extract the facial area from the depth image which is generated from 3D point cloud (x, y, z). An elliptical mask is centered in the nose tip point; this point in the most cases has the largest z value. To determinate the coordinate of nose tip, the sum of 3*3 pixel window is calculated. The window which gives the maximum depth value indicates the nose area, and the central pixel of this window represents the nose tip points.

Always we find noise in the images resulting from 3D laser scanners. Our input data is the depth images, which are noisy and have holes in some parts of the image. For that, Median filter is used to eliminate this noise and we used Linear Interpolation in order to fill the holes. With this manner, facial image is really expressive the form of human face. Detection and preprocessing of the 3D depth image are illustrated in Figure 2.

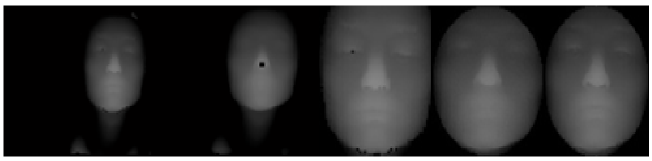

Fig. 2. Detection and preprocessing of the 3D depth image.

IV. LOCAL DESCRIPTOR

A. Local Phase Quantization (LPQ)

The Local Phase Quantization (LPQ) descriptor is proposed by Ojansivu and Heikkilä [14], the authors in this paper utilized this method in the texture descriptor and blur insensitive texture classification. They have proved that LPQ operator is insensitive to centrally symmetric blur, which includes motion [14]; based on this idea, we decided to use this method in face recognition system in the presence of expression variations challenges, which include movement in the different region in the facial image. The local phase quantization descriptor is based on quantizing the Fourier transform phase in local neighborhoods [12]. The extraction of local phase information is used by applying the 2D short term Fourier calculated above M by M neighborhood windows at each pixel x of the face image.

In this paper, we use LPQ descriptor followed by two methods of feature extraction PCA and EFM before the classification step. For more mathematical detail of LPQ operator, see [12].

B. Three-Patch LBP (TPLBP)

The TPLBP is a variation of LBP proposed by Wolf, et al [3] this method is produced by comparing the values of three patches to produce a single bit value in the code assigned to each pixel, The w*w patches are uniformly located around a ring of radius r (in the direction α with or counter clockwise) centered at the site of pixel S. The TPLBP gives promising results in face recognition [15]. This method is given by the following equation:

$$TPLBP = \sum_{i=0}^{i=S-1} f\left(d\left(p_0, p_i\right) - d\left(p_0\ , p_{i+\alpha}\, mod\, S\right)\right) 2^i \qquad (1)$$

Where: d is the distance measure between the patches and f is a threshold function which is calculated as following:

$$f\left(x\right) = \begin{cases} 1 \ \ if \quad x \geq \tau \\ 0 \ \ if \quad x < \tau \end{cases} \qquad (2)$$

τ : The threshold of comparison.

The principle of the TPLBP operator is illustrated in Figure 3.

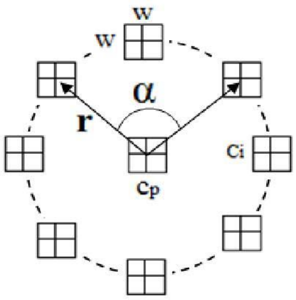

Fig. 3. The Three-Patch LBP representations.

C. Four-Patch LBP (FPLBP)

Also, FPLBP is proposed by [3] almost, with the same idea of the TPLBP which is mentioned previously, but there is a difference in the ring; with FPLBP two rings with radius r1 and r2 are used and centered in the pixel. The w*w patches distributed around these rings and the comparison occur between two center symmetric patches in the inner ring with two center symmetric patches in the outer ring positioned α patches away along the circle [3]. After the comparison, one bit in each pixel is taken into account in accordance to which of the two patches is more similar. Along of each circle, S/2 is the center symmetric pairs; this value is the final binary codes. The following equation represents the FPLBP method:

$$FPLBP = \sum_{i}^{S/2} f\left(d\left(C_{1i}, C_{2,i+\alpha}\, mod\, S\right) - d\left(C_{1,i+s/2}, C_{2,i+s/2+\alpha}\, mod\, S\right) 2^i \qquad (3)$$

The principle of the FPLBP operator is illustrated in Figure 4.

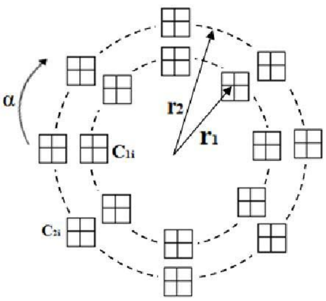

Fig. 4. The Three-Patch LBP representations.

V. HISTOGRAM FEATURE EXTRACTION

The final facial image resulting from the detection and preprocessing stage is used as input to the one of local descriptors LPQ, TPLBP and FPLBP. Then, the image is divided along x and y into sub-regions or rectangular blocks. As shown in Figure 5, for each block a histogram is extracted.

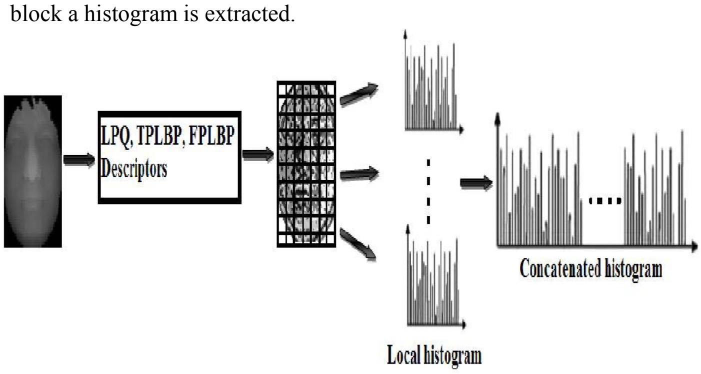

Fig. 5. Descriptors and histogram feature extraction.

The histogram of an image is the function which associates with each intensity value the number of pixels in the image having this value. Also, the histogram represents the information about micro structures such as edges, spots and flat areas in the local region of the image [15]. Finally, all the histograms of each block in the image are concatenated into one single feature vector, which represents our feature vector. The histogram (h) of the local descriptor can be computed as follows:

$$h(i) = \sum_{x,y} B(Dlocal_p(x,y) = i), i \in \left[0, 2^p - 1\right], B(v) \begin{cases} 1 \text{ when v is true} \\ 0 \ otherwise \end{cases} \qquad (4)$$

Where, Dlocal: TPLBP, FPLBP or LPQ, and P: number of points

A high dimensionality of these vectors leads in a high computational complexity and redundant information therefore, we have a less accurate classification. To avoid this problem, we performed the dimensionality reduction. For this, PCA and EFM are applied to reduce the size of the feature vectors. With this efficient process, the information become more expressive, this is what gives more accurately to the classification step.

V. CLASSIFICATION

The classification step is very important in our system. In the present work, we are interested in two types of classification: the first based on the similarity measure and the second based on the SVM classifier.

A. Similarity measure

Similarity measure is utilized in face recognition systems in order to compare two feature vectors resulting from the step of dimensionality reduction.

Although, the Euclidean Distance is optimal in the theory. But, the various experiences have found that the Euclidean Distance is surpassed by other distances. One of the best of them is the Normalized Correlation. Let X and Y are two vectors and S is the normalized correlation distance which is defined in the following equation (5):

$$S(X,Y) = \frac{X^T Y}{\|A\| \|Y\|} \qquad (5)$$

This function simply calculates the cosine of the angle between the two feature vectors X and Y. Were a high value of normalized correlation corresponds to a good similarity between these vectors.

B. Support Victor Machine (SVM)

In this paper, we have used SVM in the classification step. The SVM is a new statistical learning technique that analyzes data and recognizes patterns.

SVM is very usable in the domain of pattern recognition. SVM can be described as an attempt to search the best separating hyperplane between two classes in the input space by maximizing the distance between the hyperplane and the two classes. In our recognition system, there are two classes: Customer and Impostor, whose label will be noted with y = -1 corresponding to the Impostors class and y = 1 corresponding to the Customers class.

VI. EXPERIMENTAL RESULTS

In this section, we present the database used to evaluate the proposed approach and we give our recognition results where, LPQ, TPLBP and FPLBP operators was compared. Moreover, our results are compared to with the state-of-art techniques in 3D face recognition system.

A. Experimental Data

Facial databases must include several variations and challenges in the images of each person; this allows testing several techniques to address many difficulties and problems.

Our experiments are performed on the CASIA3D face database; CASIA 3D (WRL format) contains 123 different persons having 37 or 38 scans (models). In CASIA3D we consider not only the single variations of poses, expressions and illuminations, but also the combined variations of expressions under illumination and poses under expressions.

In our work, we use only 15 models to each individual. (1-5) scans with Variation of Illumination; (6-10) scans with Variation of Expressions (laugh, smile, anger, surprise, eye close); (11-15) scans with Expression under Illumination variation. Figure 6 and 7 illustrate an example of illumination and expression variations respectively.

Fig.6. Illumination variations of the CASIA3D database.

Fig.7. Expression variations of the CASIA3D database.

In order to test our recognition system we are followed the protocol presented in Table 1 when we separate subjects (persons) into two classes, Client and Impostor. Customer class contains 100 subjects, and impostor class is subdivided into 13 impostors for evaluation and 10 impostors for testing.

Table 1. Protocol used for recognition process

Together	Customer	Impostor
Learning	500 images (1, 4, 8, 9, 10)	0 images
Evaluation	500 images (2, 6, 7, 14, 15)	195 images (1:15)
Test	500 images (3, 5, 11, 12, 13)	150 images (1:15)

B. Results and Discussion

In the following section, we will present the results the proposed approach. We evaluate the 3D face recognition system on three local descriptors LPQ, TPLBP and FPLBP using two methods of classification SVM and similarity measure.

We summarize the best recognition performance of our system in all test and evaluation on CASIA 3D face database, as shown in table 2 using the best parameters, whereas: EER: Equal Error Rate.; RR: Recognition Rate.; FRR: False Reject Rate.; FAR: False Accept Rate.

The optimal parameters of the three descriptors are chosen experimentally after several tests. These parameters give the best performance of the recognition system (see Table 2). For the FPLBP: r1=3, S=8, w=5, α=1, τ=0.01 and for TPLBP: r_1=1, r_2=5, S=12, w=5, α=1, τ =0.01.

LPQ descriptor is based on quantizing the Fourier Transform phase in local neighborhoods M*M windows at each pixel, in our experiments the optimal value is M=3.

The first conclusion that can be made based on the experimental results as shown in Table 2, the robustness and the accuracy of our method in the presence of illumination and expression variations present in CASIA 3D face database. This confirms the effectiveness of local descriptors to deal with these problems.

Table.2. Accuracy recognition throughout evaluation and test set.

Local descriptor	Classifier	Evaluation	Test		
		EER	FAR	FRR	RR
TPLBP	Distance Measure	3.58	1.56	3.00	95.44
	SVM	1.90	0.71	2.80	96.48
FPLBP	Distance Measure	3.17	2.32	2.20	95.48
	SVM	1.90	0.71	2.60	96.68
LPQ	**Distance Measure**	**1.99**	**1.01**	**1.80**	**97.18**
	SVM	**1.20**	**0.21**	**1.60**	**98.18**

Almost, there is no significant difference in the results between TPLBP and FPLBP, in which we obtain a recognition rate of 96.44% and 96.48% respectively using SVM classifier. In addition, the highest recognition performance is obtained with LPQ descriptor, which outperformed both extension methods of LBP (TPLBP and FPLBP) and achieves very high performance (EER=1.20%, FAR=0.21%, FRR=1.60% and % RR= 98.18 %,). Also, compared with the distance measure in the classification step, SVM gives the best results with the three local descriptors.

Based on our experimental results, we can conclude that, local descriptors especially LPQ operator based on SVM classifier is one of the best ways to address the challenges of illumination and expression variations.

The histograms of local descriptors using small rectangular regions of 3D depth images give more and important distinct features. With this method, a significant improvement in the performance of 3D face recognition system was obtained. Table 3 provides a comparison of the proposed approach with the state-of-art techniques in 3D face recognition. A high recognition rate of 98.18% is obtained by our proposed method when we use LPQ descriptor.

Table 3. Comparison of Recognition Rate with state-of-art

Authors	Methods	Database	RR (%)
A.Bronstein [16] 2006	Isometry-invariant representation, geodesic distance. Euclidean embedding spaces, Canonical form matching, spherical harmonic transform (SHT).	database contain 4 subjects, with 26 facial expressions	95.00
C. Xu [17] 2009	Gabor filter, LDA, Fusion (2D&3D) Adaboost	CASIA 3D ; FRGC V2.0	93.3 (rank-1)
X. Wang [18] 2010	ICP, PCA, Gabor filter, LBP, Corresponding Point Direction Measure (CPDM)	CASIA 3D	91.71
Y. A. Li [19] 2010	geometric feature, ICP, LDA, geodesic distance	CASIA3D	91.10 (rank-1)
Y. Ming [20] 2013	Orthogonal Spectral Regression, PCA Curvature, Distance Metric, ICP, OSR, Nearest neighbor classifier	CASIA 3D ; Bosphorus ; FRGC3D	96.25
Yue Ming [21] 2012	Gabor features, patched spectral regression, LDA	CASIA 3D	96.35
Ouamane, A[5] 2013	Fusion(2D&3D), ICP, SLF, SVM, LBP,SIFT, PCA with EFM.	CASIA 3D	94.97
Our method	**PCA with EFM, LPQ, SVM**	**CASIA 3D**	**98.18**

VII. CONCULSION AND FUTURE WORK

In this paper, we have presented an automatic approach for 3D face recognition and tested its performance on CASIA 3D face database. Three local descriptors (LPQ, TPLBP and FPLBP) are used in order to address the perturbations caused by uncontrolled condition such as illumination and expression variations. After applying the local descriptor; facial images are divided and the histogram of particular regions are extracted and concatenated to obtain one feature vector. PCA with EFM were applied to reduce the dimensionality of the resulting feature vectors. Experimental results compared to those of state-of-the-art showed that our proposed method achieved a high performance of 3D face recognition with a RR=98.18% and EER=1.20%. Based on experimental results, we can conclude that LPQ descriptor outperformed both extension methods of LBP, TPLBP and FPLBP. In the future work, we will try to develop a better framework by the use of optimization process, such as, Particle Swarm Optimization or Genetic Algorithm to get more accuracy and robustness of the system.

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