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3D Face Recognition using eLBP-based Facial Description and Local Feature Hybrid Matching

Di Huang*, Member, IEEE, Mohsen Ardabilian, Yunhong Wang, Member, IEEE, and Liming Chen, Member, IEEE

Abstract—This paper presents an effective method for 3D face recognition using a novel geometric facial representation along with a local feature hybrid matching scheme. The proposed facial surface description is based on a set of facial depth maps extracted by multi-scale extended Local Binary Patterns (eLBP) and enables an efficient and accurate description of local shape changes; it thus enhances the distinctiveness of smooth and similar facial range images generated by preprocessing steps. The following matching strategy is SIFT-based and performs in a hybrid way that combines local and holistic analysis, robustly associating the keypoints between two facial representations of the same subject. As a result, the proposed approach proves to be robust to facial expression variations, partial occlusions and moderate pose changes, and the last property makes our system registration-free for nearly frontal face models. The proposed method was experimented on three public datasets, i.e. FRGC v2.0, Gavab and Bosphorus. It displays a rank-one recognition rate of 97.6% and a verification rate of 98.4% at a 0.001 FAR on the FRGC v2.0 database without any face alignment. Additional experiments on the Bosphorus dataset further highlight the advantages of the proposed method with regard to expression changes and external partial occlusions. The last experiment carried out on the Gavab database demonstrates that the entire system can also deal with faces under large pose variations and even partially occluded ones, when only aided by a coarse alignment process.

Index Terms—3D face recognition and verification, geometric facial description, extended LBP, SIFT, hybrid matching

1 INTRODUCTION

THE face has its own advantages over other biometrics for people identification and verification-related applications, since it is natural, non-intrusive, contactless etc. Unfortunately, all human faces are similar to each other in their configurations and hence offer low distinctiveness, unlike other biometrics, e.g. the iris and fingerprint. [1]. Furthermore, intra-class variations, due to factors as diverse as pose and facial expression etc. are usually greater than inter-class ones. The past decades have witnessed tremendous efforts firstly focused on 2D face images [2] and more recently on 3D face models or scans [3]. Despite great progress achieved so far within the field [2], face recognition (FR) using 2D facial texture images is still not reliable enough [4], especially in the presence of pose and lighting variations [5]. With the rapid development in 3D imaging systems, 2.5D and 3D facial scans have emerged as a major alternative in dealing with the unsolved issues in 2D face recognition, i.e. changes of illumination and pose [3], [6]. Meanwhile, even though 3D facial scans capture exact shape information of facial surfaces, and are thereby theoretically reputed to be robust to variations in illumination, they are likely to be more sensitive to expression changes. Furthermore, they generally require an accurate registration step before 3D shape-based face matching.

1.1 Related Work

Generally, how to describe facial surface is a core topic in 3D face recognition. “Good” features of facial surfaces should have the following properties [7]: first, they can tolerate within-class variations while discriminating different classes well; second, they can easily be extracted from raw facial data to allow fast processing; finally, they should lie in a space with moderate dimensionality to avoid high computational cost in matching. As a result, 3D face recognition techniques can be firstly classified according to the features they use: (1) original feature-based techniques make use of the entire face region as input to compute similarity. Several works have explored PCA directly on facial range images [8], [9], [10]; while some have applied the ICP (Iterative Closest Point) algorithm [11] or its modified version on facial point-clouds to match surfaces [12], [13], [14], [15]. The Hausdorff distance has also been investigated for face matching [16], [17]; (2) region or point feature based detects representative facial areas or points to construct feature spaces. The eye and nose areas are used in [18]; segmented facial regions and lines are utilized in [19]; anthropometric facial fiducial keypoints are employed in [20]; (3) curve feature based extracts discriminative surface curves for facial representation. In [21], three facial curves are found to intersect the facial surface using horizontal and vertical planes as

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well as a cylinder; the central profile with maximal protrusion as well as two parallel profiles are searched in [22]; a union of the level curves of a depth function is proposed to represent 3D facial surfaces [23]; (4) \textit{shape feature based} focuses on the attributes of local surfaces, such as curvatures [18], point signature [24], Extended Gaussian Image (EGI) [25], Signed Shape Difference Map (SSDM) [26], etc.

3D face recognition techniques can also be categorized according to the nature of their matching strategies, even though it is highly dependent on the facial features used. Zhao et al. [2] have roughly classified 2D face recognition approaches into three main streams: holistic, e.g. PCA [27] and LDA [28]; \textit{feature-based} such as Elastic Bunch Graph Matching (EBGM) [29]; \textit{hybrid} like Component Eigenfaces [30]. This taxonomy can be extended to 3D face recognition. The \textit{holistic stream} contains ICP-based matching [12], annotated deformable model [31], and isometry invariant description [32] \textit{etc}. This matching scheme is based on holistic facial features and hence generally requires an accurate normalization step with respect to pose and scale changes. Furthermore, it has proved sensitive to expression variations and partial occlusions. The \textit{feature-based} one utilizes local features of 3D facial scans and has been explored in several works in the literature, including point signature [24], and more recently keypoint detection and local feature matching for textured 3D face recognition by Mian et al. [33]. In this last work, an original keypoint detection method on a 3D facial surface was introduced, and a graph-based matching scheme along with a dynamic fusion strategy performed at score level. As also highlighted in [33], feature-based matching has the potential advantage of being robust to facial expression, pose and lighting changes and even to partial occlusions. The downside of this scheme is the difficulty in extracting sufficient informative feature points from similar or smooth 3D facial surfaces. Some studies also exist which present \textit{hybrid matching} combining global facial features with local ones: Region-ICP [34], multiple region-based matching [35] and the component and morphable model-based approach [36]. As this scheme tends to combine facial configuration information with local properties of faces, it is theoretically the most powerful [2]. However, it also risks inheriting both types of shortcomings: sensitivity to pose variations, difficulty in generating sufficient stable descriptive features, \textit{etc}.

1.2 Motivation and Approach Overview

In this paper, our basic assumption, as the one behind feature-based face recognition algorithms, is that, when a variation such as an expression or an occlusion occurs on a probe 3D facial scan, there still exist some small local areas, \textit{e.g}. the nose region during a facial expression, that change slightly or remain invariant as compared to the corresponding 3D facial scan in the gallery set. Once located and characterized accurately, these local regions can be utilized to identify 3D faces, thereby providing robustness to facial expressions and partial occlusions through a proper matching process.

Motivated by this intuition, this paper proposes a novel approach to 3D face recognition, making use of a geometric facial representation along with a local feature hybrid matching strategy. Our main contributions can be summarized as follows:

1. Because after basic preprocessing, \textit{e.g}. spike removal and hole filling, 3D facial surfaces to be identified are generally smooth and similar, to achieve accurate representations of facial surfaces and enhance their distinctiveness, we propose a 3D shape based geometric facial description, consisting of a set of Multi-Scale extended Local Binary Pattern Depth Faces (MS-eLBP-DFs). This method improves the discriminative power of LBP for 3D facial surface description by two solutions, \textit{i.e}. encoding exact gray value differences between the central pixel and the neighboring ones as well as embedding a Multi-Scale (MS) scheme.

2. In order to extract sufficient repeatable local features on smooth facial surfaces, we propose to apply SIFT [46] to these Multi-Scale extended LBP-based facial representations, \textit{i.e}. MS-eLBP-DFs, interpreted as simple gray level images, for the detection of keypoints and the characterization of local geometric properties.

3. A hybrid matching approach is designed to measure similarities between gallery and probe facial scans once they are represented in terms of the geometric facial description \textit{i.e}. MS-eLBP-DFs. This matching method inherits the principles of local feature matching along with graph based matching as in [33], and it also extends the latter by incorporating a facial component constraint.

4. Thanks to the local feature-based approach and the hybrid matching scheme, the proposed 3D face recognition algorithm is robust to facial expression changes and partial occlusions whilst remaining tolerant of moderate pose variations. The last property makes our method a registration-free technique for recognizing nearly frontal 3D facial scans as can be the case of most user cooperative biometric applications, \textit{e.g}. access control. This is clearly in contrast to the overwhelming majority of state-of-the-art 3D face recognition algorithms requiring the costly 3D face alignment step before face matching.

As a local feature-based 3D face recognition algorithm, the proposed method and that of Mian et al. in [33] share some similarities, including in particular the overall local-feature oriented framework (though the features used in each of the two approaches are very different), the use of the SIFT method (though SIFT is applied to extended LBP based shape representations, \textit{i.e}. MS-eLBP-DFs, instead of texture), the matching strategy combining local feature matching and graph based matching that is further extended to include a facial component constraint-based matching, and finally the weighted fusion scheme at score level with dynamic weight calculation.

The proposed method was evaluated on three public databases, namely FRGC v2.0 [48], Bosphorus [68] and Gavab DB [39]. As experimented on the FRGC v2.0 database for both the tasks of 3D face recognition and verification, our approach achieves a rank-one recognition rate of 97.6\% and a 98.4\% verification rate with a FAR of 0.1\% respectively. Since the 3D facial scans in FRGC are nearly frontal, the costly step of 3D face alignment was not re-
quired. The experiment carried out on the Bosphorus dataset further highlights the ability of the proposed method to identify nearly frontal 3D face models owning expression changes and external occlusions. When it handles large pose variations including left and right profiles which probably lead to self-occlusions, a coarse alignment based on a few landmarks is sufficient as a preprocessing step of this approach. This is demonstrated by the experiments on the Gavab dataset.

The preliminary experimental results of this work appeared in [50] and [64]. The remainder of this paper is organized as follows. The proposed geometric facial description, MS-eLBP-DFs, is shown in section II, and section III presents SIFT-based local feature extraction. The hybrid matching step is introduced in section IV. Experimental results of both face recognition and verification are described and analyzed in section V. Section VI concludes the paper.

2 Multi-Scale Extended LBP Depth Faces

Due to their descriptive power of micro-texture structures and computational simplicity, Local Binary Patterns (LBP) are among the most successful descriptors for 2D texture based face analysis [65]. In literature, LBP has been also investigated for 3D face recognition [37], [38]; however, LBP is not as discriminative as we expected for 3D facial representation since it cannot correctly distinguish similar local surfaces because of its thresholding strategy. To address this problem, two solutions are considered. First, extended LBP (eLBP), generalized from the task on 3D LBPs [38] and capable of handling different numbers of sampling points and various scales, is used. It not only extracts the relative gray value differences from the central pixel and its neighbors provided by LBP, but also focuses on their absolute differences that prove critical to describe range faces as well. Secondly, a multi-scale strategy is introduced to represent local surfaces to different extents which are then combined for a comprehensive description. Additionally, previous works simply repeated the histogram based manner as did in 2D facial analysis that firstly divides the face into a number of sub-regions, where LBP based histograms are extracted; then concatenates all these local histograms into a global one to construct a final facial feature. Unlike these tasks, we adopt an image based approach by applying eLBP directly to a range image to generate a set of Multi-Scale extended LBP Depth Faces (MS-eLBP-DFs) which retain all 2D spatial information of range faces. Finally, this approach inherits the property of computational simplicity from LBP and achieves fast processing.

In this section, we firstly recall the basics of LBP and analyze its descriptive ability for local facial surface representation. We then present extended LBP (eLBP) and the multi-scale scheme to generate a novel 3D geometric facial description, called MS-eLBP Depth Faces (MS-eLBP-DFs) that comprehensively encodes local shape variations of range faces.

2.1 LBP and Its Descriptive Power for Local Shape Variations

LBP, a non-parametric algorithm [40], was first proposed to describe local texture in 2D images. The most important properties of LBP are its tolerance to monotonic illumination variations and computational simplicity, so it has been extensively adopted for 2D face recognition in the past few years [41].

Specifically, the original LBP operator labels each pixel of a given 2D image by thresholding in a 3×3 neighborhood. If the values of the neighboring pixels are no lower than that of the central pixel, their corresponding binary bits are assigned to 1; otherwise they are assigned to 0. A binary number is hence formed by concatenating all the eight binary bits, and the resulting decimal value is used for labeling. Figure 1 illustrates the LBP operator by a simple example.

![Fig. 1. An example of the original LBP operator.](image)

Formally, given a pixel at \((x_n, y_n)\), the derived LBP decimal value is:

\[
LBP(x_n, y_n) = \sum_{n=0}^{8} s(i_n - i_c)2^n; \quad s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}
\]

where \(n\) covers the eight neighbors of the central pixel, \(i_c\) and \(i_n\) are the gray level values of the central pixel and its surrounding pixels respectively.

According to equation (1), the LBP code is invariant to monotonic gray-scale transformations, preserving their pixel orders in local neighborhoods. When LBP operates on the images formed by light reflection, it can be used as a texture descriptor. Each of the 256 \((2^8)\) LBP codes can be regarded as a micro-texton. Local primitives codified by the bins include different types of curved edges, spots, flat areas etc. Fig. 2 shows some examples. Similarly, as LBP works on range images which are based on depth information, it can also describe local shape structures, such as flat, concave, convex etc., as shown in Fig. 3.

![Fig. 2. An example of texture patterns which can be encoded by LBP](image)
one needs to derive a facial description to enhance distinctiveness for the task of face recognition.

In order to address such a problem, we propose to adopt two complementary solutions. The first solution aims to improve the discriminative ability of LBP with the eLBP coding method, and the other one focuses on providing a more comprehensive geometric description of a given neighborhood by applying a multi-scale strategy. Each solution is discussed in the following two subsections respectively.

![Fig. 3. Examples of local shape patterns encoded by the basic LBP operator (white circles represent ones and black circles zeros).](image)

![Fig. 4. A confusion case of LBP when it encodes similar but different local geometric shapes.](image)

### 2.2 Extended Local Binary Patterns

The fact that LBP is not competent to distinguish similar local shapes is due to its operation mode. It only encodes relative differences between a central pixel and its neighbors. In this section, we introduce eLBP in order to better describe local surface properties. Instead of the original LBP, eLBP not only extracts the relative gray value difference between the central pixel and its neighbors provided by LBP, but also focuses on their absolute differences which are also critical to describe local shapes. eLBP is a generalized version of the 3DLBP [38] originally proposed for histogram-based 3D face recognition.

Specifically, the eLBP code consists of several LBP codes in multiple layers that encode the exact gray value differences (GD) between the central pixel and its neighbors. The first layer of eLBP is actually the original LBP code encoding the GD sign. The following layers of eLBP then encode the absolute value of GD. Basically, each absolute GD value is firstly encoded in its binary representation and then all the binary values at a given layer result in an additional local binary pattern. The example of Fig. 1 can be expressed by eLBP as shown in Fig. 5. The first layer of eLBP code is simply the original LBP code that encodes the sign of GD, thus yielding a decimal number of 211 from its binary form (11010011). The absolute values of GD, i.e., 1, 5, 3, 2, 1, 2, 3, 0, are first encoded in their binary numbers: (001)2, (101)2, (011)2, (010)2, …, etc. Using the same weighting scheme of LBP on all the binary bits, we generate the eLBP code of its corresponding layer, e.g., L2 is composed of (01000000)2 and its decimal value is 64; L3 is composed of (00110110)2 and its decimal value is 54; finally L4 is composed of (11101010)2 and its decimal value is 234. As a result, when describing two similar local shapes, although the first layer LBP is not discriminative enough (both marked by the decimal value of 211), the information encoded in their additional layers can be used to distinguish them so long as the values of the two shapes in all corresponding layers are not exactly the same.

![Fig. 5. An example of the eLBP operator.](image)

Theoretically, in one image, the maximum value of GDs is 255 (between 0 and 255), which means that 8 additional binary units are required to code GDs (2^8=256), and thus 7 additional layers should be produced. Nevertheless, we do not need so many layers in eLBP. Preprocessed range faces are indeed very smooth; the GDs in a local surface generally do not vary dramatically. Some preliminary statistical work reveals that more than 80% GDs are smaller than 7 between points within eight pixels. Therefore, the number of additional binary units, k, is determined by GD. Meanwhile k can also be exploited to control the trade-off between the description expressiveness of local shapes and the computational simplicity of eLBP. All the GDs which are larger than 2^k-1 can be assigned to 2^k-1 to decrease computational cost. In this study, three additional layers are extracted and analyzed to illustrate their contributions to the final accuracy.

### 2.3 Multi-Scale Strategy

The original LBP operator was extended later with different sizes of local neighborhood to deal with various scales [40]. The local neighborhood of the LBP operator is defined as a set of sampling points evenly spaced on a circle centered on the pixel to be labeled. These sampling points which do not fall exactly on the pixels are expressed us
ing bilinear interpolation, thus allowing any radius value and any number of points in the neighborhood. Figure 6 shows different LBP neighborhoods. The notation \((P, R)\) denotes the neighborhood of \(P\) sampling points on a circle of radius \(R\). By adopting the same protocol, the eLBP operator can handle different sampling points and scales as well.

![Fig. 6. LBP operator examples: circular (8, 1), (16, 2), and (8, 2).](image)

Some LBP histogram-based tasks change the neighborhood of the LBP operator for improved performance. By varying the value of radius \(R\), the LBP of different resolutions is thus obtained. The multi-scale strategy was first used for texture classification [40], and it was also introduced to 2D face recognition [43] [44]. In [45], Shan and Gritti studied MS-LBP for facial expression recognition by firstly extracting MS-LBP histogram-based facial features and then using AdaBoost to learn the most discriminative bins. They reported that the boosted classifiers of MS-LBP consistently outperform those based on single-scale LBP, and the selected LBP bins distribute at all scales. MS-LBP can hence be regarded as an efficient method for facial representation. When considering it in 3D face analysis, this multi-scale technique can be applied to enhance the descriptive power of LBP.

### 2.4 Multi-Scale Extended LBP Depth Faces (MS-eLBP-DFs)

LBP facial representation can be achieved in two ways: one is by LBP histogram; the other is by LBP face. The general idea of the former is that a human face can be regarded as a composition of micro-patterns described by LBP. The images are divided into a certain number of local regions, from which LBP histograms are extracted. These histograms are concatenated and thus contain both local and global information about faces. The second method is to generate LBP based maps. It regards the decimal number of the LBP code as the pixel values of an LBP map, and thus produces the corresponding LBP face. Due to its own strategy, an LBP histogram loses some 2D spatial information for representing faces. In this study, the second, eLBP face, is investigated.

For a facial range image, we generate a set of MS-eLBP-DFs for facial representation, i.e. an original LBP map (describing relative gray value differences between the central pixel and its neighbors) as well as its additional maps (representing exact gray value differences between the central pixel and its neighbors). These MS-eLBP-DFs can be achieved by varying the neighborhood size of the eLBP operator, or by first down-sampling range faces and then adopting an eLBP operator with a fixed radius. Some face samples are shown in Fig. 7. In that figure, the number of sampling points is 8, and the radius value varies from 1 pixel to 8 pixels. As we can see, the preprocessed range face is very smooth, whilst the resulting MS-eLBP-DFs contain much more detail of local shape variations.

![Fig. 7. MS-eLBP-DFs of a range face image with different radii from 1 to 8 (from left to right).](image)

### 3 Local Feature Extraction

Once the MS-eLBP-DFs have been produced, the widely-used SIFT features [46] are extracted from them and exploited to calculate a similarity score between two 3D facial scans in the subsequent matching process.

SIFT applies the Difference-of-Gaussian (DOG) scale-space to detect keypoints in 2D images. The raw images are repeatedly convolved with Gaussians of different scales separated by a constant factor \(k\) to produce an octave in scale space. As for an input image, \(I(x, y)\), its scale space is defined as a function, \(L(x, y, \sigma)\), produced by convolution of a variable scale Gaussian \(G(x, y, \sigma)\) with the input image \(I\), and the DOG function \(D(x, y, \sigma)\) can be computed from the difference of two nearby scales:

\[
D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)I(x, y) \\
= L(x, y, k\sigma) - L(x, y, \sigma)
\]  

(2)

Then, extremes of \(D(x, y, \sigma)\) are detected by comparing each pixel with its 26 neighbors in \(3 \times 3\) regions at current and adjacent scales (see Fig. 8). At each scale, gradient magnitude, \(m(x, y)\), and orientation, \(\theta(x, y)\), are computed using pixel differences in (3) and (4).

![Fig. 8. Extremes (maxima or minima) of the difference-of-Gaussian images are detected by comparing a pixel (marked with "X") to its 26 neighbors in a 3×3 window at current and adjacent scales (marked with circles) [46].](image)

\[
m^2(x, y) = (L(x + 1, y) - L(x - 1, y))^2 + (L(x, y + 1) - L(x, y - 1))^2
\]  

(3)
\[ \theta(x, y) = \tan^{-1} \frac{L(x, y + 1) - L(x, y - 1)}{L(x + 1, y) - L(x - 1, y)} \]  

For each detected keypoint, a feature vector is extracted as a descriptor from the gradients of the sampling points within its neighborhood. See Fig. 9 for more details. To achieve orientation invariance, coordinates and gradient orientations of sampling points in the neighborhood are rotated relative to keypoint orientation. Then a Gaussian function is used to assign a weight to the gradient magnitude at each point. The points close to the keypoint are given more emphasis than the ones far from it (see [46] for SIFT parameter settings). The orientation histograms of 4x4 sampling regions are calculated, each with eight orientation bins. Hence a feature vector with a dimension of 128 (4x4x8) is produced.

![Image gradients](image.png)

Fig. 9. Computation illustration of the keypoint descriptor [46].

The SIFT operator works on each MS-eLBP-DF separately. Because each MS-eLBP-DF highlights the local shape changes of an original smooth facial range image by encoding local binary patterns at different scales and thus providing various details, many more SIFT-based keypoints can be detected for the following matching step than in the original smoothed range face. Some statistical work was done using all the 3D facial scans in the FRGC v2.0 database. The average number of descriptors extracted from each of MS-eLBP-DFs is 553, while that of each original facial range image is limited to 41 and the detected keypoints are often located on the edge of the face. As a result, the number of detected keypoints is increased by 10 times more on MS-eLBP-DFs as compared to the original face range image; and the number of keypoints only covers 0.3% of pixels in each MS-eLBP-DF that has an average resolution of 400x400. Figure 10 shows the SIFT-based keypoints extracted from one facial range image and its four associated eLBP-DFs respectively.

Meanwhile, we also studied the repeatability of these keypoints detected on MS-eLBP-DFs across different scans of the same subject based on three manually labeled facial landmarks, i.e. the nose tip and two inner corners of eyes. 25 subjects that have more than 4 facial scans were randomly selected in FRGC v2.0 for this experiment. To each keypoint K detected on an MS-eLBP-DF, we can compute a vector of three distances, \( (a, b, c) \), each of which is the one between the keypoint and one of these three landmarks. These three distances are then used as the coordinates of K. Now a keypoint X detected by SIFT on an MS-eLBP-DF with the coordinates \((a_x, b_x, c_x)\) is considered as in correspondence or matched with the keypoint Y detected from another MS-eLBP-DF possessing the coordinates \((a_y, b_y, c_y)\), as long as the difference between each pair of coordinates, i.e. \(a_x-a_y, b_x-b_y, c_x-c_y\) falls within \(4\) mm in absolute value. This definition is similar to the one as in [33] which considers that two keypoints are matched when their distance falls within \(4\) mm on two registered facial surfaces. Based on such a definition, the repeatability reaches 84.2% for neutral facial scans. For expressive faces, this repeatability at \(4\) mm drops to 79.4% due to the 3D face shape changes. Note that these figures are comparable to that in [33] which proposed an original keypoint detection method based on local shape changes as well. Their repeatability is 86% for neutral facial scans and 75.6% for non-neutral facial scans. Their following experiments in section 5 show that this level of repeatability is quite sufficient to distinguish intra-class variations from inter-class ones for 3D facial scans with moderate pose changes, facial expressions and even partial occlusions when the hybrid matching scheme developed in the following section is applied.

4 The Hybrid Matching Process

Once local features have been extracted from MS-eLBP-DFs, a hybrid matching process is carried out, which combines a local matching step using the SIFT-based features with a global one under the facial component and configuration constraints.

4.1 Local Feature-Based Matching

Given local facial features extracted from each MS-eLBP-DF pair of the gallery and the probe face scan respectively, two facial keypoint sets can be matched. Matching one keypoint to another is accepted only if the matching distance is less than a predefined threshold, \(t\) times the distance to the second closest match. Here, \(N_{\text{ms}}, n\) denotes the number of matched keypoints in the \(n\)th layer of an eLBP-DF pair, generated by eLBP from range face images with a parameter setting of \((P, R)\).

4.2 Holistic Facial Matching

Unlike the samples used in the domain of object detection, all human faces have the same physical components and share a similar global configuration. Holistic matching is thus carried out to constrain the matched local features with respect to the facial components and configuration.

1) Facial Component Constraint: we propose to divide the entire facial range image into non-overlapped sub-regions, each of which contains roughly one component of nearly frontal faces. Different from the division scheme used for histogram statistics, the one in our method is to restrict the matched keypoints of gallery and probe face scans only to those with similar physical meaning. That means the matched keypoints from the same facial region should be more important. Instead of the costly clustering process [47] to automatically construct sub-regions based on keypoint locations from training samples, we simply use facial component position, and divide the face area into \(3\times3\) rectangle blocks of the same size. The similarity
measurement of the facial component constraint is defined from this facial composition scheme. An MS-eLBP-DF, \( I \), is represented as \((m_1, m_2, ..., m_k)\); \( k \) is 9 in our case and \( m_i \) is the number of detected SIFT keypoints that fall within the \( i_{th} \) component. The local SIFT-based descriptors in all the \( k \) components can be denoted by:

\[
I = (f_1, ..., f_{k^m}, f_2, ..., f_{k^m}, ..., f_k, ..., f_{k^m})
\]

where \( f_i \) means the \( j_{th} \) descriptor in the \( i_{th} \) facial component. Then the similarity between a gallery face \( I_g \) and a probe face \( I_p \) is computed by:

\[
C(I_p, I_g) = \frac{1}{k} \sum_{i=1}^{k} (\max(\frac{\langle f_i^p, f_i^g \rangle}{\|f_i^p\| \cdot \|f_i^g\|}))
\]

where \( x \in [1, ..., m_p] \); \( y \in [1, ..., m_g] \); \( < > \) denotes the inner product of two vectors, and \( | . | \) denotes the norm of one vector. A bigger \( C \) indicates the most similar attributes of the two faces represented by MS-eLBP-DFs. We thus obtain similarity values, \( C_{I_p, I_g} \) for each MS-eLBP-DF.

2) Facial Configuration Constraint: the former constraint on facial component emphasizes the importance of the matching score between local features of the same facial component-based area in the gallery and probe set, and we further improve the holistic constraint by facial configuration inheriting the local feature based graph matching implemented in [33].

All facial range images are normalized to a certain size to build a public 2D coordinate system. For each 3D face scan, the MS-eLBP-DFs are extracted from the range image. Therefore, all the keypoints of the proposed facial surface representations share the same XY-plane with the range face image, and the pixel values of the corresponding facial range image can be regarded as the Z-axis values of these keypoints. Hence, each keypoint has its position in 3D space. After local feature-based matching, a 3D graph is formed for each MS-eLBP-DF of a probe \( F_p \), by simply linking every two keypoints which have a matching relationship with keypoints detected on the corresponding MS-eLBP-DF of a gallery face \( F_g \). The matched keypoints of \( F_g \) also construct a corresponding graph of \( F_p \). Since all the facial range images are of the same scale, intuitively, if faces \( F_g \) and \( F_p \) are from the same subject, their corresponding graphs should have similar shapes in 3D space.

The similarity measure between the two graphs can be defined as:

\[
D = \frac{1}{n} \sum_{i=1}^{n} \left| d_{p_i} - d_{g_i} \right|
\]

where \( d_{p_i} \) and \( d_{g_i} \) are the lengths of corresponding edges in the probe and gallery graphs respectively. The value \( n \) is the total number of edges. If the number of matched keypoints is \( n_e \), \( n_e \) will be \( n_e^* (n_e - 1) / 2 \). Equation 7 is an efficient way to measure the spatial error between the matched keypoint pairs of probe and gallery features. As in the facial component constraint, here, \( D_{I_p, I_g} \) denotes the similarity score of each MS-eLBP-DF.

4.3 Similarity Fusion

In summary, the matching process of gallery and probe facial range images contains three types of similarities: the number of matched keypoint pairs \( N \), similarity \( C \) of the facial component constraint and similarity \( D \) of the facial configuration constraint. Except for \( D \), all the other similarity measures have a positive polarity (a bigger value means a better matching relationship). A range face of the probe set is matched with every face in the gallery, resulting in three vectors \( S_N, S_C \) and \( S_D \). The \( n_{th} \) element of each score vector corresponds to the similarity score between the probe and the \( n_{th} \) gallery face. Each vector is normalized to the interval of \([0, 1]\) using the min-max rule. Elements of \( S_D \) are subtracted from 1 to reverse its polarity. The final similarity of the probe face with the ones in the gallery is calculated using a basic weighted sum rule:

\[
S = w_N * S_N + w_C * S_C + w_D * (1 - S_D)
\]

We further make use of the original weight calculation as proposed by Mian et al. in [33] to dynamically determine their corresponding weights: \( w_N, w_C, \) and \( w_D \) during the online step:

\[
w_S = \frac{\text{mean}(S) - \min_i(S_i)}{\text{mean}(S) - \min_i(S)_i}
\]

where \( i \) corresponds to the three similarities: \( N, C, \) and \( D \) and operators \( \text{max}(S) \) and \( \text{max}(S) \) produce the first and second maximum value of vector \( S \). The gallery face which has the maximum value in vector \( S \) is declared as the identity of the probe face image when the decision is to be made on each MS-eLBP-DF independently.
3D face samples with extreme pose changes (left and right profiles).

5.1 Experiments on the FRGC v2.0 Dataset

5.1.1 Database and protocol description

Some experiments were evaluated on FRGC v2.0 [48], one of the most comprehensive and popular datasets, containing 4007 3D face scans of 466 different subjects. One facial range image was extracted from each 3D face model. A preprocessing step was applied to remove noises with a median filter and fill holes using cubic interpolation, and the technique details can be found in [57]. Thanks to the relative tolerance to moderate pose changes of hybrid matching, we did not perform any registration on these 3D face models, in contrast to most works such as [31], [49], [56] etc. The facial range images were automatically cropped using a basic bounding box, which was roughly located according to the vertical and horizontal integral projection of the mask provided by a 3D scanner indicating if the point was valid or not in that position. Cropped faces have moderate pose, expression changes, as well as partial occlusions caused by hair. All the faces are normalized to 150×150 pixels. Fig. 11 shows some preprocessed samples for the following recognition step.

Fig. 11. Examples of preprocessed 3D facial scans of the same subject from the FRGC dataset.

The proposed method was evaluated by face recognition and verification tasks. In order to compare our method with the state of the art, we followed the same experimental protocol that the first 3D face scan with a neutral expression from each subject makes up a gallery of 466 samples and the remaining face scans (4007-466=3541) are treated as probes. The probe face scans were divided into two subsets according to their facial expression labels to evaluate its robustness to facial expression variations. The first subset is made up of facial scans with a neutral expression; whilst the other one with facial scans possessing non-neutral facial expressions. Besides the experiment of Neutral vs. All, two additional experiments: Neutral vs. Neutral and Neutral vs. Non-Neutral were also included. In the Neutral vs. Neutral and Neutral vs. Non-Neutral experiments, only the neutral and non-neutral subsets were used, respectively.

Based on its default setting in SIFT matching [46], we compared the values of t from 0.5 to 0.9 with an increasing step of 0.05, and in the range of [0.6, 0.8], the performance basically keeps stable and outperforms the others. We thus set t at 0.6 in the following experiments.

5.1.2 The influences of eLBP parameters (Experiment A)

The four sub-tables in Table I list the results based on depth faces of each eLBP layer with different parameters. Recall that $P$ is the number of sampling points and $R$ is the radius value.

In these sub-tables, all eLBP accuracies at different scales with different numbers of sampling points display recognition rates better than 90%, greatly outperforming the ones based on original LBP operators (eLBP L1). The accuracies displayed in the last row labeled as the ‘eLBP’ performance are fusion results according to the weighted sum rule in (8) combining the scores provided by the first three layers ($L_1$, $L_2$ and $L_3$) using the same parameter setting; similarity scores at $L_4$ are omitted because of their low performance. As we can see from Table I, using 8 sampling points achieves better results on $L_1$, and $L_2$ for almost all radius values (except $R = 2, 3$), respectively; whilst the setting with 16 sampling points results in better performance on $L_3$ (except $R=2$ and $L_4$ respectively.)

### TABLE I

<table>
<thead>
<tr>
<th>$P$</th>
<th>$R$</th>
<th>$R$</th>
<th>$R$</th>
<th>$R$</th>
<th>$R$</th>
<th>$R$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$eLBP_L1$</td>
<td>81.6%</td>
<td>84.8%</td>
<td>86.9%</td>
<td>87.7%</td>
<td>87.6%</td>
<td>86.2%</td>
</tr>
<tr>
<td>$eLBP_L2$</td>
<td>75.2%</td>
<td>83.3%</td>
<td>85.7%</td>
<td>87.1%</td>
<td>87.6%</td>
<td>87.3%</td>
</tr>
<tr>
<td>$eLBP_L3$</td>
<td>76.9%</td>
<td>74.7%</td>
<td>71.6%</td>
<td>68.8%</td>
<td>67.4%</td>
<td>63.7%</td>
</tr>
<tr>
<td>$eLBP_L4$</td>
<td>4.5%</td>
<td>8.0%</td>
<td>12.7%</td>
<td>16.0%</td>
<td>25.9%</td>
<td>33.2%</td>
</tr>
<tr>
<td>$eLPB$</td>
<td>90.0%</td>
<td>90.9%</td>
<td>92.0%</td>
<td>92.6%</td>
<td>92.4%</td>
<td>92.3%</td>
</tr>
</tbody>
</table>

5.1.3 Face identification performance (Experiment B)

Using the weighted sum rule described in (8), we then fused the similarity measurements of eLBP with 8 sampling points and different values of radius from 2 to 8, and compared the rank-one face recognition rate achieved with the state of the art in Table II. Except for ICP, all the results are cited from the original papers.

In order to test the discriminative power of LBP and eLBP to characterize local geometric shapes, Shape Index (SI) faces are also produced and associated with the proposed hybrid matching for comparison in 3D face recognition. Recall that an SI face is generated by computing
the shape index value on each pixel location from a facial range image and quantizing that values to the range of gray level images, i.e. [0, 255]. Further technique details can be found in [50]. With a rank-one recognition rate of 91.8% as indicated in table II, SI faces outperform any of the single scale LBP-DFs (i.e. the layer of eLBP L1). Meanwhile, most of the results based on single scale eLBP-DF surpass that of SI faces; furthermore, when fusing the matching scores of the eLBP-DFs at different scales to achieve MS-eLBP-DFs, the rank-one recognition rate is increased by more than 5 points, from 91.8% for SI face to 97.6% for MS-eLBP-DFs. These results clearly indicate how well Multi-Scale eLBP describes geometric shape variations. On the other hand, from the comparison with the state of the art, we can see that our result is comparable to the best results reported in literature.

### 5.1.4 Robustness to facial expression changes (Experiment C)

Using the same experimental protocol, we also compared the performance of the proposed approach with those in the literature for robustness analysis on facial expression changes (see Table III). The results of our approach are 99.2% and 95.1% for the Neutral vs. Neutral and Neutral vs. Non-Neutral experiment, respectively. The recognition rates on Subset I andSubset II are comparable to the best ones of the state-of-the-art (Subset I in [33] and Subset II in [67]). Moreover, Table III also indicates that the MS-eLBP-DFs outperform the SI face in both the additional experiments on Subset I and II, and the performance degradation of MS-ELBP-DFs is much lower than that of SI face. These accuracies hence suggest that our approach tends to be insensitive to facial expression changes.

### 5.1.5 Face verification performance (Experiment D)

The proposed approach was evaluated for face verification as well using the three protocols, i.e. Neutral vs. All, Neutral vs. Neutral, Neutral vs. Non-Neutral, and the results are displayed in Table IV. From the first column (VR I), we can see that our accuracy is also among the best ones of the state of the art, while the results in the third column (VR III) illustrate once again that the proposed method performs quite well when recognizing expressive faces. Both the results match the phenomenon in face recognition. Fig. 12 indicates the verification rates by the ROC curves in the three experiments in Table IV.

### 5.1.6 Evaluation by aging factors (Experiment E)

Further experiments were carried out on ROC I, ROC II, and ROC III, and these three ROC curves are based on the three masks provided by the FRGC database.
defined over the square similarity matrix with a dimensionality of $4007 \times 4007$, and they are of increasing difficulty reflecting the time elapsed between the probe and gallery acquisition sessions. The comparisons are shown in Table V.

As we can see from Table V, the performance of the proposed method on ROC I, ROC II and ROC III is slightly lower but still close to the best of ones in the literature. Meanwhile, it is noteworthy that our method does not require any registration for nearly frontal face scans such as those in the FRGC dataset. This is clearly in contrast to works [26], [31] and [66]. In [31], Kakadiaris et al. used ICP-based alignment with a coarse to fine strategy for preprocessing, and two kinds of features, i.e. Haar and Pyramid were extracted from both normal and geometry maps. In [26], a self-dependent registration step was employed, and a large training database with neutral and non-neutral facial scans is required to learn inter-class and intra-class changes, and fused Haar-, Gabor- and LBP-based facial features for the final decision. In [66], a Simulated Annealing based approach was adopted for range image registration and similarity calculation for corresponding regions of different facial surfaces which were segmented in the previous step.

### 5.2 Experiments on the Bosphorus Dataset

#### 5.2.1 Database and protocol description

To further confirm the effectiveness of the proposed approach to identify nearly frontal faces without any registration and prove its robustness to expression and pose variations as well as partial occlusions, the Bosphorus database is considered as well, consisting of a large number of 3D face models with extreme pose changes, expression variations (both emotions and action units), and typical occlusions that may occur in real life. The database includes totally 4666 scans collected from 105 subjects, each of whom possesses around 34 expressions, 13 poses, and 4 occlusions. In our experiments, a subset of the dataset containing only nearly frontal face model is collected, and it thus has a total of 3301 scans with roughly 34 different expressions and 4 external occlusions per subject. Since each subject from Bosphorus only has one or two neutral samples while the others are the scans with facial expressions or partial occlusions as we can see in Fig. 13, this subset is potentially much more challenging than FRGC v2.0 to the proposed approach. With rare exceptions like [67] and [69], so far very few works in 3D face recognition have tested their approach on this dataset.

![Example 3D facial scans](image)

**Fig. 13.** Some example 3D facial scans of the same subject from the Bosphorus dataset.

Similar to the preprocessing step that was carried out on FRGC v2.0, we only conducted spike removal and hole filling. As the experimental protocol, we constructed a gallery set containing the first neutral facial scan for each subject, and the remaining ones made up of the probe set. Hence, the sizes of gallery and probe set are 105 and 3196, respectively. As in the experiments on the FRGC dataset, there was no registration of 3D face scans.

#### 5.2.2 Experiments on nearly frontal faces with expression changes and occlusions (Experiment F)

In the identification scenario, we computed the rank-one recognition rate. Table VI lists the performance of differ-
Preferred approaches for comparison. It can be seen from Table VI that the proposed method achieved a recognition rate up to 97.0%, further illustrating its effectiveness to recognize nearly frontal faces without registration and highlighting its robustness to facial expression variations and external occlusions. In comparison with the state of the art by using a similar experimental protocol, the recognition rate is comparable to the one in [69], both of which are slightly inferior to that reported by [67]. The difference between our experimental setup and the one in [67] lies in that the probe set used in [67] excluded the faces with occlusions. Moreover, as the method in [67] also made use of a training set formed by scans from 20 subjects in order to learn LDA subspaces, their probe set was formed by the 3D facial scans of 85 subjects.

**TABLE VI**

**RANK-ONE RECOGNITION RATES ON THE BOSPHORUS DATASET.**

<table>
<thead>
<tr>
<th>Approaches</th>
<th>Rank-one RR</th>
</tr>
</thead>
<tbody>
<tr>
<td>SI Faces</td>
<td>89.7%</td>
</tr>
<tr>
<td>MS-LBP-DFs</td>
<td>93.4%</td>
</tr>
<tr>
<td>MS-eLBP-DFs</td>
<td>97.0%</td>
</tr>
<tr>
<td>Maes et al. 2010 [69]</td>
<td>97.7%</td>
</tr>
<tr>
<td>Alyüz et al. 2010 [67]</td>
<td>99.3%*</td>
</tr>
</tbody>
</table>

* The experimental protocol in [67] has some differences from that in this study and [69].

**5.3 Experiments on the Gavab Dataset**

**5.3.1 Database and protocol description**

To analyze the performance on severe pose changes and even partially occluded 3D facial scans, we also tested our method on the Gavab dataset. To the best of our knowledge, Gavab is the most noise-prone dataset currently available to the public. This database consists of Minolta Vi-700 laser facial range scans of 61 different subjects. The subjects, of whom 45 are male and 16 are female, are all Caucasian. Each subject was scanned 9 times for different poses and facial expressions. The scans with pose variations contain one facial scan while looking up (+35 degree), one while looking down (-35 degree), one for the right profile (+90 degree), one for the left profile (-90 degree) as well as one with random poses. The scans without pose changes include two different frontal facial scans, one with a smile, and one with an accentuated laugh. Figure 14 shows some examples of faces in this dataset.

![Fig. 14. Examples of all the 3D facial scans of the same subject from the Gavab dataset [58].](image)

A similar preprocessing step was utilized as in FRGC to remove spikes and fill holes. Since the Gavab contains many severe pose changes, we performed a coarse alignment based on three landmarks for all facial scans. When the two inner corners of the eyes and the nose tip of one scan are available at the same time (all face scans excluding the extreme poses such as the right and left profiles), we used our previous method [55] to find the three landmarks automatically and computed rotation and translation parameters; while for each of these left or right profiles, we manually landmarked four points, i.e., the inner and outer corner of one eye, nose tip, and the corner of the nose, which are visible in that profile. After coarse registration, one range image is extracted from each facial scan; these range images hence only contain partial faces due to the self-occlusion caused by pose variations, and all facial range images are further resized to 150 × 150 pixels.

In our experiments, the first frontal facial scan of each subject was used as the gallery; while the others were treated as probes. We calculated rank-one face recognition rates, and Table VII shows matching accuracies for different categories of probe faces: (A) displays the results without pose variations; while (B) lists those only with the facial scans with pose changes. In (A), the neutral subset contains one frontal facial scan of each subject, and the expressive subset includes a smile, accentuated laugh and random gesture (random facial expression), three scans of each subject. To the best of our knowledge, work [58] is the only one that carried out experiments on the entire Gavab dataset before this work. Therefore, we compared our results with theirs on the subset of four severe pose variations as well as the overall performance. It is worth noting that the difference between their work and ours is that Drira et al. manually landmarked nose tips on all the face scans in the dataset for an ICP-based fine registration, while we only manually landmarked facial scans of right and left profiles (c) and (d) in Table VII (B), and for all the faces, only a coarse alignment is utilized to rotate and translate them.

**5.3.2 Evaluation on the faces with large pose variations (Experiment F)**

From Table VII (A), we can see that for frontal neutral probes, the rank-one recognition rate is 100% as in [58]; while regarding expressive faces, our approach surpasses all the others. Moreover, when evaluating the robustness to severe pose variations (Table VII (B)), we achieved an overall accuracy of 91.4% on these four subsets; whilst that reported by [58] is 88.9%.

To sum up, the experimental results on the Gavab dataset clearly prove that only aided by a coarse alignment, our method can deal with large pose changes and even partial occlusions.

**TABLE VI**

**COMPARISONS OF RANK-ONE RECOGNITION RATES ON THE GAVAB DATASET: (A) WITHOUT POSE VARIATIONS; (B) ONLY WITH POSE VARIATIONS.**

<table>
<thead>
<tr>
<th></th>
<th>I. Neutral</th>
<th>II. Expressive</th>
<th>I + II</th>
</tr>
</thead>
<tbody>
<tr>
<td>Li et al. [59]</td>
<td>96.67%</td>
<td>93.33%</td>
<td>94.68%</td>
</tr>
<tr>
<td>Moreno et al. [60]</td>
<td>90.16%</td>
<td>77.90%</td>
<td>NA</td>
</tr>
<tr>
<td>Mahoor et al. [61]</td>
<td>95.00%</td>
<td>72.00%</td>
<td>78.00%</td>
</tr>
<tr>
<td>Berretti et al. [62]</td>
<td>94.00%</td>
<td>81.00%</td>
<td>84.25%</td>
</tr>
<tr>
<td>Mousavi et al. [63]</td>
<td>NA</td>
<td>NA</td>
<td>91.00%</td>
</tr>
<tr>
<td>Drira et al. [58]</td>
<td>100.00%</td>
<td>NA</td>
<td>94.67%</td>
</tr>
<tr>
<td>MS-eLBP-DFs</td>
<td>100.00%</td>
<td>93.99%</td>
<td>95.49%</td>
</tr>
</tbody>
</table>
face and the probe rotated by 15 degrees can still clearly discriminate the facial scans of the same subject from the ones of different subjects. Indeed, the average number of matched keypoints in the former case is above 20 even as the face is rotated by 15 degrees while this number over the whole Gavab dataset excluding the left and right profiles is close to 10 in the latter case. However, when probe facial scans are rotated by 20 degrees, it becomes difficult to discriminate intra-class variations from inter-class ones in terms of the matched keypoint pairs. We conducted the experiment 10 times, the phenomena are similar.

5.4 Experiment Summary

In the sub-section 5.1, 5.2 and 5.3, eight experiments (Experiment A-H) are carried out on three public datasets, i.e. FRGC v2.0, Bosphours and Gavab. The results achieved in Experiment B, D and E demonstrate that our method, without the registration step for nearly frontal faces displays comparable to the best ones so far presented in the literature. Moreover, Experiments C and F show that the proposed approach is robust to facial expression variations whereas experiment F further highlights its tolerance to partial external occlusions. Additionally, Experiment G indicates that supported by a coarse registration step applied on only a few landmarks, our approach can deal with the faces with large pose variations and even self-occlusions.

At the same time, we observe the computational expense of the proposed approach along with the experiments conducted on the FRGC v2.0 database. Currently, an unoptimized implementation of the proposed method with MATLAB (R2010a) can perform one match between one pair of eLBP-DFs of the gallery and probe faces in about 0.32s using a machine where Intel(R) Core(TM) i5 CPU (2.60 GHz) and 4 GB RAM are equipped. Since the similarity scores based on different eLBP-DFs can be calculated independently, if implemented in a parallel computing device, our method is quite promising in providing decisions in real time.

6 CONCLUSION

We have presented an effective method to 3D face recognition using a novel geometric facial representation and local feature hybrid matching. The proposed facial representation is based on MS-eLBP and allows for accurate and fast description of local shape variations, thus enhancing the distinctiveness of range faces. SIFT-based hybrid matching that combines local and holistic analysis further robustly associates keypoints between two faces of the same subject. The proposed method was evaluated in 3D face recognition and verification, achieving a recognition rate of 97.6% and a 98.4% verification rate with a 0.001 FAR respectively on the FRGC v2.0 database which consists of nearly frontal 3D facial scans with rich facial expression changes. Additional experiments on the Bosphorus database further confirm the advantages of the proposed approach with regard to facial expression variations and external partial occlusions. The results achieved on the Gavab DB dataset containing severe pose changes
clearly illustrate that the entire system also provides a promising solution to recognizing partially occluded faces. Moreover, generally costly registration was not needed thanks to the relative tolerance of the proposed hybrid matching strategy to nearly frontal faces like the ones in the FRGC v2.0 and the subset of Bosphorus. When dealing with extreme poses, e.g., left or right profiles, a coarse alignment step based on a few manually landmarked points was sufficient in preprocessing as indicated by the experiments on the Gavab database.

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**REFERENCES**


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Dr. Chen has been the Chairman and a Program Committee Member for various international conferences and journals. He has been a Reviewer for many conferences and journals, e.g. the IEEE SIGNAL PROCESSING LETTERS, Computer Vision and Image Understanding, the IEEE TRANSACTIONS ON SYSTEMS, MAN, AND CYBERNETICS, the Proceedings of the International Conference on Image Processing, the IEEE TRANSACTIONS ON IMAGE PROCESSING, and Pattern Recognition Letters. He was a Guest Editor for the special issue on Automatic Audio Classification of the European Association for Signal Processing (EURASIP) Journal on Audio, Speech, and Music Processing.

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