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Conformal parameterization and curvature analysis for 3D facial recognition

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***Abstract*—This work proposes a new algorithm for 3D face recognition. The algorithm uses 3D shape data without color or texture information and exploits local curvature information which is a measure with high discriminant capability and robust to deformations such as rotation and scaling. In order to reduce high dimensionality of typical face surfaces our approach uses a conformal parameterization, preserving angles of original faces and simplifies the correspondence problem. Experimental results are presented and discussed using CASIA and Gavab databases.**

***Keywords*-3D face recognition; curvature analysis; conformal parameterization;**

I. Introduction

Face recognition is a problem that has remained relevant in recent years due to its wide range of applications such as access control, surveillance, human-computer interaction and biometric identification systems. Despite the variety of techniques that have been developed, the problem remains open especially because a person can have various visual appearance in uncontrolled environments owing to expressions, makeup, head rotation, color and scale variation, occlusions, among others.

Recent studies have shown that the use of data from 3D scans instead of intensity images partially covers the problem of dependence on conditions in which the images are acquired (mainly regarding lighting and makeup), it also provides a better description of the shape of the face for reliable distinction between cheeks, forehead and chin [1], [2].

The paper is organized as follows. Section II presents the methodology of the proposed algorithm. Experiments description and results are shown in section III. Finally, discussion and conclusions of this work are given in section IV.

II. Methodology

A. Curvature analysis

3D face scans usually contain sensors noise. So, the first step of the algorithm is to apply a median filter to remove spikes and then smooth the 3D facial surfaces. Next, the tip of the nose is automatically located through shape index [1] by selecting the point with shape index near to 1 and the largest z-value . After that, the points that fall within a sphere centered on the tipnose are retained to discard information of the neck, shoulders and hair.

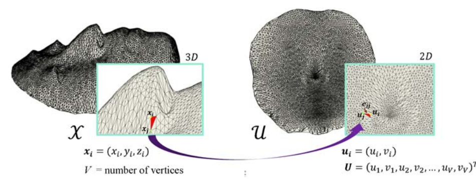

Figure 1: Conformal parameterization of triangulated 3D facial surfaces.

The mean curvature are calculated for each point on the facial surface [3] in order to locate the convex and concave regions; then, through a thresholding [2] of this geometric information it is possible to locate the points corresponding to the inner corners of the eyes. The latter is the basis of alignment step and extraction of central region of the face [4] after performing parameterization.

B. Parameterization

The main stage of the proposed algorithm is a 2D parameterization; that is a correspondence between the original facial surfaces $\mathcal{X}$ and a homeomorphic mesh $\mathcal{U}$ such that each node on the original three-dimensional mesh is mapped to a pair of coordinates (u, v) in the planar region $\mathcal{U}$ (see Figure 1).

1) Notation: We denote $\mathbf{u}_i = (u_i, v_i)$ the corresponding 2D position on $\mathcal{U}$ of the i-th node of a mesh $\mathcal{X}$. The vector $\mathbf{U}$ denotes the column vector $(u_1, v_1, u_2, v_2, \ldots, u_V, v_V)^T$ where V is the number of vertices in the mesh. Also, e_{ij} denotes the edge in $\mathcal{U}$ between vertices u_i and u_j.

B is a $2V \times 2V$ identity diagonal matrix with ones corresponding to boundary vertices and zeros elsewhere. The matrix e is such that $e_{i,1}$ (resp. $e_{i,2}$) is 1 for each u-coordinate (resp. v-coordinate) and 0, otherwise.

2) Conformal parameterization: To find a conformal parameterization $\mathbf{P}$, we use the approach formulated in [5] for the eigenvalue problem corresponding to the constrained minimization,

$$\mathbf{P} = \arg \min_{\substack{\mathbf{U} \\ \mathbf{U}^t B e = 0 \\ \mathbf{U}^t B \mathbf{U} = 1}} \mathbf{U}^t L \mathbf{U} \tag{1}$$

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where L is a sparse symmetric matrix containing information of the triangles angles and areas obtained through the calculation of the discrete Dirichlet energy of the map. The implementation was done in Matlab Mesh toolbox [1].

III. Experimental Results

A. Data

For the first database, we consider the scans of 30 subjects of the CASIA [2] database and 30 of the Gavab [3] database. For each person, we take two frontal scans under neutral expression, three scans with expressions, and four scans with variation of posture. The postures variations include the following variants: person looks to the right, to the left, up and down.

B. Experiments

For recognition we utilized Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and KNN-neighbors algorithms. In our experiments, the training set I with a neutral expression model, set II with two neutral expression models and set III with a neutral and a smile model of 30 subjects in the dataset were formed.

1) Recognition in the presence of expressions: The first experiment verifies the effectiveness of using curvature information, segmentation, and conformal parameterization. In order to perform segmentation, the tip of the nose on the conformal parameterization was located, the central part of the face was extracted and the data were mapped to the unit circle. The test set in this experiment contains all neutral and expression models of our databases which are not included in the training set. Results are shown in Table I.

Dataset	**Geometric information**	Free boundary	Circular Segmentation
CASIA	3D vertices	73 %	-
	Conformal parameterization + mean curvature	63.33 %	82.66 %
Gavab	3D vertices	87.5 %	-
	Conformal parameterization + mean curvature	65.83 %	90.83 %

Table I: Recognition results using training set I over models with expressions.

2) Recognition in presence of expressions and pose variation: The second experiment shows the effectiveness of the use of expression models in the training set. Different training sets (II-III) are considered, while the test sets contains only pose models. Results are shown in Table II.

[1]http://www.dgp.toronto.edu/ rms/software/matlabmesh/

[2]http://biometrics.idealtest.org/

[3]www.gavab.etsii.urjc.es/

Database	Training set	
	CASIA	Gavab
II	87.5 %	84.16
III	83.33 %	85 %

Table II: Recognition results using conformal parameterization, mean curvature and circular segmentation with training sets II and III over models with pose variation.

IV. Conclusions

In this work, we propose a facial recognition algorithm which deals with expressions and pose variations employing spectral conformal parameterization. The algorithm preserves angles of the original face surface while reduces the dimensionality of the facial models. In addition, our approach uses local curvature information to preserve more geometric information from the original 3D faces.

The results obtained from the first experiment showed that the combination of the conformal parameterization and mean curvature yields better performance than the original 3D coordinates when using circular segmentation. We cannot make a similar conclusion on the second experiment, because the missing data of models with posture variation affects strongly to recognition.

Future work includes performing segmentation of almost expression-invariant regions to extract information with the most discriminating cabability of faces.

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