Partial face biometry using shape decomposition on 2D conformal maps of faces

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Abstract

In this paper, we introduce a new approach for partial 3D face recognition, which makes use of shape decomposition over the rigid[1] *part of a face.*

To explore the descriptiveness of shape dissimilarity over an isometric part of a face, which has lower probability to be influenced by expression, we transform a 3D shape to a 2D domain using conformal mapping and use shape decomposition as a similarity measurement. In our work we investigate several classifiers as well as several shape descriptors for recognition purposes. Recognition tests on a subset of the FRGC data set show approximately 80% rank-one recognition rate using only the eyes and nose part of the face.

1 Introduction

Automatic identification and verification of humans based on facial information continues to be an active research area mainly because this contact free and non intrusive techniques are easily acceptable socially. Majority of face recognition algorithms use 2D intensity images, despite a significant progress, there are still considerable challenges in use in uncontrolled environments due to variance in pose, illumination, expression and occlusion[8]. During recent years 3D face models has been used as a potential solution to deal with the two unsolved problems in 2D face recognition, namely variations in lighting conditions and pose [2], thereby improving the effectiveness of face recognition systems. While 3D face models are theoretically insensitive to lighting condition changes, they still require to be pose normalized before 3D facial shape-based matching. Moreover, as 3D face models describe 3D facial shapes, they are also more sensitive to facial expression changes as compared to their 2D counterparts. As 3D facial shape matching is rather hard, several works in the literature propose to map 3D face models into some low-dimensional space, including the local isometric facial representation [3], the annotated facial model (AFM) [10], or conformal mapping [14]. Some works, for simplification, try also to investigate partial human biometry, meaning recognition based only on part of a face, as for example in [6], where authors used the nose region for identification purposes. In this work we explore how conformal mapping to 2D space[14] can be applied to partial face recognition.

While pose changes and lighting variance can be resolved by the use of third dimension, by pose normalization and lighting insensitive scanning techniques, the expression changes is still a problem. In this article we avoid this problem by recognition based only on the rigid part of the face, which cannot be severely affected by muscles. To deal with the computational cost of 3D face recognition we utilize conformal maps of 3D surface to a 2D domain, thus simplifying the 3D mapping to a 2D one (for which all standard image classification methods are applicable). While conformal maps requires a certain amount of computation, they have global optimal solution unlike ICP which suffers from local minimums.

The remainder of this paper is organized as follows: section 2 gives the whole process overview as well as a brief introduction to conformal maps. Section 3 describes in details the face preprocessing and cropping method, while section 4 introduce how to create face

[1] A part of eyes and nose, where human muscles cannot deform it as much as lower lips part, which gives approximately isometric characteristic.

1051-4651/10 $26.00 © 2010 IEEE
DOI 10.1109/ICPR.2010.372

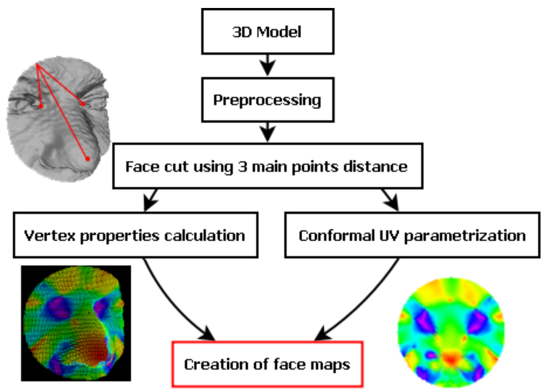

Figure 1. Face maps creation flow chart.

maps using conformal transformation along with the Shape Index description. Finally section 5 presents several similarity algorithms. Section 6 presents an conclusion and future research directions.

2 Process overview and mathematical formulations

We introduce in this section first the overview of our approach and then the basics of conformal geometry-based parameterization.

2.1 Process overview

The principal issue addressed in this paper is to create facial feature maps which can be used for recognition by applying previously developed 2D recognition techniques. Creation of 2D maps from 3D face surfaces can handle model rotation and translation, as well as allow to use the faster and better understand 2D recognition techniques.

To create face maps which are later used for recognition, we started with models preprocessing (hole, spike removal). Next step was to segment the rigid part of a face, which has less potential to change during expression [1]. Finally we performed UV conformal parameterization as well as shape index calculation for every vertex. To create a face map we combined UV parameters and Shape Index values to construct a shape value distribution over the conformal parameterization, the process can be seen on Figure 1.

2.2 Conformal UV parameterization for face normalization

It can be proven that there exists a mapping from any surface with a disk topology to a 2D unit disk [9], which is one-to-one, onto, and angle preserving. This mapping is called conformal mapping and keeps the line element unchanged, except for a local scaling factor[7]. From a practical point of view, the conformal parameterization is easy to control. Hence conformal parameterization is crucial for 3D shape matching and recognition. Consider the case of mapping a planar region S to the plane D.

Suppose S is a topological annulus, with boundaries $\partial S = \gamma_0 \,.\, \gamma_1$ as shown in Figure 2. First, we compute a path γ_2 connecting γ_0 and γ_1. Then we compute a harmonic function $f : S \to R$, such that:

$$\begin{cases} f_{\gamma_0} &= 0 \\ f_{\gamma_1} &= 1. \\ \Delta f &= 0 \end{cases} \qquad (1)$$

The level set of f is shown in Figure 2. Then ∇f is a harmonic 1-form.

We slice the surface along γ_2 to get a new surface $\tilde{S}$ with a single boundary. γ_2 is replaced by two boundary segments γ_2^+ and γ_2^- on $\tilde{S}$. Then we compute a function $g_0 : \tilde{S} \to R$, such that

$$\begin{cases} g_0|_{\gamma_2^+} &= 1 \\ g_0|_{\gamma_2^-} &= 0 \end{cases} \qquad (2)$$

g_0 takes arbitrary value on other vertices. Therefore ∇g_0 is a closed 1-form defined on S. Then we find another function $g_1 : S \to R$, such that $\nabla g_0 + \nabla g_1$ is a harmonic 1-form $\nabla.(\nabla g_0 + \nabla g_1) = 0$.

Then we need to find a scalar λ, such that $*\nabla f = \lambda(\nabla g_0 + \nabla g_1)$, where $*$ is a the Hodge star operator $(*(fdx + gdy) = fdy - gdx$, where $fdx + gdy$ is a differential one form). The holomorphic 1-form is given by

$$\omega = \nabla f + i\lambda(\nabla g_0 + \nabla g_1). \qquad (3)$$

Let $Img(\int_{\gamma 0} \omega) = k$, the conformal mapping form S to a canonical annulus given by

$$\Phi(p) = exp^{\frac{2\Pi}{k} \int_q^p \omega}, \qquad (4)$$

where q is the base point and the path form q to p is arbitrary chosen.

For more details about conformal parameterization please refer to [14].

3 Face discriminative part segmentation using 3 landmarks

To deal with expressions and to explore the field of partial face recognition[6] we use the upper rigid part of

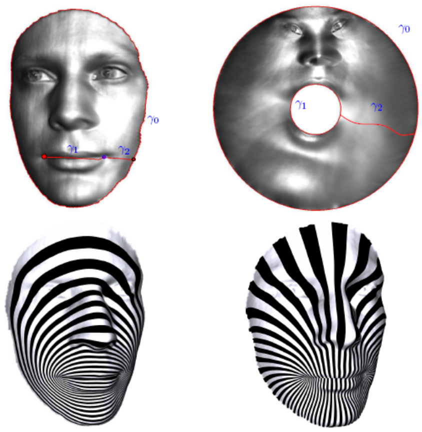

Figure 2. Harmonic 1-forms. Top row, the cut on the surface. Bottom row, the level sets of the harmonic 1-form ∇f and its conjugate harmonic 1-form $\lambda(\nabla g0 + \nabla g1)$.

a face [1]. This part of a face is influenced by expression less than the lower part.

To crop this region of the face we used three main face landmarks, the nose tip and the inner corners of eyes; in our experiments we used the manual points described in [12]. We crop the discriminative face part using the sum of Euclidean distances of each face point to 3 landmarks and setting a threshold to 50 mm.

4 3D face mapping to 2D space

4.1 UV conformal parameterization

Direct application of conformal mapping as introduced in [14] is not feasible on 3D face models as it requires a surface with disk topology (genus 0 surface, with a single boundary). For this purpose, we have made a small hole in the face surface (by removing one vertex) in the center of the cropping region; later this inner boundary will become the inner boundary of the conformal map and the border of the face will become the outer boundary of the conformal map, as can be seen on Figure 3.

To create such a conformal face map, the UV conformal parameterization of a 3D face is used; each 3D vertex after parameterization has 2D UV coordinates through which the whole model can be projected to 2D space.

All conformal maps were also normalized for size and rotation using above mentioned manual landmarks, projected from the 3D space.

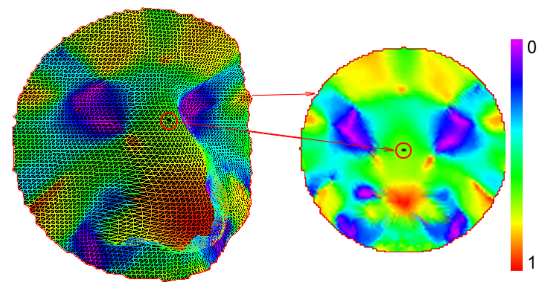

Figure 3. Projected 3D face model to a 2D space conformal mapped to a disc. (better seen in color)

4.2 Shape Index

Since the UV conformal parameterization transfers a 3D model to a 2D map, certain 3D properties have to be transfered over to the 2D face map. To avoid variations due to lighting conditions on texture images, we chose to project Shape Index values. We also projected alternative geometric measure.

Shape Index is a normalized curvature representation, computed at each point of a 3D surface. This local curvature information about a point is independent of the coordinate system. The Shape Index at point p is calculated using the maximum (k_1) and the minimum (k_2) local curvature [5]: $SI(p) = \frac{1}{2} - \frac{1}{\pi} tan^{-1} \frac{k_1(p)+k_2(p)}{k_1(p)-k_2(p)}$, where k_1 and k_2 are principal curvatures at point p. This calculation results into $< 0, 1 >$ shape scale. Shape Index scale represents numerous shapes starting from a spherical cup (0 value) ending on spherical cap (1 value) - Figure 3 [12, 13].

5 Face maps similarity computation

The previous step results in face map images which are the input for the recognition algorithm. In this work we used (2D)^{2}PCA [2][4, 15], as well as nearest neighbor classifier with L_1 and L_2 norms.

For test purposes we randomly choose 231 subjects from The FRGC2.0 data set [11]. This data set which contains numerous subjects with different facial expressions, was collected during 2003-2004 academic year and hence it includes time variations. Table 1 shows all results for different neighborhood sizes for Shape Index and Mean curvature, as well as different similarity measurement methods.

[2](2D)^{2}PCA - a variant of PCA with better performance, is used for feature dimension reduction and similarity computation.

	I	II	III
$(2D)^2$PCA			
ShapeIndex 25mm	72.85%	81.65%	65.71%
ShapeIndex 20mm	75.34%	82.1%	69.46%
ShapeIndex 15mm	77.1%	82.78%	72.15%
ShapeIndex 10mm	76.14%	84.5%	68.86%
Mean Curv. 15mm	67.09%	72.8%	62.12%
Nearest Neighbor			
L_1			
ShapeIndex 25mm	74.77%	82.27%	68.26%
ShapeIndex 20mm	75.26%	82.09%	69.31%
ShapeIndex 15mm	**79.18**%	84.5%	74.55%
ShapeIndex 10mm	77.42%	85.19%	70.65%
L_2			
ShapeIndex 15mm	75.74%	82.96%	69.46%
1 Loop ICP	70.21%	-	-

I - Neutral vs. All
II - Neutral vs. Neutral
III - Neutral vs. Expression

Table 1. Rank-1 recognition rate on 231 subjects from FRGCv2.0 data set.

6 Conclusion and future directions

In this paper we proposed to combine the conformal geometry, partial face biometry and differential geometry tools for recognition. 3D face recognition has many advantages, but large computation cost. Using 3D data as an input and projecting 3D features to 2D maps has advantages of 3D invariance to lighting and pose like also 2D similarity efficiency.

In our work we used the rigid face part from a subset of 231 subjects and 1249 models as a query, we achieved approximately 80% rank-one recognition rate; compared to [6] where authors used nasal curves and achieved 76.1% rank-one recognition rate and [8] where authors achieved 75.3% rank-one recognition rate using the shape index decomposition.

Future work will include study of facial regions for conformal mapping and the use of other geometric measurements, such as normal vectors or geometric images as well as fused-score combination.

7 Acknowledgment

This work was partially carried out within the French FAR3D project supported by ANR under the grant ANR-07-SESU-004 FAR3D.

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