Robotics and Autonomous Systems 62 (2014) 1768–1776

Contents lists available at ScienceDirect

Robotics and Autonomous Systems

journal homepage: www.elsevier.com/locate/robot

3D face recognition: An automatic strategy based on geometrical descriptors and landmarks

Enrico Vezzetti, Federica Marcolin *, Giulia Fracastoro

Department of Management and Production Engineering, Politecnico di Torino, Italy

HIGHLIGHTS

- A new 3D face recognition algorithm is proposed, developed in Matlab.
- 17 landmarks are automatically extracted relying on facial geometrical properties.
- Geodesic and Euclidean distances, nose volume, and ratios are computed.
- These descriptors are summed in a final score and used to compare faces.
- Recognition rate is 90.29% over a dataset of 244 faces belonging to 38 people.

ARTICLE INFO

Article history:
Received 9 January 2014
Received in revised form
16 July 2014
Accepted 25 July 2014
Available online 15 August 2014

Keywords:
Face recognition
Landmark
Geometry
3D face
Shape index
Geodesic distance

ABSTRACT

In the last decades, several three-dimensional face recognition algorithms have been thought, designed, and assessed. What they have in common can be hardly said, as they differ in theoretical background, tools, and method. Here we propose a new 3D face recognition algorithm, entirely developed in Matlab®, whose framework totally comes from differential geometry. First, 17 soft-tissue landmarks are automatically extracted relying on geometrical properties of facial shape. We made use of derivatives, coefficients of the fundamental forms, principal, mean, and Gaussian curvatures, and shape and curvedness indexes. Then, a set of geodesic and Euclidean distances, together with nose volume and ratios between geodesic and Euclidean distances, has been computed and summed in a final score, used to compare faces. The highest contribution of this work, we believe, is that its theoretical substratum is differential geometry with its various descriptors, which is something totally new in the field.

1. Introduction

Automated human face recognition (FR) is a non-trivial computer vision problem of considerable practical significance. It has applications including automated secured access, automatic surveillance, forensic analysis, fast retrieval of records from databases in police departments, automatic identification of patients in hospitals, checking for fraud or identity theft, and human–computer interaction [1].

The literature on FR is wide and various. We have selected among the numerous contributions the most significant ones that, similarly to us, work in 3D with facial landmarks and/or possibly employ geometrical concepts to the algorithm. Gupta et al. [1] proposed the new Anthroface 3D recognition algorithm after automatically detecting 10 landmarks through the support of Gaussian and mean curvatures. The algorithm compares 123 distances among a set of Euclidean and geodesic ones, performing significantly better than the well-known eigensurfaces, fishersurfaces, and Iterative Closest Point (ICP) algorithms. In many points this method is close to ours, although our landmarking procedures totally rely on geometrical background. Zhao et al. [2] used their Statistical Facial Feature Model (SFAM) to perform facial Action Unit (AU) recognition. The SFAM is a partial 3D face morphable model containing both global variations in landmark configuration (morphology) and local ones in terms of texture and shape around each landmark. 19 landmarks were here considered. Similarly to us, the Shape Index proposed by Koenderink and Van Doorn [3] was computed to describe local surface properties. Also Passalis et al. [4] used the Shape Index, that, together with Spin Images, was employed to support automatic landmarking. In particular, in this work a new 3D FR method is proposed that uses facial symmetry to handle pose variations. Then, an Annotated Face Model is registered and fitted to the scan. The result is a pose-invariant "geometry image". İnan and Halici [5] proposed a 3D FR approach based on local shape descriptors to discriminate three-dimensional face scans of different

* Corresponding author. Tel.: +39 0110907205.
E-mail address: federica.marcolin@polito.it (F. Marcolin).

http://dx.doi.org/10.1016/j.robot.2014.07.009
0921-8890/

individuals. Uniformly resampled 3D face data are used to generate the Shape Index, curvedness, Gaussian and mean curvature values on each point of the data. Hence, they obtained bi-dimensional matrices of these descriptors representing three-dimensional geometry information.

Following Bronstein et al.'s [6–8] idea that different facial expressions of the same person are isometrics, namely geodesic distances between facial reference points are equal for all emotional expressions of the same person, other researchers worked with geodesic distances as features to be compared between faces to perform FR. Berretti et al. [9,10] proposed a 3D FR solution in the presence of expression variations. 3D face models are represented by identifying the iso-surfaces originated by the set of points which are at the same geodesic distance from the nose tip. The iso-geodesics and their relationships are then described by developing through the modeling technique of three-dimensional Weighted Walkthroughs (3DWWs) capable to quantitatively represent spatial relationships between 3D surfaces. Similarly, Feng et al. [11] presented a 3D face representation and recognition approach. 3D face is represented by a set of level curves of geodesic function starting from the nose tip, which is invariant under isometric transformation of the surfaces. Ouji et al. [12] presented an FR approach based on dimensional surface matching. The presented matching algorithm relies on ICP that rigidly aligns facial surfaces and perfectly provides the posture of the presented probe model. Then, the similarity metric consists in computing geodesic maps on the overlapped parts of the aligned surfaces. Mpiperis et al. [13] proposed a geodesic polar parameterization of the facial surface aimed at 3D FR. Face matching is performed with surface attributes defined on the geodesic plane. Li and Zhang [14,15] investigated the use of multiple intrinsic geometric attributes, such as angles, geodesic distances, and curvatures, for 3D FR. Geodesic distances, and Gaussian and mean curvatures are then employed as descriptors for faces. Jahanbin et al. [16] introduced a multimodal framework for FR based on local attributes calculated from range and portrait image pairs. They applied statistical feature analysis to 2D and 3D Gabor, and Euclidean and geodesic anthropometric feature sets to select the most discriminative features while discarding redundancies.

The paper is structured as follows. Section 2 deals with methodology: Section 2.1 is the landmarking phase; in Sections 2.2–2.4 geodesic and Euclidean distances between landmarks, and other extracted features are presented; Sections 2.5 and 2.6 concern evaluation of geometrical features and final score for matching, respectively. Results are exposed in Section 3. Then, some conclusions are drawn, and, after references, Appendix is added to figure out the geometrical background of the work.

2. Method

To perform face recognition, we used a different geometrical information of the face, extracted in correspondence to the position of automatically extracted landmarks. Landmarks, originally introduced by Farkas [17], are defined as precise locations on biological forms that hold some developmental, functional, structural, or evolutionary significance [18]. Among the facial features to be compared between faces, geodesic distances are the core ones. Then, in order to increase the accurateness, we added Euclidean distances, and, after having obtained nose volume, some ratios between Euclidean and geodesic distances and the behavior of the Shape Index in the *pronasal*. The entire process has been programmed in Matlab®.

The correctness of landmark localization process has been tested by the support of a plastic surgeon, who manually identified correct landmark positioning. The "true landmark" identification has been gained in both visual and contact terms by the surgeon. Once a landmark is found, the surgeon marks it with a point directly on the person's face. Afterwards, through texture mapping [19], overlapping on the 3D model is performed and the Euclidean distance between the real landmark and the respective point given by the algorithm is computed.

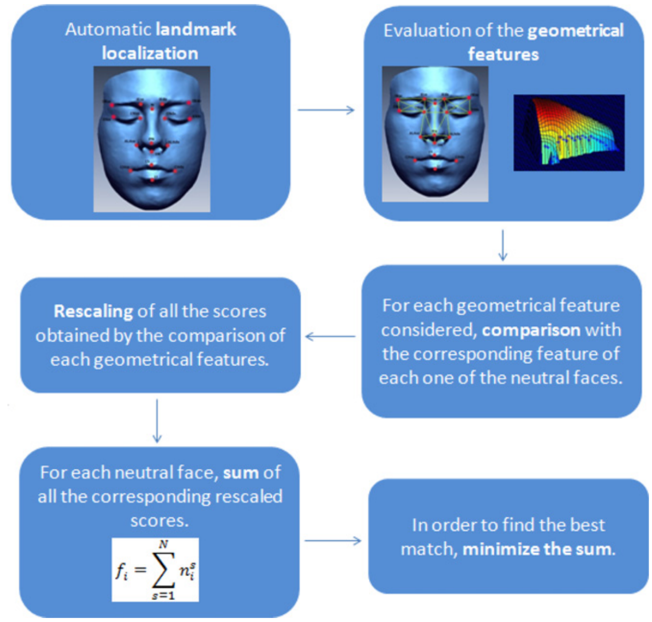

Fig. 1. The whole process of our face recognition algorithm.

In Fig. 1 we have summarized the whole process of our FR algorithm.

2.1. Landmark extraction

The method used for automatic landmarking is explained in [20]. Considering the morphological features of the face, in order to extract the landmarks, it was necessary to employ a refining procedure that first identifies the region, and then extracts the specific landmarks maximizing or minimizing one appropriate descriptor. Relying on the different peculiarities of the different facial regions where the landmarks are located, different combinations of the first, second and mixed derivatives (Figs. 2 and 3), the Coefficients of the Fundamental Forms E, F, G, e, f and g (Figs. 4 and 5), the curvatures K, H, k_1 and k_2 (Figs. 6 and 7) and Shape and Curvedness Indexes S and C (Fig. 8) have been employed as descriptors. Figs. 2–8 represent these descriptors applied point-by-point to facial shells. The meaning of these geometrical descriptors is reported in Appendix.

The accurateness of the method explained in [20] has been enhanced and eight other landmarks were added, reaching a total of 17 landmarks extracted (Fig. 9): the *pronasal* (PN), the *subnasal* (SN), the two *alae* (ALA), the two *endocanthions* (EN), the two *exocanthions* (EX), the *nasion* (N), the two *inner eyebrows* (IE), the two *outer eyebrows* (OE), the two *chelions* (CH), the *labrum superior* (LS) and the *labrum inferior* (LI).

Similar procedures have been employed to extract these new landmarks. For length reasons, we do not report here the whole procedure, but, in order to evaluate the accurateness of our method, we computed the distance between the landmark localized with our algorithm and the correct landmark position. In Table 1 the mean error distance and its standard deviation are shown for each landmark, the unit of measure is the millimeter.

To obtain mean errors and standard deviations, we used only a subset of our dataset, considering only the scans of 5 people, in total 35 scans (for each person we considered 7 different facial expressions).