Multi patches 3D facial representation for Person Authentication using AdaBoost

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***Abstract*—In this paper, we investigate the(problem of 3D face authentification) use of AdaBoost-based learning algorithm which select the relevent curves in the face. We use the shape of 3D curve for face authentication. The basic idea is the analysis of the shape of local facial set of cuves. The set of curves are extracted using level curves based representation centered on facial feature point landmarks. We apply our framework to study and compare this set through the computation of the geodesic distance between corresponding curves on different 3D facial models. AdaBoost considers each curve as a weak classifier and selects iteratively relevant curves and show that there is significant improvement in results. The effectiveness of this technique is evaluated on a subset taken from BU-3DFE(3D Facial Expression Database - Binghamton University) database. The proposed approach increase authentication performances using AdaBoost classifier compared to a simple fusion of scores from all curves.**

I. INTRODUCTION

In recent years there has been a growing interest for biometrics. Presented as powerful technology used in different fields such security and surveillance, biometrics research permits to study the behavioral and/or physiological characteristics of people to recognize them or to verify their identities. In particular, fingerprint and iris-based systems showed good performances. However such techniques require Users coperation, and it turned out that is intrusive for some people. Since face recognition is contactless and less restrictive, it emerges as a more attractive and natural biometric. Unfortunately, as described in [1], face recognition technologies still face difficult challenges such as lighting conditions, pose variations, scaling, etc. In the last few years, face recognition using 3D shape of the face has emerged as a major research trend for its theoretical robustness to lighting condition and pose variations. However, the challenge is open on the robustness of these approaches to facial expressions variations [2].

In this work, we focus on the shape analysis of the face. The basic idea is to approximate the face surface by a finite set of level curves. Using the Riemannian geometry we define geodesic paths between each set of corresponding curves, and distances between them. To compare any two faces, we try to combine similarity scores produced by each pairewise curves. We use AdaBoost algorithm to learn a final classifier who identify then combine the most relevant curves. Chang and all [3], have proposed for 3D face recognition in the presence of varied facial expressions. It is based on combining the match scores for matching multiple overlapping regions around the nose. This approach uses multiple overlapping regions around the nose to handle the problem of expression variations. In [4], we have demonstrated the usefulness of the proposed framework to analyze and comapre the shapes of the nasal regions. However, in In [5], we found that all level curves have different discriminative weights. The analysis of recognition rate of each nasal curve taken individually, shows clearly that some curves have higher recognition rates. We propose in this work a method to select most relevant curves of each region on the face using the well-known machine learning algorithm, AdaBoost, which combines these curves to produce an authentication classification algorithm.

II. PREPROCESSING OF 3D SCANS AND DATABASE DESCRIPTION

A. BU-3DFE database description

The BU-3DFE, [6] is a publicaly available 3D facial expression database, which includes both prototypical 3D facial expression shapes and 2D facial textures of 2,500 models from 100 subjects. This is the first attempt at making a 3D facial expression database available for the research community, with the ultimate goal of fostering the research on affective computing and increasing the general understanding of facial behavior.

In the BU-3DFE database there are 56 females and 44 males, ranging age from 18 years to 70 years old. The subjects are well distributed across different ethnic or racial ancestries, including White, Black, East-Asian, Middle-east Asian, Hispanic Latino and others, all of them were students of the Binghamton University. A neutral scan was captured for each subject then they were asked to perform six expressions namely anger (AN), disgust (DI), fear (FE), happiness (HA), sad (SA) and surprise (SU). The expressions were well defined, since the majority of the participants in face scanning sessions were undergraduates from the Psychology Department, and they vary according to four levels of intensity (low, middle, high and highest or 01-04). Thus, there are 25 3D facial expression models per subject in the database. Yin et al. [6] made the data easier to use with providing the cropped face 3D scans generated from the processing

978-1-4244-5998-8/10/$26.00

of the original raw data, which were clean (head-shoulders boundaries necks and clothing). Therefore we can find a total of 2,500 cropped face models in the database. Associated with each model, a set of 83 facial landmarks that defines feature regions on the face surface. Regions that undergo specific deformations due to single muscles movements when conveying facial expression [7].

III. Riemannian analysis of patche surfaces

To analyze the shapes of 2D curves several approaches were developed, like those based on Fourier descriptors or moments or the median axis. However, it seems that none of these methods has imposed either from the conceptual or computational point of view, to describe the shape of curves. Recent works in this area consider a formal definition of shape spaces as a Riemannian manifold of infinite dimension on which they can use the classic tools for statistical analysis. The recent results of Michor and Mumford [8] and Klassen et al. [9] in the case of 2D curves show the efficiency of this approach. Joshi et al. [10] have recently proposed a generalization of this work to the case of curves defined in $\mathbb{R}^n$. We will adopt this work to our problem since our 3D curves are difined in $\mathbb{R}^3$.

A. Curves analysis in $\mathbb{R}^3$

We start by considering a closed curve β in $\mathbb{R}^3$. A natural parametrization of β is proposed using $\beta : \mathbb{S}^1 \to \mathbb{R}^3$. We will assume that the parameterization is non-singular, i.e. $\|\dot{\beta}(t)\| \neq 0$ for all t. The norm used here is the Euclidean norm in $\mathbb{R}^3$. Note that the parameterization is not assumed to be arc-length; we allow a larger class of parameterizations for improved analysis. To analyze the shape of β, we shall represent it mathematically using a *square-root velocity function* (SRVF), denoted by $q(t)$, given by:

$$q(t) \doteq \frac{\dot{\beta}(t)}{\sqrt{\|\dot{\beta}(t)\|}} \ . \tag{1}$$

Where $q(t)$ is a special function that captures the shape of β. The conventional metric for comparing the elastic shape of the curves becomes a metric in $\mathbb{L}^2$ under the representation [10]. Similar ideas were presented by Younes [11]. We define the set of closed curves in $\mathbb{R}^3$ by:

$$\mathcal{C} = \{q : \mathbb{S}^1 \to \mathbb{R}^3 | \int_{\mathbb{S}^1} q(t)\|q(t)\|dt = 0\} \ \subset \ \mathbb{L}^2(\mathbb{S}^1, \mathbb{R}^3)\}. \tag{2}$$

Where $\mathbb{L}^2(\mathbb{S}^1, \mathbb{R}^3)$ denotes the set of all integrable functions from $\mathbb{S}^1$ to $\mathbb{R}^3$. The quantity $\int_{\mathbb{S}^1} q(t)\|q(t)\|dt$ is the total displacement in $\mathbb{R}^3$ while moving from the origin of the curve until the end. Thus, $\mathcal{C}$ represents the set of all closed curves in $\mathbb{R}^3$. It is then fitted with a Riemannian structure using the following scalar product: for two tangent vectors $u, v \in T_q(\mathcal{C})$, we define:

$$\langle u, v\rangle = \int_{\mathbb{S}^1} \langle u(t), v(t)\rangle \, dt \ . \tag{3}$$

For each $q \in \mathcal{C}$, the tangent space is defined by:

$$T_q(\mathcal{C}) = \{v : \mathbb{S}^1 \to \mathbb{R}^3 | \, \langle v, w\rangle = 0, \ w \in N_q(\mathcal{C})\} \ .$$

Where $N_q(\mathcal{C})$ denotes the space of normal vectors of q. The curves are represented in the Hilbertian space which allow us to use advantage of properties of this space, see [10]. Besides, to define a shape representation should be independent of different rotations and reparameterization. This is traduced mathematically by a quotionnement compared to the rotation group $SO(3)$ and the reparameterization group Γ.

We define the orbits of the rotation group $SO(3)$ and the re-parameterization group Γ as equivalence classes in $\mathcal{C}$. The elements of the set:

$$[q] = \{\sqrt{\dot{\gamma}(t)} O q(\gamma(t)) | O \in SO(3), \quad \gamma \in \Gamma\} \ .$$

are then equivalent to the same form q, and all these equivalence classes inherits the Riemannian structure of $\mathcal{C}$ and then represents our space of study. It is noted:

$$\mathcal{S} \doteq \mathcal{C}/(SO(3) \times \Gamma).$$

Using our framework we are able to compute the geodesic path between two elements of $\mathcal{S}$, in the Riemannian metric given by equation 3. Given two curves β_1 and β_2 represented by their SRVF respectively q_1 and q_2, we seek to find a geodesic path between the orbits $[q_1]$ and $[q_2]$ in the space $\mathcal{S}$. We use in this context, a numerical method called the *path-straightening* method which consist in connecting the two points $[q_1]$ and $[q_2]$ through an arbitrary path α and then update this path repeatedly in the negative direction of the gradient of energy defined by:

$$E[\alpha] = \frac{1}{2} \int_s \langle \dot{\alpha}(s), \dot{\alpha}(s)\rangle \, ds.$$

It has been prouved in [12] that the critical points of E are geodesic paths in $\mathcal{S}$. We denote by $d([q_1], [q_2])$ the geodesic distance or length of the geodesic in $\mathcal{S}$, between two curves β_1 and β_2.

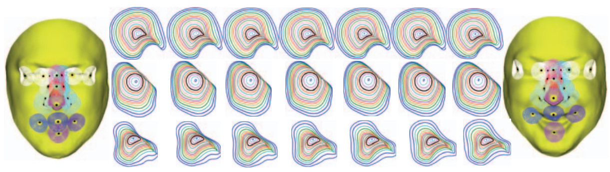

Fig. 1. Some examples of geodesic paths between patch of the same subject.

The figure 1 illustrates the path between corresponding patches extracted from two different sessions belonging to th same person (intra-class geodesics), while the figure 2 illustrates the geodesic path between patches extracted from the 3D model of two different persons (inter-class geodesics).

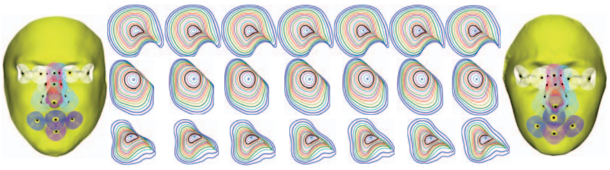

Fig. 2. Some examples of geodesic paths between patches of different subjects.

B. Surface analysis

In this section we extend our study from shapes of patch curves to shapes of patch surfaces. We represent the surface of each patches region S^p where $1 \leq p \leq 13$ by a collection of patche curves:

$$S^p \leftrightarrow \{c_\lambda, \lambda \in [0, \lambda_0]\} \ .$$

Where c_λ represents the curve associated to $DisGeo = \lambda$. Each patch is then represented as an element of $\mathcal{C}^{[0,\lambda_0]}$. In our framework, the two shapes of patches regions are compared by their corresponding curves. For two patches S_1^1 and S_2^1, and their curves $\{c_\lambda^1, \lambda \in [0, \lambda_0]\}$ and $\{c_\lambda^2, \lambda \in [0, \lambda_0]\}$ respectively.

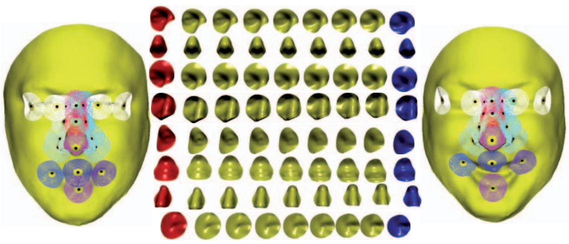

Fig. 3. Some examples of geodesic paths between patche surfaces of the same subject.

The figure 3 illustrates examples of geodesic paths between patch surfaces belonging two different sessions of the same person, While the figure 4 illustrates geodesic paths between patch surfaces of two different subjects.

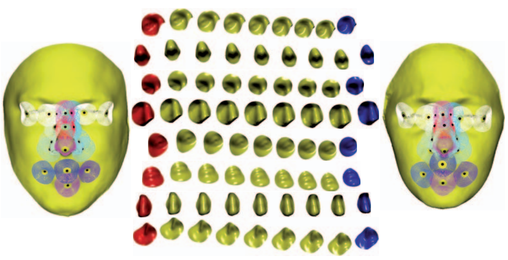

Fig. 4. Some examples of geodesic paths between patche surfaces of different subjects.

IV. 3D Face Authentication Using Binary Classification Problem

Once scores are computed for all the patches, we propose a technique to combine these results to build a reliable authentication algorithm?

We use the well-known machine learning algorithm, AdaBoost, introduced by Freund and Schapire in [13], to learn a *strong classifier* based on a weighted selection of *weak classifiers*. In our case, the level curves represent the weak classifiers. The boosting can then optimize their performances. AdaBoost is based on iterative selection of weak classifiers by using a distribution of training samples. In each iteration, the classifier is provided and weighted by the quality of its classification. AdaBoost has been used successfully in diverse applications like face detection [14] where it provides a strong binary classifier (face/non-face). In the following we formulate problem of 3D face authentication as a binary classification problem then we describe our experiments and results.

A. AdaBoost for binary classification

The AdaBoost algorithm requires a training phase. This phase requires a set of training samples x_n including both impostors access and genuines access belonging to $\chi = \{x_n\}$. These samples are completely disjointed to samples used for testing. To learn and then test AdaBoost algorithm, we use 250 scans of 10 different subjects taken from BU-3DFE database, each subject have 25 sessions. We decompose this set into two subsets: the first for training and the second for testing. Then, we compute a similarity matrix for each phase for each level curve. The training/test similarity matrix consists of similarity scores obtained by comparing all sessions from the training/test subset with themselfs. Some sessions used in this experiments are illustrated in figure 5.

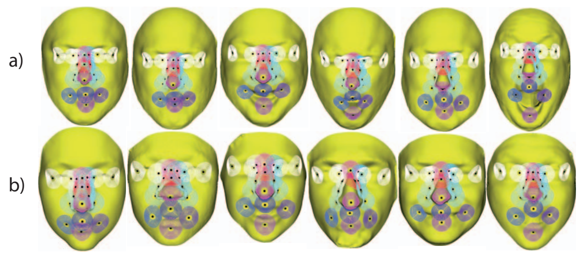

Fig. 5. Some examples of preprocessed 3D models, used in our experiments, from BU-3DFE database. a) different sessions of the same subject, b) different sessions of different subjects

V. Experimental Results

As described in Section IV, we use two subsets of the BU-3DFE database with a set to learn the AdaBoost algorithm and a second to evaluate the classification results. We will use the evaluation rates used in conventional biometrics and particularly in the authentication scenario such as the *VR (Verification Rate)*, the *FAR (False Accept Rate)*. The similarity scores used are extracted randomly from the training matrix (or test) for the training phase (or test).

The Table I presents the results on training set and on testing set. We used 1500 *genuine access class* and 1500 *impostor access class*. The experiments were conducted by by taking randomly a samples of genuines and impostors access. AdaBoost gives an average of VR 100% on training set and 97.4% on the test set.

TABLE I
RESULTS GIVEN BY ADABOOST OF AUTHENTICATION ON THE TRAINING SET AND TESTING SET

Database	Verification rate(VR)	False Acceptance Rate(FAR)
Training database	**100.00%**	**0.13%**
Testing database	**98.27%**	**13.40%**

A more detailed analysis of this classifier shows that the classifiers associated to curve 11, represents the more important weight in the final classifier. The figure 6 shows the similarity matrix of this curve, each diagonal block $[25x25]$ represents genuine access while the rest of matrix represents imposters access.

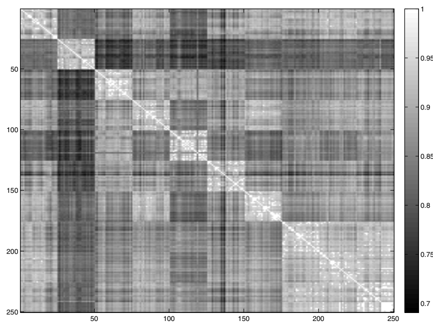

Fig. 6. The Similarity matrix of the curve 11

The figure 7 shows the ROC curve of the curve 11 selected by AdaBoost, the sum rule of all the patch curves. This figure shows clearly that the curves 11 gives good results comparing to sum rule. Therefore, this result confirms our hypothesis, all patch curves have not the same weight of discriminating.

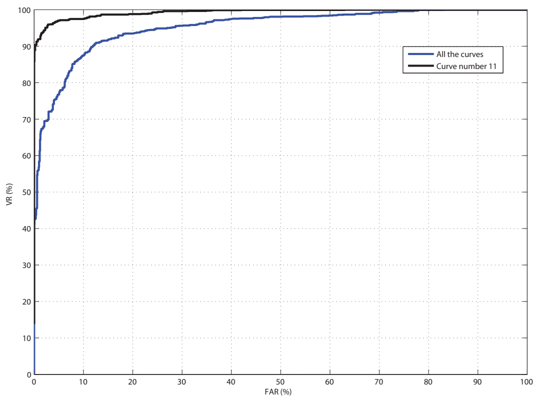

Fig. 7. ROC curve of results found for curve 11, sum rule of all patche curves

VI. CONCLUSIONS

In this paper we presented a new technique of 3D patche curves for person authentication. First, we formulated the problem of authentication as a classification problem with binary decision: Impostor access/Genuine access. Then, we proposed using the AdaBoost algorithm to optimize the performance of classification. Based on a set of training set, AdaBoost select classifiers associated to the most relevant curves on the patches by attribute most important weights to their associated weak classifiers. Finally, we presented experiments on testing sets of varying sizes.

ACKNOWLEDGEMENTS

This work was partially supported by the project ANR-07-SESU-004, the Contrat de Projet Etat-Région (CPER) Région Nord- Pas-De calais Ambient Intelligence and la bourse d'excellence Franco-Marocaine supported by Foreign French Minister.

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