3D Face Recognition Using Facial Curves, Sparse Random Projection and Fuzzy Similarity Measure

Naouar Belghini, Soufiane Ezghari, Azeddine Zahi
System Intelligent and Application Laboratory (SIA)
FST
Fez, Morocco
Firstname.Lastname@usmba.ac.ma

Abstract— **In this paper, we propose a fuzzy similarity based classification approach for 3D face recognition. In the feature extraction method, we exploit curve concept to represent the 3D facial data, two types of curves was considered: depth-level and depth-radial curves. As the dimension of the obtained features is high, the problem "curse of dimensionality" appears. To solve this problem, the Random Projection (RP) method was used. The proposed classifier performs Fuzzification operation using triangular membership functions for input data and ordered weighted averaging operators to measure similarity. Experiment was conducted using vrml files from 3D Database considering only one training sample per person. The obtained results are very promising for depth-level and depth-radial curves, besides the recognition rates are higher than 98%.**

Keywords- 3D face recognition; facial curves, sparse random projection; fuzzy logic; similarity measure; OWA operator.

I. INTRODUCTION

Face recognition using the 3D information of face has become a major research area. In this context, several approaches have been proposed and applied. A common approach adopted towards 3D face representation is based on the extraction of 3D facial curves. The basic idea of this approach is to provide an approximate representation of the facial geometry by extracting representative facial curves from 3D faces. In other words, this approach alters surface matching with curve matching.

We present, in this paragraph, some works related to approaches based curve‟s face representation to perform facial recognition using 3D data.

In [1] authors propose a 3D face matching framework that allows profile and contour based face matching, some combinations of curves was studied to perform time-efficient face retrieval. The obtained rate of recognition was about 97% on FRGCv2 database.

Berretti and Del Bimbo used in [2] geodesic stripes to identify faces. The approach captures characterizing features of the face by measuring the spatial displacement between iso-geodesic stripes. The method encodes the relevant information into a compact representation in the form of a graph. The rate of recognition was about 94.1% on FRGCv2 database.

Authors in [3] propose a 3D face recognition approach that measures the evolution of iso-geodesic distance curves. It compares two neighboring iso-geodesic distance curves, and then formalizes the evolution between them as a one-dimensional function. The proposed method formalizes the 3D facila data by an evolution angle functions, and computes the distance between two faces using this function.

Authors in [4], represent the facial surfaces by collections of radial and iso-level curves, extracted curves were compared using a Riemmannian framework, and boosting was used to select the most discriminative ones. With 17 curves 12 radial and 5 iso-level, the recognition rate was achieved 98.02%.

More recently, in [5], authors propose a geometric framework for analyzing 3D faces, with the goals of comparing, matching, and averaging their shapes. They represent facial surfaces by radial curves deriving from the nose tips and use elastic shape analysis of these curves to develop a Riemannian framework to analyze shapes of the full facial surfaces.

This was a brief overview about some relevant existing work in the field of 3D face representation using facial curves. But in the field of face recognition, and in parallel with the phase of feature extraction, a good classifier is essential to achieve a robust face recognition system.

In the last decade, a wide range of classifiers have been used to design systems for face recognition. Especially fuzzy classifier systems have been used because of its ability to tolerate imprecision and to manage information‟s uncertainty [6]. Indeed, unlike classical logic which requires a deep understanding of a system, and a precise numeric values, fuzzy logic incorporates an alternative way of thinking, which allows modeling complex systems using high level of abstraction.

In this paper, we offer an approximate representation of the facial geometry by extracting facial-level curves from 3D faces. Then, dimensionality reduction using sparse random projection method is investigated to perform a face recognition solution based on fuzzy similarity using ordered weighted averaging operators.

The remainder of the paper is organized as follow: section 2 present the features extraction method. Section 3 describes the proposed solution for face recognition. Section 4 presents and discusses the experiment results. Finally, conclusions are presented.

II. FEATURE EXTRACTION METHOD

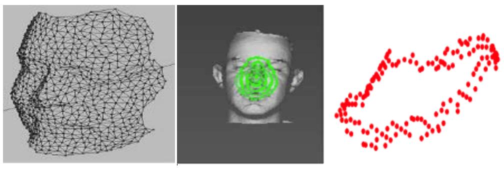
Before the extraction of the facial curves, the nose tip is first detected and considered as origin of the coordinate system. Let S be a surface denoting the scanned face. In practice, the surface S is represented by a triangular mesh defined by vertices and edges. We choose the nose tip (r) as a reference point onto S. The adopted approaches to represent facial surfaces by facial curves, are described below:

A. Depth-level curves extraction

We define a level radial curve $\beta_{Rmin,Rmax}$ as follow:

$$\beta_{Rmin,Rmax} = \{p \in S / R_{min} < dist(r,p) < R_{max}\} \quad (1)$$

Then all faces will be presented by a collection of closed curves considering different values of R_{min} and R_{max} radius.



a) b) C)
Figure 1. a)3-D face. b). extracted curves C) Example of $\beta_{Rmin,Rmax}$ curve

We consider our descriptor as the z coordinate of points taken from the union of different level curves relative to the nose tip.

Table 1 shows the total number of points obtained when considering the union of β curves covering the whole face with a thickness of 5 (R_{max}-R_{min} = 5).

TABLE I. AN EXAMPLE OF THE TOTAL NUMBER OF POINTS OBTAINED WHEN CONSIDERING SOME FACE SAMPLES.

Person Id	Face Id	radius Max	total number of points
1	1.1	201	8173
	1.3	182	7613
2	2.1	130	8863
	2.3	198	8129
3	10.1	202	9389
	10.3	137	9180

B. depth-radial curves extraction

Let β_α denotes the radial curve on *S*, β_α can be obtained by slicing the facial surface by a plane P_α that has the nose tip as origin and makes an angle α, with the plane containing the reference curve.

Figure 2 shows the procedure of extracting the radial curves; the intersection of P_α with S gives the radial curve β_α indexed by the angle α. Figure 2 shows an example of some extracted radial curves.

We consider our descriptor as the z coordinate of points taken from the union of different radial curves and relative to a reference point (the nose tip).

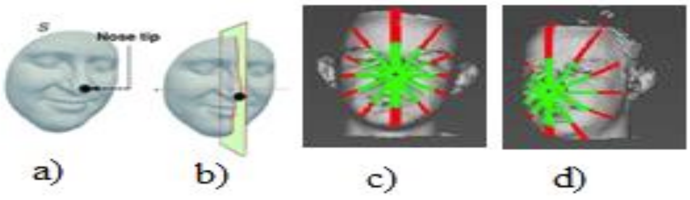


Figure 2. a) nose tip detection. b) the firt curve β_α^r is obtained by slicing the facial surface by P_α having as origin the nose tip. c) & d) images illustrate the intersection between the facial surface and P_α with different α

C. Random Projection for dimensionality reduction

In the previous sections, we explain how to extract facial curves from 3D facial data. We introduce the method called random projection to project the input vector into a lower dimension. It is an efficient method that preserves the structure of data without introducing significant distortion [7]. It has been applied on various types of problems like machine learning [8]. We investigate the random projection method to optimize the structure of our fuzzy system.

Let X Є R^n .The method multiplies X by a random matrix RP Є R^{n*k} : Y^k = RP * X

The idea is to preserve as much the "structure" of the data while reducing the number of dimensions it possesses; projections are based on the Johnson-Lindenstrauss lemma [9] that states that a set of N points in a high dimensional Euclidean space can be mapped down onto a K>= O(log(n)/ϵ^2) dimensional subspace such that the distances between the points are approximately preserved (for any 0 <ϵ < 1).

Achlioptas provided the sparse matrix projection that refer to a powerful concentration bounds [9]

$$r_{ij} = \begin{cases} +1 & p=1/2 \\ -1 & p=1/2 \end{cases} \quad \text{and} \quad r_{ij} = +\sqrt{3} \begin{cases} +1 & p=1/6 \\ 0 & p=2/3 \\ -1 & p=1/6 \end{cases} \quad (2)$$

Based on studies presented on [10], we will use, in the experimental section, Achlioptas‘s sparse matrix projection defined by:

$$r_{ij} = \begin{cases} +1 & p = 1/2 \\ -1 & p = 1/2 \end{cases} \quad (3)$$

III. THE PROPOSED SOLUTION

A. General architecture

The proposed model works in four steps. First, the system takes the input vector V from the extracted features. Next, we apply RP to reduce their dimension in order to optimize calculations and ameliorate the recognition rate. Then we express the extracted *z* features by linguistic terms (as *low, high, very high)* using fuzzy sets [11], this operation called the fuzzification, and finally to recognize faces we propose a fuzzy similarity based classification method.

The general architecture of the system can be described as below:

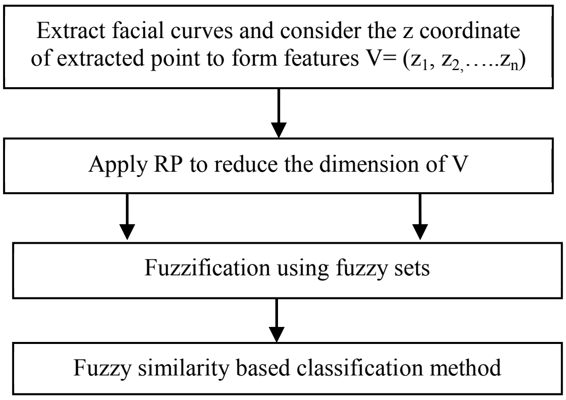


Figure 3. The architecture of the proposed solution

B. The Proposed fuzzy similarity based classification model

The proposed classifier in this paper recognizes a new face based on the similarities to the classified faces. The class assigned to the new face is the one that maximizes the similarity. The classification model is built using two principal components (1) the *knowledge base*, which contains the *learning base*, the *description of linguistic variables* and the *similarity measure*, (2) the classification procedure which assigns a class to a new face.

1) Knowledge base

a) learning base

It contains the classified faces. Each person face has one capture, where each capture is characterized by t features. So the learning base is represented by a matrix, which the number of rows is the number of person and each row contains the values of the t features and the associated class number (Figure 4).

$$\begin{array}{c} P_1: \\ \vdots \\ P_N: \end{array} \begin{bmatrix} f_{11} & \dots & f_{1t} & C_1 \\ \vdots & \dots & & \vdots \\ f_{N1} & \dots & f_{Nt} & C_N \end{bmatrix}$$

Figure 4. Data matrix representing the learning base

b) Linguistic variables:

This part contains linguistic variables [6] describing the features selected. Each linguistic variable is defined by an adequate number of fuzzy sets which are associated with linguistic terms and membership functions. Latter is defined by its shape which can be triangular, trapezoidal, Gaussian, semi-trapezoidal, etc. in this work Triangular shape is retained for intermediate fuzzy sets and semi-trapezoidal shape for the first and the last ones. In the literature many techniques have been proposed to extract fuzzy sets from numerical data. The most of them are based on clustering methods [12][13][14]. The technique used in this work consists in three main steps. First we use the well-known Fuzzy C-Means clustering algorithm with various numbers of clusters [15] to partition every feature data in the learning base. Second, we select the adequate number of clusters (fuzzy sets) according to the very promising Xie-Beni(XB) validating index [16][17][18]; the number minimizing the XB criterion is selected. In the last step we build membership functions from cluster centers generated in the previous steps. Figure 5 shows an example of linguistic variable described by k membership functions generated from the k cluster centers.

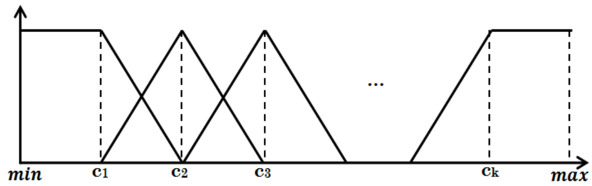


Figure 5. Membership functions built from the cluster centers $(c_i)_i$

c) Fuzzy Similarity Measure

Modern applications such as object retrieval, multi-criteria decision making, etc. need parameterized similarity measures in the sense of including the notion of feature importance and the precision of retrieved object. In the literature, many parameterized similarity measures are proposed [19][20][21]. In this work we are concerned with the measure designed in [20]. This measure is based on the Ordered Weighted Averaging operator (OWA) introduced by Yager in [22]. It evaluates the overall similarity $d(e_1, e_2)$ of two samples e_1 and e_2, by combining the individual similarities of e_1 and e_2 associated with the various features f_i describing e_1 and e_2, $d_{f_i}(e_1, e_2)$. So, the evaluation of similarity is performed in two main steps:

- Evaluation of individual similarities: many similarity measures have been proposed in [23] such as: $sum - product$, $max - min$, *etc.* we have retained the $sum - min$ measure defined by the following formulas :

$$d_{f_i}(e_1, e_2) = \sum_{j=1}^{k} \min(\mu_j^{f_i}(e_1), \mu_j^{f_i}(e_2)) \qquad (4)$$

  Where f_i are linguistic variables describing the samples e_1 and e_2, and $\mu_j^{f_i}$ are membership functions representing features f_i.

- Evaluation of the overall similarity: in this step the individual similarities, $d_{f_i}(e_1, e_2)$, are aggregated by using an OWA operator. So, the overall similarity, $d(e_1, e_2)$, is associated with a weighting vector $W = (w_1, w_2, \dots, w_n)$ which has the following properties:

$$w_1 + w_2 + \dots + w_n = 1;\ 0 \le w_j \le 1;\ \ j = 1,2, \dots, n;$$

Such that:

$$d(e_1, e_2) = \sum_{j=1}^{t} w_j\, d_{f_j}(e_1, e_2) \qquad (5)$$

Where $d_{f_j}(e_1, e_2)$ is the j^{th} largest individual similarity calculated by equation (5).

In [24], Yager shows that we could use the Regular Increasing Monotone Quantifier (RIM) such as *„all"*, *„most"*, *'many'*, *„at most* α*„* or *„there exists"*, to obtain a weighting

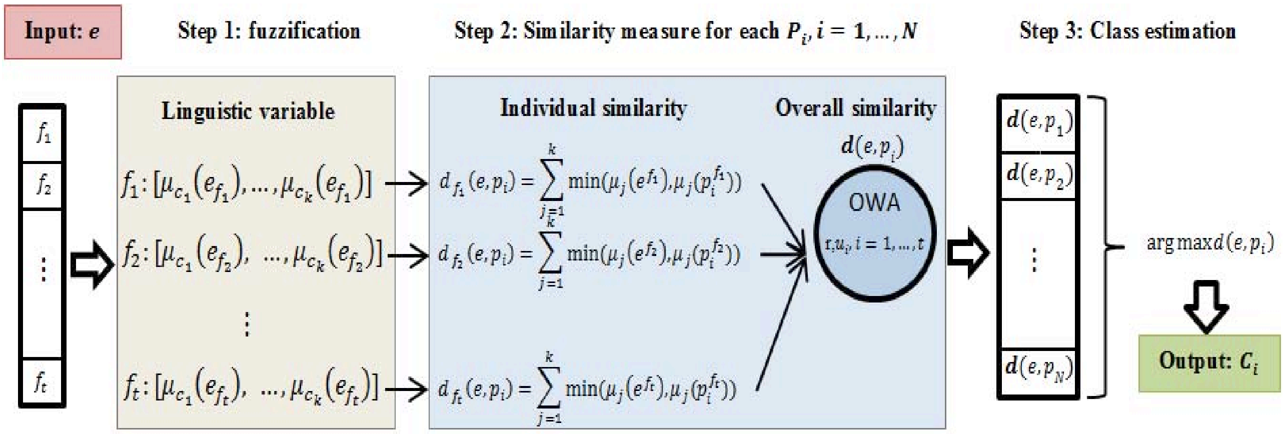


Figure 6. Fuzzy similarity based classification process

vector W associated with an OWA aggregation. Assume that Q is a RIM quantifier, the weighting vector W is obtained by the following formula:

$$w_i = Q\left(\frac{i}{t}\right) - Q\left(\frac{i-1}{t}\right) i = 1, \ldots, n \quad (6)$$

Where t design the number of aggregated individual similarity. In [25], many families of RIM quantifiers are provided; we have chosen the parameterized power quantifier $Q(x) = x^r$; $r > 0$. The parameter r , indicates the proportion of features considered in the evaluation of the overall similarity; for example $r = 2$ represents the linguistic quantifier „most" i.e. most of features are satisfied in overall similarity.

2) Classification process

The proposed model classifies a new face e in three steps (figure 6):

- First, the system takes the new input sample e and fuzzifies its features value, e_{f_i}, using membership functions of linguistic variables in the knowledge base. Each feature f_i provides a vector that contains membership degrees of the values, e_{f_i}, to various linguistic terms.
- Second, we evaluate the overall similarity using the equation (5) between the new input sample and the samples in the learning base. The result gives the vector of similarities measures.
- Finally, we assign the new input sample to the class that maximizes the similarity measure.

$$class(e) = \arg\max d(e, p_i)$$

Where $d(e, p_i)$ are the overall similarities between the new input sample, e, and the learning samples, p_i.

IV. EXPERIMENTAL RESULTS

The experiments were conducted and evaluated based on a set of 40 individuals from FRAV3D DB using VRML file (3D image). A total of 16 captures per person were taken in every session, with different conditions (Table II). Only one sample (the frontal pose) was used in the learning database and the rest for test.

TABLE II. DESCRIPTION OF THE ACQUISITION ORDER

Label	Type of image
01 - 04	Frontal
05 - 06	Right turn 25º (respect to Y axis)
07 - 08	Left turn 5º (respect to Y axis)
09	Severe right turn (respect to Z axis)
10	Soft left turn (respect to Z axis)
11	Smiling face
12	Open mouth
13	Looking upwards (turn respect to X axis)
14	Looking downwards (turn respect to X axis)
15 - 16	Frontal view with lighting changes

We use the learning base to generate the linguistic terms for each feature (see linguistic variables section). Figure 7 shows an example of the graphical representation of linguistic terms for two extracted feature frame faces.

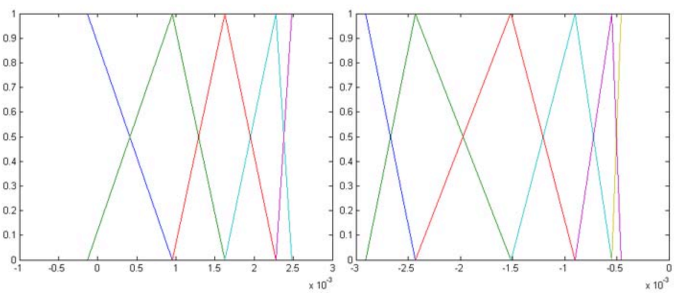


Figure 7. Graphical representation of linguistic terms

We experiment the fuzzy similarity based classification system considering the following scenario when building the input vectors, we extract the first 2000 values of the original feature (points in green color) that represent the central part of the face (Figure 8). Then we apply the (RP) method to reduce the dimension from 2000 to 200 and 100, and we apply the OWA operator described in the previous section considering that different RIM parameters values (Table III).

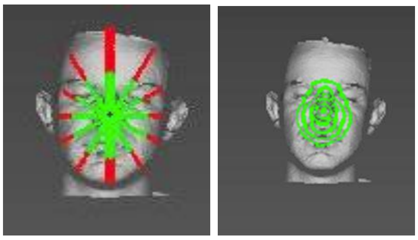


Figure 8. graphical representation of the considered points a) radial curves b)level curves

The table below shows the recognition rate when considering 40 people from the 3D FRAV database.

TABLE III. OBTAINED RESULT USING DEPTH LEVEL CURVES

Dimension of feature vector	RIM parameter (r)	Recognition rate Depth-level curves (%)	Recognition rate Depth- Radial curves (%)
2000	2	*weak*	*weak*
	100		
	8000		
200	2	97.33	97.84
	100	98.12	99.69
	8000	99.69	99.84
100	2	96.55	98.12
	100	99.53	99.84
	8000	99.96	99.84

By analyzing the results, we may conclude that the proposed approach improve the face recognition rate. We remarked that the RP as dimensionality reduction method is reliable and gives better performance for the recognition task. Also the given results with different RIM quantifier attest that a high RIM parameters, r, increase the recognition accuracy, which means that with high RIM parameters value, we include more feature in similarity assessment so the similarity becomes more precise.

And by comparing the obtained results when considering depth-radial and depth-level curves, we conclude that representing faces using radial curves approach, which represent the central part of the face, gives better recognition rate.

CONCLUSION

In this paper we have developed a robust and efficient solution for face recognition using depth-radial curves with fuzzy similarity based classification method. The experiments were conducted using only one sample per person in the training Database (the frontal pose). We show how the introduction of RP as dimensionality reduction method was reliable and gives better performance with the proposed classification method. Indeed the recognition rate is high than 98%. Besides the fuzzification of features allow imprecision tolerance in features values. Furthermore the proposed classifier adopted an overall similarity measure using OWA operator guided by RIM fuzzy quantifier enables to express the degree of precision in similarity measure linguistically and gives a good assumption of the extracted features.

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