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Evaluation of Discrimination Power of Facial Parts from 3D Point Cloud Data

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***Abstract*—Feature selection from facial regions is a well-known approach to increase the performance of 2D image-based face recognition systems. In case of 3D modality, the approach of region-based feature selection for face recognition is relatively new. In this context, this paper presents an approach to evaluate the discrimination power of different regions of a 3D facial surface for its potential use in face recognition systems. We propose the use of weighted average of unit normal vector on the facial surface as the feature for region-based face recognition from 3D point cloud data (PCD). The iterative closest point algorithm is employed for the registration of segmented regions of facial point clouds. A metric based on angular distance between normals is introduced to indicate the similarity between two surfaces of same facial region. Finally, the intra class correlation based discrimination score is formulated to find out the key facial regions such as the eyes, nose, and mouth that are significant while recognizing a person with facial surface PCD.**

I. Introduction

Face recognition has been remained as one of the most challenging research areas in computer vision and pattern recognition. In the literature, there are many approaches that have been adopted to find the best possible automatic face recognition system [1]. Though most of the initial works were based on holistic facial features, the landmark-based features selected from facial regions have also been examined. Examples of the region-based features for whole faces can be found in the methods reported in [2]. Different partitioning schemes to find facial features have also been studied [3]. In some cases, whole face images cannot be obtained or some of the key regions of the faces can be contaminated with heavy noise such as occlusions. Considering those difficulties, the region-based approaches have been considered for face recognition as well as for face detection [4]. For example, the facial parts are used to recognize identity from CCTV footage in computational forensics [5]. Algorithms for recognizing faces after plastic surgery have also incorporated the region-based approach [6]. Li et al. [7] reported an approach for face recognition by matching non-corresponding region of facial images. Although region-based approaches are quite familiar in the intensity-based 2D modality, it is relatively new and yet to be thoroughly studied in case of 3D modalities of facial imaging.

In pursue of accuracy, the 3D modalities such as 3D depth image and 3D voxel data are becoming increasingly popular as compared to 2D pixel data of images. Several works have been reported on face recognition with 3D modality using depth image as well as 3D surface data (see for example, [8] and references therein). The 3D modality has been adopted to construct algorithms that are immune to expression variability. Since the nasal region undergoes less geometric deformation in presence of facial expression, the nasal region-based recognition system has also been reported [9]. It is apparent that a comparative study of recognition capability of different regions of 3D facial surface is necessary to develop an efficient face recognition algorithm.

(a) (b) (c)

Fig. 1: Examples of facial surfaces represented by PCD. (a) Face without occlusion. (b) Face occluded by beard. (c) Partially scanned face.

In this paper, a comparison of discriminatory scores of different facial regions is drawn from 3D point cloud data (PCD). A few examples of facial surface represented by PCD is shown in Fig. 1. It can be seen from this figure that the extraction of facial regions becomes challenging due to occlusions or pose variations. Hence, a rigid registration algorithm called the iterative closest point (ICP) is used for the alignment of the surfaces of extracted facial regions represented by PCD. The similarity metric is defined based on alignment of the corresponding unit normal vectors on surface PCD of face regions. Finally, the intraclass correlation coefficient (ICC) of the similarity scores is estimated to obtain the discrimination score of different regions of facial point clouds.

The paper is segmented into several sections. The proposed approach of evaluation of discrimination power is described in Section II. Section III represents the experimental setup, the results obtained, and the validation of the results by comparing with previous works. Finally, Section IV provides conclusion.

II. Proposed Approach of Evaluation

The proposed approach of evaluation follows different steps including the definition of facial regions, segmentation of regions, feature selection, registration, and calculation of discrimination scores. In order to improve the readability of this paper, these steps are described in different subsections.

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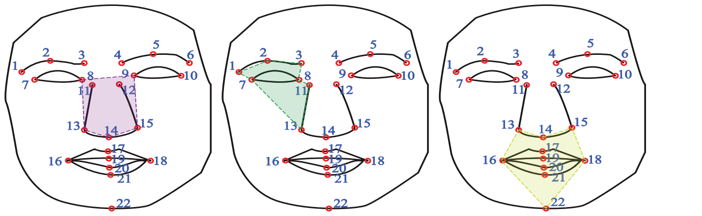

(a) (b) (c)

Fig. 2: Landmarks obtained by algorithm [10], and polygons formed by connecting the landmarks for the three regions, namely, (a) nose, (b) eye, and (c) mouth.

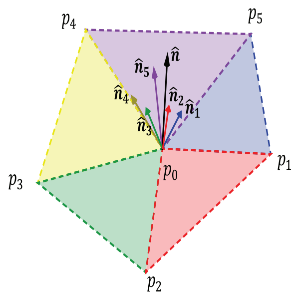

Fig. 3: Normal vectors using local Voronoi mesh for $K = 5$.

A. Defining Different Facial Regions

To compare the discrimination capability of different facial parts, suitable regions on faces are automatically generated from landmarks. In particular, we are inspired by the automatic localization algorithm of landmarks on faces reported in [10]. As we are focused in PCD, the regions are selected by segmenting the facial surface according to certain polygon connecting the landmarks. Specifically, we define three regions, namely, *nose*, *eye*, and *mouth* in terms of 2D polygons formed by connecting certain landmarks, viz., [8, 9, 15, 14, 13], [1, 2, 3, 8, 11, 13, 7] and [12, 14, 15, 18, 21, 16], respectively, as shown in Fig. 2. To select the 2D polygons, the third component of the PCDs representing the vertices are ignored.

B. Segmentation of Facial Surface Represented by PCD

After defining the regions in terms of polygons, it is necessary to segment the surface accordingly. To do so every point in the facial point cloud surface has been checked whether the point belongs to the entire set of points that are within the convex hull of the polygon vertices. Let the total number of points in the PCD of a region be N. First, the polygons are discomposed into all possible triangles. Then, the query point q_i $(i \in \{1, 2, 3, \cdots, N\})$ is checked whether it is within such a triangle. The checking process of a point whether it is within a triangle is performed by using the following steps:

1) The vertices l_1, l_2 and l_3 of a triangle is arranged in anti-clockwise order.
2) It is checked whether the point sets $[l_1 l_2 q_i]$, $[l_2 l_3 q_i]$ and $[l_3 l_1 q_i]$ are arranged in anti-clockwise order. This can be done by determining the area of the triangle formed by each point sets. If the area is positive then their order is anti-clockwise. For example, if (x_1, y_1, z_1), (x_2, y_2, z_2) and (x_3, y_3, z_3) are three corners of a triangle, then the area can be determined as
$$A = \frac{1}{2}\begin{vmatrix} x_1 & y_1 & 1 \\ x_2 & y_2 & 1 \\ x_3 & y_3 & 1 \end{vmatrix} \tag{1}$$
3) If all these query turned out to be true, then the point q_i is considered to be inside the triangle.

Finally, we take the union of the point sets that are inside the triangles compounding the polygon that forms the face region.

C. Feature of Face Regions

In this paper, the unit normal vector of the 3D point cloud surface has been chosen as facial features considering that the angle between two unit normal vectors can indicate effective discriminatory power. There are several ways through which normal vector on a surface at a given point can be computed. We determine the normal vector at point p_0 by taking the weighted average of the normal vectors on the local mesh triangles of the point. These local Voronoi mesh triangles are found by 2D Delaunay triangulation [11] ignoring the third components of all the points of PCD. Unit normal vector on a surface on specific point can be calculated easily if all the neighboring points of the normal vector can be identified. The local Voronoi mesh can be formed by using these neighboring points. In the mesh, only those triangles that have at least one vertex at point of interest p_0 are counted. All the vertices of the triangles except p_0 are the neighboring points. These neighboring points together compose the local Voronoi mesh. For example, K neighboring points will result in K triangles with common vertices at p_0 as shown in Fig. 3. Let p_i be the ith neighboring point of p_0 and $\vec{n_i}$ be the normal on ith triangle $(i \in \{1, 2, 3, \cdots, K\})$. Then the weighted average of the unit normal vector $\vec{n}$ can be computed as

$$\vec{n} = \sum_{i=1}^{K} w_i \vec{n_i} \Big/ \sum_{i=1}^{K} w_i \tag{2}$$

where $w_i = \dfrac{|\overrightarrow{p_0 p_i} \times \overrightarrow{p_0 p_{i+1}}|}{2}$ and $w_i \vec{n_i} = \dfrac{\overrightarrow{p_0 p_i} \times \overrightarrow{p_0 p_{i+1}}}{2}$

D. Registration of Facial Regions

Since the proposed evaluation method incorporates the angle between two normal vectors originated from two different PCD of a face region, the result is susceptible to misalignments of imaging conditions. This problem is tackled by using a suitable registration algorithm. There are many rigid and non-rigid registration algorithms for 3D shapes. In this paper, we implemented the ICP-based [12] rigid registration algorithm to remove the effect of scanning angle. The output of the ICP algorithm provides a 3×3 rotational matrix $\mathbf{R}$ and a 1×3 translation vector $\mathbf{T}$ for the transformation of one point cloud to align to the another after every iteration by minimizing the error metric E given by [12]

$$E = \frac{1}{2} \sum_{i=1}^{\Gamma_r} ||P_i \mathbf{R} + \mathbf{T} - Q_i||^2 \tag{3}$$

where P_i and Q_i are the corresponding vectors formed from ith corresponding points of two different PCDs and Γ_r is the number of points in a PCD. Let $\mathbf{L}$ be the misaligned PCD of size $N \times 3$ representing a facial surface. Then, the registered PCD $\mathbf{M}$ can be found as [12]

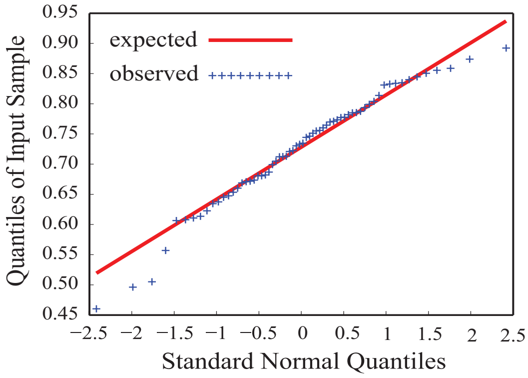

Fig. 4: Sample quantile-quantile plot of similarity metric γ_r.

$$\mathbf{M} = \mathbf{L}\hat{\mathbf{R}} + \mathbf{1}_N \hat{\mathbf{T}} \tag{4}$$

where $\hat{\mathbf{R}}$ and $\hat{\mathbf{T}}$ are obtained by minimizing the error metric of the ICP and $\mathbf{1}_N$ is a row vector of length N with all elements being one.

E. Discrimination Score of Facial Regions

We define similarity metric in terms of the cosine of the angles between the corresponding unit normal vectors of two point clouds. Let there be two point clouds $\mathbf{J}$ and $\mathbf{M}$ representing same region of two faces. If the cloud $\mathbf{J}$ has Γ_r number of points, then there will be equal number of normal vectors for each of the points of a region r ($r \in \{$ *eyes*, *nose*, *mouth* $\}$). Since the clouds are registered, a set of nearest neighbor of Γ_r points can be established between the clouds $\mathbf{J}$ and $\mathbf{M}$. The nearest neighbor is determined by the popular kD-tree search algorithm [13]. Then the similarity metric of a region r in terms of dot product of unit normal vectors $\overrightarrow{n}_J(m)$ and $\overrightarrow{n}_M(m)$ on mth point of the clouds $\mathbf{J}$ and $\mathbf{M}$ can be estimated as

$$\gamma_r = \frac{1}{\Gamma_r} \sum_{m=1}^{\Gamma_r} \overrightarrow{n}_{\mathbf{J}}(m) \cdot \overrightarrow{n}_{\mathbf{M}}(m) \tag{5}$$

Fig. 4 shows that typical quantile-quantile plot of γ_r is almost a straight line, which means that γ_r follows closely a Gaussian distribution. Thus, the discrimination score of a region can be obtained in terms of the ICC of similarity metric γ_r given by [14]

$$\rho_r = \frac{(\phi_{br} - \phi_{wr})}{\phi_{br} + (1-\lambda)\phi_{wr}} \tag{6}$$

where ϕ_{br} and ϕ_{wr} represent the 'between-class mean-square' and 'within-class mean-square', respectively, and are given by

$$\phi_{br} = \frac{\lambda \sum_{\ell=1}^{K} (\mu_r^\ell - \mu_r)^2}{K-1} \tag{7}$$

$$\phi_{wr} = \frac{\sum_{\ell=1}^{K} \sum_{k=1}^{\lambda} (\gamma_r^\ell(k) - \mu_r^\ell)^2}{K(\lambda - 1)} \tag{8}$$

where μ_r is the overall mean of the similarity scores considering all the subjects, μ_r^ℓ being the mean of the scores within the class label ℓ, λ is the number of samples for each subject, and K is the total number of subjects.

III. Experiments and Results

To determine the rank of discriminatory facial parts experiments are conducted on database having faces represented by the PCD. The description of the data set of faces, experimental setup, and the results obtained are given in separate subsections.

A. Database

The PCDs of 3D faces from Bosphorus database [15] are used in the experiments. The database contains faces of 104 subjects. There are faces for each subject with variations in terms of expressions, orientation, and occlusion. In order to evaluate the discrimination power of facial regions, we selected only the front view faces that are free of occlusion. The generic dataset of the experiment considers 8 subjects with 8 point clouds per subject chosen randomly from the database. The 24 landmarks provided by the database [10] are used to segment the regions of 3D faces.

B. Setup

The background points were eliminated by taking only the points that have coordinate values greater than a threshold of -2×10^8. In the implementation of ICP algorithm, the maximum number of iteration was chosen as 100, the parameter "extrapolation" was set true to evaluate the direction of iteration, and other parameters were kept same as prescribed in [16]. The kD-tree algorithm was implemented by carrying out search for all the nearest points. The 2D Delaunay triangulation was applied on the XY plane ignoring the third dimension of the points, while estimating the unit normal vector.

C. Results

Table I shows the estimated between- and within-class mean-squares, and discrimination scores ρ_r for different regions of facial surface PCD. It can be seen from this table that the region *eye* has the greatest score among the facial parts. The region *nose* has the second most discrimination score, and the lowest score is shown by the *mouth*. Table I also shows that the region *nose* has the lowest between-and within-class mean-squares, thus indicating the less variability in different faces in nasal region. In other words, the nasal region of faces is immune to expression, the primary cause of distortion in the faces of dataset. In case of region *mouth*, though the value of between-class mean-square is high, the within-class mean-square is also high. This fact indicates that the region *mouth* has the lowest discrimination score in order to distinguish faces of the subjects. Such a result is expected due to the fact that in practice the region *mouth* suffers the most for facial deformations in the presence of expressions. The moderate levels of between- and within-class mean-squares of the region *eye* signify that this region is the best for distinguishing faces as compared to other regions even in the presence of facial distortions due to expressions.

We compare the results obtained in the experiments for the regions of 3D facial surface with that reported for the 2D intensity images of faces [5]. Fig. 5 shows the identification performance of the regions *eye*, *nose*, and *mouth* when the well-known features such as the Eigenface and Adaboost are used. It is seen from this figure that the identification rate from region *eye* is the highest as compared to other regions. These

TABLE I: Discrimination score of regions of 3D facial PCD.

Regions	Between-class mean-square ϕ_{br}	Within-class mean-square ϕ_{wr}	Discrimination score ρ_r
Eye	0.248368	0.008972	0.4879
Nose	0.181765	0.007131	0.4666
Mouth	0.326715	0.016726	0.3983

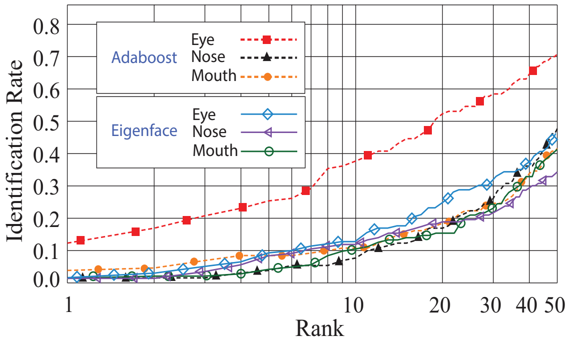

Fig. 5: Identification performance of well-known features of facial regions obtained from 2D intensity images [5].

results ensure that the discrimination power evaluated in this paper for the point cloud of face regions are consistent with the previously reported observations. One question may arise here as to why the discrimination scores of facial point clouds are not so high. A low-level of discrimination score can be explained by the fact that it is really difficult to recognize a person only with one region of face. In practice, the rank - 1 identification rates of facial region-based approaches are less than 25% [5]. Higher identification rates can be attained by fusing or accommodating the interrelation of the features of different facial regions. In few instances of experiments, it is observed that the ICP-based registration process converges towards one of the local minima instead of the global minima. Such registration errors can lead to a low-level discrimination power of facial regions. Fig. 6 shows the examples of incorrect and correct registrations along with their estimated similarity metrics for the facial region *eye* of same and different persons. It is recommended that high cares should have been taken on the registration process for facial region-based recognition, especially in the presence of expression variability.

IV. Conclusion

In this paper, the discrimination powers of regions of a face have been evaluated using the facial surface represented by 3D PCD. Three regions of point clouds, namely, *eye*, *nose*, and *mouth* have been segmented by using the automatically generated landmarks. To compare two point clouds of a facial region, the ICP-based rigid registration algorithm has been employed. The similarity between two PCD is estimated in terms of cosine angles of weighted average of unit normal vectors on 3D facial surface as feature. According to the statistics of similarity metric, the ICC-based scoring has been used to evaluate the significance of facial regions for discriminating the subjects. Experimental results on regions of facial point clouds reveal that the ranking of the facial regions according to their discrimination capability are *eye*, *nose* and *mouth*. This result is consistent with the observations of region-based face recognition conducted on the 2D intensity images of faces.

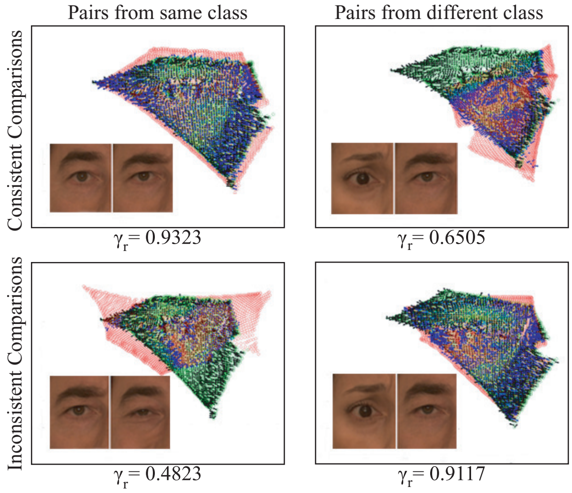

Fig. 6: Examples of correct and incorrect registration for the segmented region *eye* of same and different persons.

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