3D Expression-Invariant Face Recognition
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Abstract—This document gives a short overview of 3D face recognition methods invariant for expression variations and describes in more detail a method using point cloud kernel correlation. This method is also evaluated using 2 frequently used databases.

I. INTRODUCTION

During the last decade, research in face recognition has been shifted from 2D to 3D representations to deal with pose variations and varying lighting conditions. However, a remaining challenge is the intra-subject deformation due to expression variations. In literature, several algorithms try to deal with those expression variations to obtain expression-invariant face recognition.

II. STATE-OF-THE-ART

Expression-invariant face recognition methods could be subdivided into 4 categories. Historically the first methods dealing with expression variations are the region-based methods. Parts of the face that are more or less rigid during expression variation form the basis of recognition. Most popular regions to select in advance are the region of the nose [1], [2], [3], [4], [5], cheek [1], chin [1], eyebrows [1], eyes [2], forehead [2], [6], region above the mouth [7], [8], [9]. Other algorithms automatically select the more rigid regions while matching [10], by training a prior defined regions [11], [12] or fuse a priori defined regions by applying different weights [13].

Another approach for expression-invariant recognition is the use of a statistical model. Mostly a Principal Component Analysis (PCA) is used either to model expressions directly [14], [15] or by including non-neutral faces in the training set [16], [17], [18].

A third group of methods use a geometric model. According to [19], geodesic distances between corresponding points remain constant under expression variation. Several methods [20], [21], [22], [23] also propose a method based on this invariance of geodesic distances.

The last category are the robust methods. Those [24], [25], [26], [27], [28] do not handle the expressions explicitly, but perform well under a certain amount of expression variation.

III. POINT CLOUD KERNEL CORRELATION

A. Kernel Correlation for use in Face Recognition

Kernel correlation (KC) is an affinity measure in point sampled vision problems that was originally proposed by Yanghai Tsin in [29], [30]. It is a robust similarity measure for unstructured point clouds. Most important for us is the Leave-one-out Kernel Correlation (LOO-KC), a robust measure for the compatibility between point y and point set χ. This measure can thus be directly used for 3D point cloud registration, using a cost function that combines the LOO-KC’s of all points in a to-be-registered (floating) point set to the reference (static) point set. This cost function is a function of pairwise distances between all points s ∈ S and f ∈ F, and is therefore very robust.

A next application for KC, thanks to its robustness, is use it as a similarity measure in face recognition across face expressions. In order to be able to use the kernel correlation as a similarity measure, we must extend the KC formula to take two point clouds into account. We do this by using an approach similar to the cost function approach, but now normalized using the number of points in the floating point set.

Now, when comparing face scan S to face scan F, we can rank the faces in order of likeliness that F is a scan of the same face as S by sorting this measure KC_S. Higher KC_S values means that it is more likely to be a scan of the same face, and vice versa.

B. Validation

To show the effectiveness of the proposed method, we performed the SHREC 2008 - Shape Retrieval Contest of 3D Face Scans experiment [31]. The database used is a subset of the GavabDB1 database [32]. The GavabDB consists of 7 laser range scans from 61 subjects. GavabDB is a difficult database, with large face expressions, much missing data, spikes…

IV. RESULTS

The results for the proposed method in the SHREC test are quite promising: whithout any other preprocessing than cropping, we archive good results with 90.6% Recognition Rate and a Mean Average Precision of 0.702. With this, we perform as good as the third best algorithm that took part in the SHREC 2008 contest.

V. CONCLUSIONS

In this work, we have used a relatively new 3D point cloud registration approach, combined with the introduction of the use of a similarity measure for comparing 3D point clouds, and more specific 3D point cloud face models. The main advantage of the method is that because of its robustness, almost no preprocessing of the 3D models is needed and face recognition can be performed even with an amount of expression variation. Other advantages are the absence of the need for training or point correspondences.

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REFERENCES


