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A Comparative Study of 3-D Face Recognition Under Expression Variations

Dirk Smeets, Peter Claes, Jeroen Hermans, Dirk Vandermeulen, and Paul Suetens

***Abstract*—Research in face recognition has continuously been challenged by extrinsic (head pose, lighting conditions) and intrinsic (facial expression, aging) sources of variability. While many survey papers on face recognition exist, in this paper, we focus on a comparative study of 3-D face recognition under expression variations. As a first contribution, 3-D face databases with expressions are listed, and the most important ones are briefly presented and their complexity is quantified using the iterative closest point (ICP) baseline recognition algorithm. This allows to rank the databases according to their inherent difficulty for face-recognition tasks. This analysis reveals that the FRGC v2 database can be considered as the most challenging because of its size, the presence of expressions and outliers, and the time lapse between the recordings. Therefore, we recommend to use this database as a reference database to evaluate (expression-invariant) 3-D face-recognition algorithms. We also determine and quantify the most important factors that influence the performance. It appears that performance decreases 1) with the degree of nonfrontal pose, 2) for certain expression types, 3) with the magnitude of the expressions, 4) with an increasing number of expressions, and 5) for a higher number of gallery subjects. Future 3-D face-recognition algorithms should be evaluated on the basis of all these factors. As the second contribution, a survey of published 3-D face-recognition methods that deal with expression variations is given. These methods are subdivided into three classes depending on the way the expressions are handled. Region-based methods use expression-stable regions only, while other methods model the expressions either using an isometric or a statistical model. Isometric models assume the deformation because of expression variation to be (locally) isometric, meaning that the deformation preserves lengths along the surface. Statistical models learn how the facial soft tissue deforms during expressions based on a training database with expression labels. Algorithmic performances are evaluated by the comparison of recognition rates for identification and verification. No statistical significant differences in class performance are found between any pair of classes.**

***Index Terms*—Biometrics, databases, expression variation, face recognition, facial expression, meta-analysis, 3-D face.**

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I. Introduction

SINCE the beginning of this century, the pace of development and improvements of biometric technologies has accelerated considerably as a consequence of the increased attention to security issues. However, the discipline of biometrics is older than that. Some believe that handprints, nearby paintings in a cave that is estimated to be at least 31 000 years old, are the first form of biometry. True biometric systems began to emerge in the second half of the 20th century, coinciding with the development of increasingly more powerful computer systems, with major advances since the 1990s [1]. Biometric systems can be divided into two classes depending on the characteristics that are used. One class uses physiological characteristics that are related to the shape and appearance of the body and body parts, such as fingerprint, finger knuckles, face (2-D and 3-D), DNA, hand and palm geometry, iris texture, and retinal vasculature. Systems belonging to the second class use behavioral characteristics, such as gait, handwriting, keyboard typing, and speech [2]. According to Jain *et al.* [3], biometric systems need to satisfy four requirements: universality, distinctiveness, permanence, and collectability.

Faces are probably the most common biometric identifier that is used by humans to recognize people. Computer-based face recognition is either feature based (using the shape and position of facial features, such as eyes, nose, and lips) or holistic (using the overall analysis of the facial image). Research in automatic face recognition has been conducted since the 1960s and has resulted in commercially available systems with acceptable performance using 2-D images. However, these systems impose a number of restrictions (fixed pose, controlled illumination) [4], [5]. In order to lift these restrictions, recent research has shifted from 2-D to 3-D face representations [6]–[8]. This shift is also demonstrated by the setup of large evaluation studies of 3-D face-recognition algorithms. Indeed, in 2006, the Face-Recognition Grand Challenge (FRGC) [9] was the first large comparison, followed by the Shape Retrieval Contest (SHREC) in 2007 [10], 2008 [11] and 2011 [12]. However, note that 3-D face acquisition is typically more controlled than 2-D face acquisition. Two remaining difficulties in 3-D face recognition are intersubject similarity and intrasubject variability. The difference between two 3-D representations of different subjects can be quite small, making correct recognition not straightforward. High intersubject similarity occurs, for instance, with identical twins, father and sons, or mothers and daughters. The second challenge, intrasubject variability, is because of intrasubject skin deformation, which can be caused by internal/gradual (expressions, ageing) or external/abrupt changes (cosmetic changes), or a combination of both. It has been shown that deformations

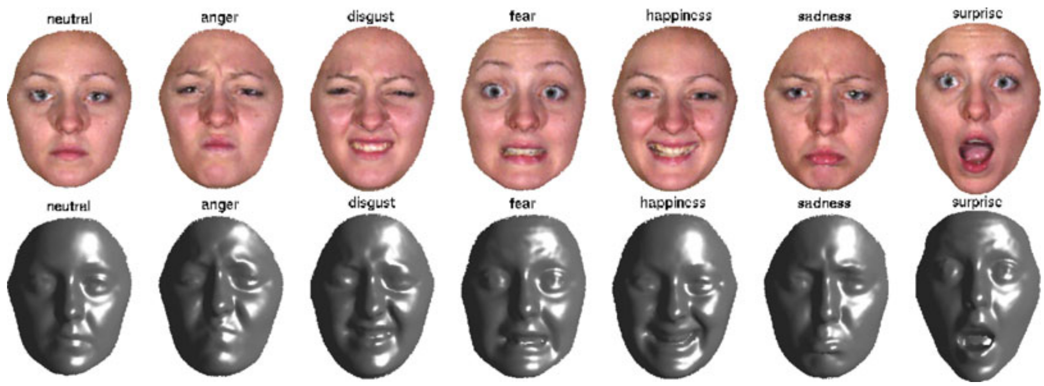

Fig. 1. Three-dimensional faces with different expressions with and without texture, coming from the BU-3DFE database [15].

because of cosmetic surgery negatively affect the performance of some state-of-the-art 3-D face-recognition methods [13]. Deformations because of internal conditions are mainly caused by changes in facial expressions. Deformations because of facial expressions are reported as one of the main challenges of 3-D face recognition in [14] and are the subject of this paper. In Fig. 1, some 3-D expression scans of facial surfaces with and without texture are shown.

Dual to the problem of expression-invariant face recognition is the emerging challenge of expression recognition [16], [17]. Although face recognition should be stable under expression variations, expression recognition needs to be invariant to identity changes. Recent surveys provide a good overview of the state of the art in expression recognition [18] and expression analysis [18], [19] starting from 2-D images.

An extensive number of surveys for 3-D face recognition in general already exist, see, e.g., [7], [14], [20]–[33]. From these, the most influential for 3-D face recognition is presented in [22]. In this paper, on the other hand, we focus on a comparative analysis of 3-D face-recognition methods that deal specifically with expression variations, since more recently a lot of research results have accumulated in this subfield. In the previous work [32], expression variations and conceptual approaches to deal with them during 3-D face recognition are also shortly discussed, albeit in a different field of expertise without focusing on the underlying methodology, technical algorithms, and available databases. As the second contribution, in this paper, we provide an exhaustive overview of existing 3-D face databases with facial expressions, while the most important ones are briefly discussed. A complexity analysis of these databases is performed using a baseline face-recognition algorithm. As a consequence, it is possible to rank the databases according to their inherent difficulty, allowing to compare more objectively the performances of the various methods that are available in the literature. We determine and quantify the most important factors that influence the face-recognition performance. As a result, this analysis offers an objective comparison of the performances of state-of-the-art methods.

This paper is structured as follows. In Section II, we discuss and compare the different 3-D face databases that contain expression variations. Published methods for 3-D face recognition are discussed in Section III based on a classification into three classes. In addition, they are compared based on their published recognition performances. In Section IV, some remaining fundamental problems in 3-D face recognition are discussed. Conclusions and future challenges are listed in Section V.

II. Three-Dimensional Face Databases with Expressions

A. *Overview of Databases*

Many research organizations have built various 3-D face databases to evaluate 3-D face-recognition algorithms. Publicly available face databases that contain facial expressions are listed in Table I, indicating the number of scans and the number of subjects in each database. The most important databases (frequently mentioned in the literature and publicly available) of Table I will be discussed and compared using a baseline algorithm, in order to measure their complexity w.r.t. face-recognition performance. The databases that are considered are FRGC v1, FRGC v2, BU-3DFE, Bosphorus, SHREC'08, FRAV 3D, and CASIA. An example scan from each of these databases is shown in Fig. 2. Although the surface representations differ according to how they are stored in the database, each representation essentially codes for 3-D facial information, and all can be converted to the same representation, if required by a particular face-recognition methodology.

The most popular 3-D expression databases are the FRGC databases [9]. The Grand Challenge probably has had and still has a large impact on the development and testing of face-recognition algorithms. The FRGC databases are, therefore, considered as the reference databases for validation of 3-D face-recognition algorithm. The 3-D scans, which are 640 $\times$ 480 range images, were taken under controlled illumination conditions by a "Minolta Vivid 900/910" scanner (laser range scanning technique) with coregistered RGB texture information. Data are divided into a training dataset (FRGC v1), which contain 943 3-D scans, and a validation dataset (FRGC v2), which contain 4007 3-D scans from 466 persons. Compared with the training set, the validation set contains additional expressions, such as anger, happiness, sadness, surprise, and disgust, as well as puffy faces.

Another reference database that is acquired especially for expression recognition and expression-invariant face recognition

TABLE I
OVERVIEW OF DATABASES WITH EXPRESSIONS

database	institute	# im.	# subj.	type	texture	URL
Biometrics [8], [34]	University of Notre Dame	1906	277	range im.	yes	http://www.cse.nd.edu/~cvrl/CVRL/Data_Sets.html
FRGC v1 [9]	University of Notre Dame	943	200	range im.	yes	http://www.frvt.org/FRGC/
FRGC v2 [9]	University of Notre Dame	4007	466	range im.	yes	http://www.frvt.org/FRGC/
ND2006 [35]	University of Notre Dame	13450	888	range im.	yes	http://www.nd.edu/~cvrl/
GavabDB [36]	Universidad Rey Juan Carlos	549	61	range im.	no	http://www.gavab.etsii.urjc.es/recursos_en.html
FRAV3D [37]	Universidad Rey Juan Carlos	1696	106	mesh	yes	http://www.frav.es/databases/FRAV3d/
UoY [38]	University of York	5250	350	mesh	yes	http://www-users.cs.york.ac.uk/~nep/research/3Dface/tomh/3DFaceDatabase.html
BJUT-3D [39]	Beijing University	?	500	mesh	yes	http://www.bjpu.edu.cn/sci/multimedia/mul-lab/3dface/overview.htm
Bosphorus [40]	Boğaziçi University	4666	105	point cloud	yes	http://www.cmpe.boun.edu.tr/~dibeklioglu/documents/bioid2008_db.pdf
BU-3DFE [15]	Binghamton University	2500	100	mesh	yes	http://www.cs.binghamton.edu/~lijun/Research/3DFE/3DFE_Analysis.html
BU-4DFE [41]	Binghamton University	60600	101	3D video	yes	http://www.cs.binghamton.edu/~lijun/Research/3DFE/3DFE_Analysis.html
CASIA [42]	Chinese Academy of Sciences	4059	123	range im.	no	http://www.ia.ac.cn:8080/english/
Texas 3DFRD [43]	University of Texas	1149	118	range im.	yes	http://live.ece.utexas.edu/research/texas3dfr/
FSU [44]	Florida State University	222	37	mesh	no	-
MSU [45]	Michigan State University	533	90	range im.	no	-
ZJU-3DFED [46]	Zhejiang University	360	40	mesh	yes	-
Beckman [47]	Beckman Institute	?	475	mesh	yes	-

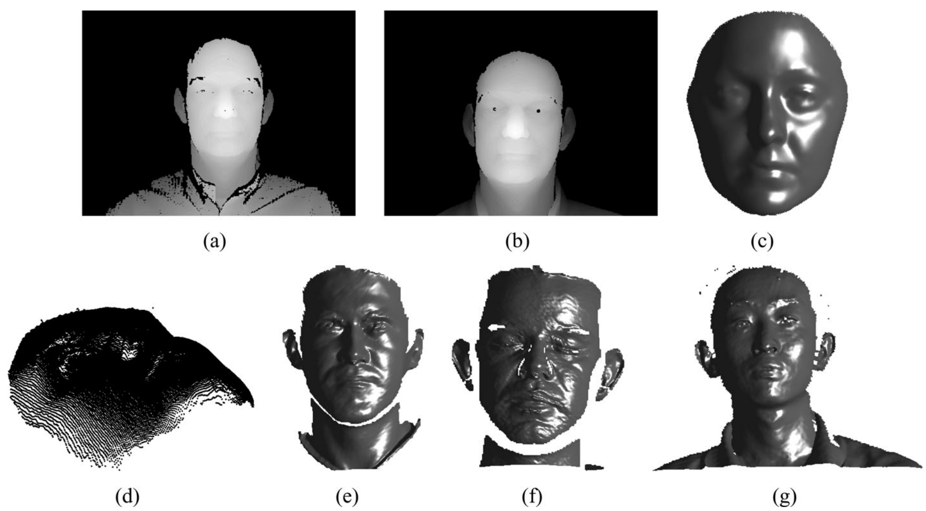

Fig. 2. One scan from each of the most used 3-D face databases containing expression variations is shown: (a) FRGC v1, (b) FRGC v2, (c) BU-3DFE, (d) Bosphorus, (e) SHREC'08, (f) FRAV, and (g) CASIA.

is the BU-3DFE database [15]. The 2500 3-D scans from 100 persons, with ages ranging from 18 to 70 years, are acquired with a "3dMD" scanner (stereo photogrammetry technique) and consist of 20 000–35 000 polygons and 1300×900 texture images. The database contains six types of expressions each with four levels of expression strength per subject. This makes it possible to evaluate degradation of recognition performance as a result of an increasing level of expression strength. The classification of the basic facial expressions into the six classes, i.e., anger, happiness, sadness, surprise, disgust, and fear, was proposed in [48]. The author also showed that facial expressions of emotion are not culturally determined, but universal across human cultures and thus biological in origin. Another advantage of the BU-3DFE database is the presence of fiducial points, which can be used in the development and evaluation of marker-based face-recognition algorithms.

A third important 3-D database is the Bosphorus database [40]. The facial expressions are composed of a selected subset of action units, as well as the six basic emotions (same as for BU-3DFE). The database consists of 4666 scans from 105 subjects and is acquired with the "Inspeck Mega Capturor II 3D" scanner (structured-light technique) leading to 3-D point clouds of approximately 35 000 points. Besides expression variations, pose variations and occlusions are also present in the database.

Another database that is often used to validate 3-D face-recognition algorithms that deal with expression variations is the GavabDB [36], which is acquired with a "Minolta VI-700" digitizer (laser range scanning technique). For each of the 61 subjects, nine scans are taken that include two frontal scans, three expression scans, and four scans with pose variations (35° up, 35° down, left and right profiles). A subset, excluding the profile scans, was used during the SHREC in 2008 [11]. An important advantage of this subset is that the faces are partially pose normalized (nose tip indicated).

The FRAV 3D database is also acquired with a "Minolta Vivid-700" scanner and contains 106 subject with 16 scans each (six frontal, eight nonfrontal poses, one smiling, and one open mouth). The CASIA databases, which are acquired with the "Minolta Vivid 910" scanner, contain 4059 facial scans from 123 persons, with different expressions (smile, laugh, anger, surprise, closed eyes) and pose variations.

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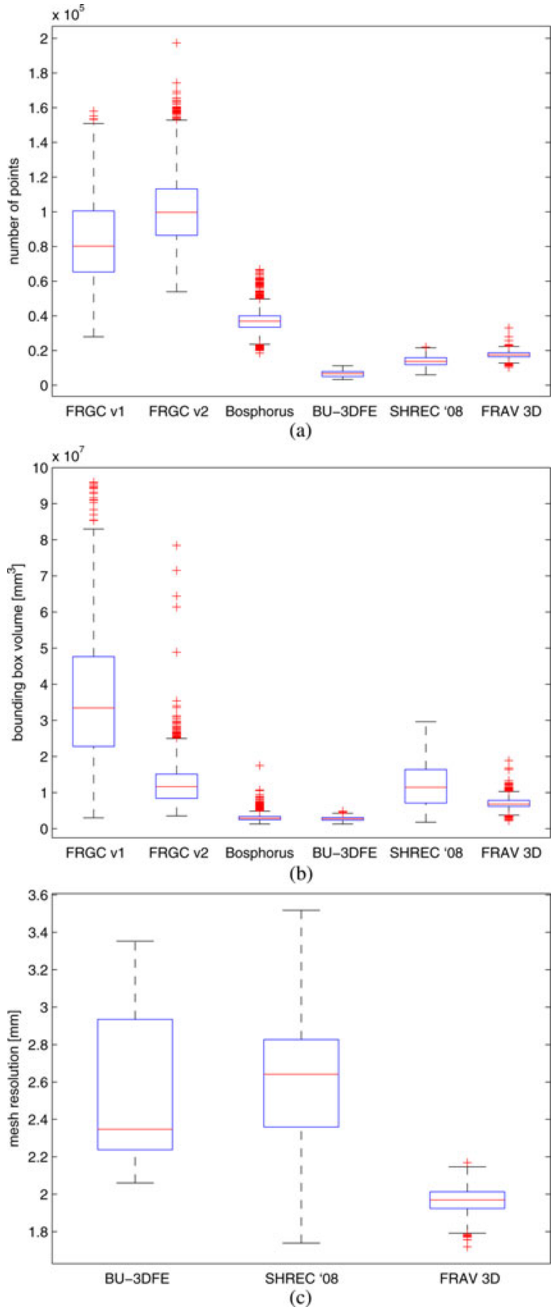

Fig. 3. Some important characteristics of the described databases, containing for each database (a) boxplot of the number of points, (b) bounding box volume, and (c) mesh resolution.

The main characteristics of the databases listed earlier are given in Fig. 3(a)–(c), containing for each database the boxplot of the number of points, the bounding box volume, and the mesh resolution, respectively.

In Fig. 3, it is shown that the number of points, as well as the bounding box, in the FRGC database is clearly higher (larger) than in the other databases. Moreover, the number of points per scan differs a lot within the FRGC database. This can be because of the use of different lenses on the Minolta 910, or equivalently, because of a change in distance of the subjects to the scanner. The larger the bounding box, the more nonfacial outliers can be expected, e.g., because of the presence of the chest in the scan. In Fig. 3(c), it is shown that the mesh resolution of the BU-3DFE database, the SHREC'08 dataset, and the FRAV 3-D database is similar.

B. Recognition Metrics

Biometric technologies aim at recognizing people by the use of two mutually exclusive scenarios. First, in the authentication or verification scenario, the problem is to verify that a person is indeed who he/she claims to be. This involves a one-to-one matching of the face image to be verified (the probe image) to one or more of the template images in the database (the gallery images) of the allegedly same person. Iris and fingerprint recognition is appropriate for solving this problem, but face recognition potentially also has this capability. Second, in the identification scenario, no identity is given *a priori* and the person is to be compared with several or all subjects in a gallery to establish his or her identity. This requires a one-to-many matching. In addition, for this problem, face recognition could provide a solution.

The verification and identification performance are measured by the receiving operating characteristic (ROC) curve and the cumulative match curve (CMC), respectively [5]. The ROC curve plots the false rejection rate (FRR) versus the false acceptance rate (FAR). The FAR is the fraction of probes that have wrongly been recognized as being the claimed identity. The FRR is the fraction of probes that have incorrectly been classified as being different from the claimed identity. The equal error rate (ERR) is the point on the ROC curve for which the FAR is equal to the FRR and can therefore be seen as an important scalar characteristic of the verification performance. Another often used point on the ROC is the FRR at 0.1% FAR, which has been advocated by the FRGC program. In [49], the performance point selected as the reference for the FRR at 0.1% FAR is 20%. The CMC plots the recognition rate (RR) versus the rank number. The Rank-1 recognition rate (R_1RR) is the percentage of all probes for which the best match in the gallery belongs to the same person and is, therefore, a good identification measure. The percentage of the best and the second-best correct matches is the Rank-2 recognition rate and so on for higher ranks. Another measure for identification is the percentage of closest matches (nearest neighbors) in a leave-one-out all-to-all matching scenario, which is also often termed as the recognition rate (RR). Here, we will denote it as NN. Note that this RR is mostly higher than the R_1RR.

C. Complexity Analysis Using Baseline Face-Recognition Algorithms

The performance of 3-D face-recognition methods will differ for different databases because of the inherent complexity of the databases. Moreover, most methods are designed on a particular database, introducing the risk of reduced performance on other databases. In order to quantify differences because of the inherent database complexity, one can use a standard baseline technique for 3-D face recognition on the different datasets.

TABLE II
COMPARISON WITH PCA OR ICP, FOUND IN THE LITERATURE

method	DB	# prob.	# temp. (subj.)	R_1RR
PCA [14]	-	-	70	55%
PCA [44]	FSU	185	37	82%
PCA [53]	FSU	300	50	58.4%
PCA [46]	ZJU	360	40	79.7%
PCA [54]	UND	877	100	80%
PCA [55]	UND	1590	355	61.3%
ICP [54]	UND	877	100	85%
ICP [55]	UND	1590	355	61.5%
ICP [56]	UND	1538	353	68.5%
ICP [57]	Gavab	120	30	51.7%
ICP [57]	Gavab	150	150(30)	65.3%
ICP [58]	FRGCv2	4007	466	73.4%
ICP [59]	Bosph.	1847	81	68.4%

The standard techniques for face recognition can be divided into two groups: principal component analysis (PCA)-based methods and algorithms using iterative closest points (ICP). The ICP algorithm, which was introduced in [50] and [51], iteratively aligns 3-D surfaces by the minimization of the squared Euclidean distance between closest points. Eigenfaces for 2-D face recognition were first used in [52]. Each $n \times m$ 2-D image is represented as a feature vector in the $n.m$ dimensional space. PCA finds the best vectors, which are called eigenfaces, in this space to describe the variations between faces. Lighting, pose, and scale variations are the main sources of bad classification. This technique is easily extended to 3-D (2.5-D) face recognition by replacing the color images by depth images.

1) Literature Comparison: We first quantify the differences of the reference databases based on a performance comparison of the baseline techniques using results that are found in the literature. These are shown in Table II.

As can be seen, the difference in performance between datasets can be really large (R_1RR $\in [55, 80]$ for PCA and R_1RR $\in [51.7, 85]$ for ICP). However, the implementation of the baseline techniques by the different authors can differ slightly as well. Therefore, we reimplemented the standard ICP algorithm as detailed in the next section and used it to perform the standard recognition experiments on these reference databases.

2) Comparison With ICP Implementation: As the baseline algorithm, we implemented the standard ICP algorithm. In the first step of each iteration, for each point on the floating surface (the surface to be transformed), the closest point on the target (fixed) surface is determined, generating pairs of corresponding points on these surfaces. In the second step, rigid transformation parameters are estimated by the minimization of the squared Euclidean distances between corresponding points. In the third step of each iteration, this rigid transformation is applied to the floating surface points. The iterative alignment process stops when the maximum number ($N = 25$) of iterations is reached, limiting the computation time. The root-mean-squared (RMS) distance between corresponding, i.e., closest, points is chosen to be the final dissimilarity between the two registered 3-D surfaces. This RMS distance is assumed to be smaller, when two facial surfaces belong to the same versus a different person.

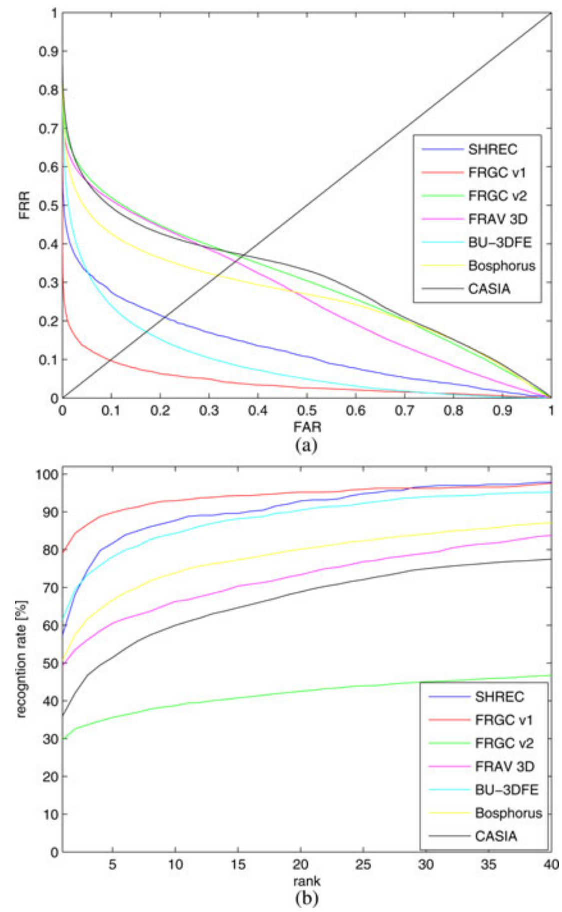

Fig. 4. (a) ROC and (b) CMC to compare the different databases using the ICP algorithm.

TABLE III
PERFORMANCE COMPARISON OF THE DIFFERENT EXPRESSION DATABASES

database	EER	R_1RR	NN
FRGC v1	9.78%	78.29%	81.12%
BU-3DFE	17.16%	64.17%	95.56%
SHREC	20.96%	58.20%	90.40%
Bosphorus	31.79%	50.77%	85.85%
FRAV	35.39%	49.28%	85.19%
CASIA	37.07%	35.95%	86.43%
FRGC v2	36.55%	28.10%	66.16%

The baseline algorithm is used for intradatabase face comparison providing a dissimilarity between any two faces in the same database. For identification, the first scan of each subject is selected as gallery image, while all other scans are considered as probe images. Every probe image is compared with every gallery image. For verification, every pair of faces is compared. The results for verification are shown by the ROCs in Fig. 4(a), while in Fig. 4(b), CMCs for the different databases in the identification scenario are plotted. Both figures illustrate the inherent complexity of the considered databases w.r.t. 3-D face recognition using ICP as a common baseline recognition algorithm.

The EER, R_1RR, and NN are listed in Table III, summarizing the face-recognition performance of the baseline ICP algorithm

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TABLE IV
FACTORS THAT INFLUENCE THE PERFORMANCE OF THE BASELINE ALGORITHM

	FRGC v1	FRGC v2	BU-3DFE	Bosphorus	GavabDB	FRAV3D	CASIA
Pose variations				√	√	√	√
Expression variations	√	√	√	√	√	√	√
Outliers	√	√		√	√	√	√
Texture	√	√	√	√		√	√

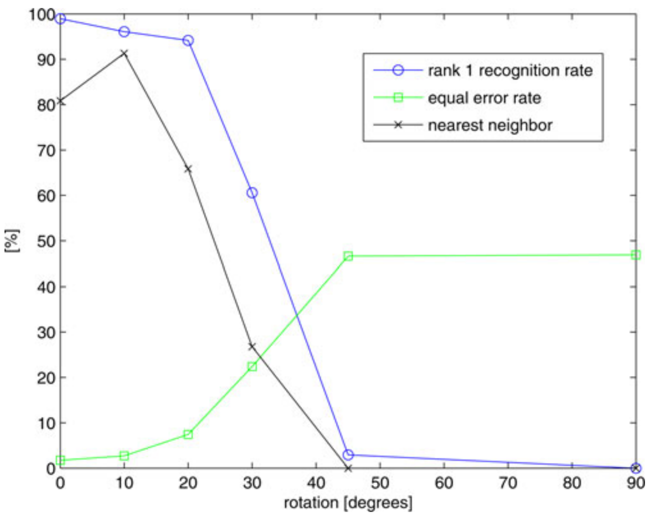

Fig. 5. R_1RR, the equal error rate, and the nearest neighbor rate as a function of the rotation of the neutral face in the Bosphorus database.

for each database. The databases are arranged according to a decreasing performance as measured by the R_1RR.

Based on this comparison, it is clear that the FRGC v2, CASIA, FRAV3D, and Bosphorus databases are the most challenging for the ICP algorithm. Because of its frequent use in the literature and its challenging nature, we recommend to use the FRGC v2 database further as a reference database to evaluate the overall performance of (expression-invariant) 3-D face-recognition algorithms. In the next section, we examine factors that explain the differences in performance for the different databases.

D. Discussion of Factors That Influence the Performance

The main factors influencing the performance of the baseline algorithm are pose variations, expression variations, the set-up of the experiment, the presence of outliers and the use of texture. In Table IV, we summarize the databases for which these factors are relevant.

In an attempt to quantify these factors, we use the Bosphorus database [40] and the BU-3DFE database [15] since they are annotated with pose and expression information.

1) Pose Variations: A first factor that influences the performance of the baseline method are large pose variations, which severely degrade the performance because the ICP-algorithm gets stuck in a local optimum. Different subsets of the Bosphorus database [40] are used to quantify the effect of face rotation on the performance of the baseline algorithm. Each subset consists of the first neutral scan and one scan per yaw-rotation (0°, 10°, 20°, 30°, 45°, or 90°) per subject.[1] The results are shown in Fig. 5, demonstrating a severe performance drop when the rotation is 45° or more.

2) Expression Variations: Another data-related factor of particular interest that influence the results is the presence of expressions in the probe set. We examine three aspects: the expression type, the expression strength, and the number of expressions in the database.

a) Expression type: Different subsets of the BU-3DFE and Bosphorus databases are used to quantify the effect of the type of expression on the performance of the baseline algorithm. The results are shown in Fig. 6. Although there are some differences between both databases, the "happy" expression seems to be challenging in both databases.

b) Expression strength: The expression strength also has a strong influence on algorithmic performance. The baseline ICP algorithm is used to perform the recognition experiments on four different subsets of the BU-3DFE database [15] with four levels of expression strength. In Fig. 7, the results are shown, demonstrating a clear performance decrease with an increasing level of expression strength.

c) Number of expressions: If more nonneutral probes are used, a performance decrease of 5.8% and 8.1% is observed in [60] and [55], respectively. This aspect can also be quantified using the baseline method. In Fig. 8, the R_1RR, the equal error rate, and the nearest neighbor rate against the number of different expression types in the BU-3DFE and Bosphorus databases are shown. The more expressions are considered, the lower the performance in terms of R_1RR and equal error rate. This tendency is not preserved for the nearest neighbor rate. This can be explained since more scans of the same subject are present in the dataset. The factor of an increasing number of subjects is examined in Section II-D3.

3) Design of the Experiment: The third source is the design of the experiment. An important factor is the number of templates. One of the conclusions in [61] about the results of the (2-D) Face-Recognition Vendor Test (FRVT) 2002 was the following:

> "For identification and watch list tasks, performance decreases linearly in the logarithm of the gallery size."

In a first experiment, this finding is validated by varying the number of gallery images, while keeping the number of subjects over the number of gallery images constant (a ratio of 1:25). The results are shown in Fig. 9, confirming the findings that are presented in [61] with Pearson's correlation coefficient:

[1]For 0°, there is not always a scan available. This explains the lower nearest neighbor rate.

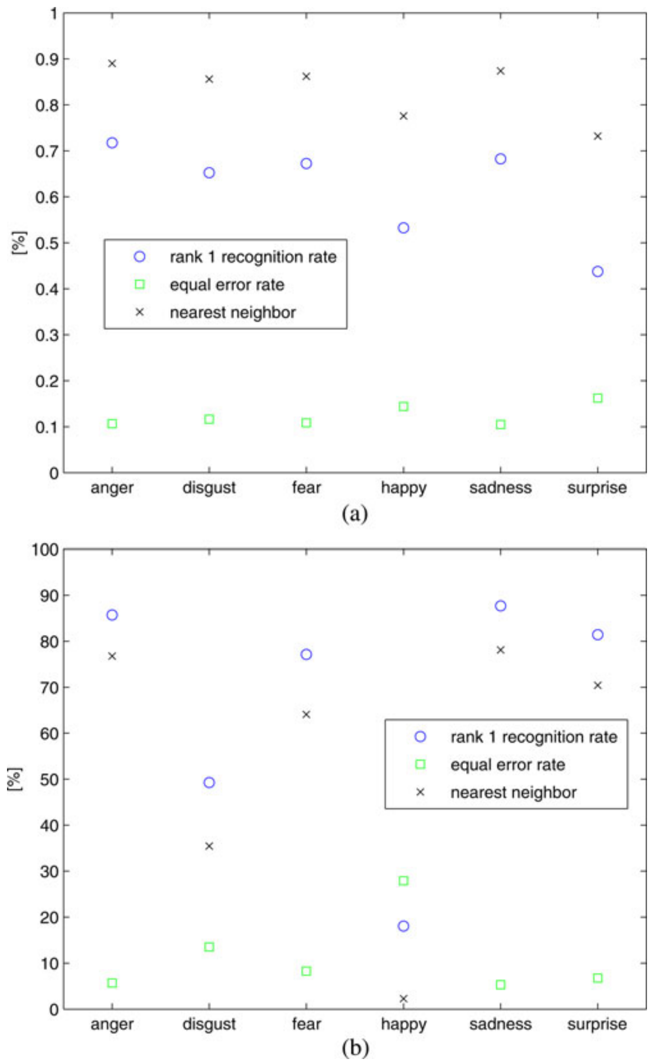

Fig. 6. R_1 RR, the equal error rate, and the nearest neighbor rate as a function of the expression type in (a) BU-3DFE database and (b) Bosphorus database.

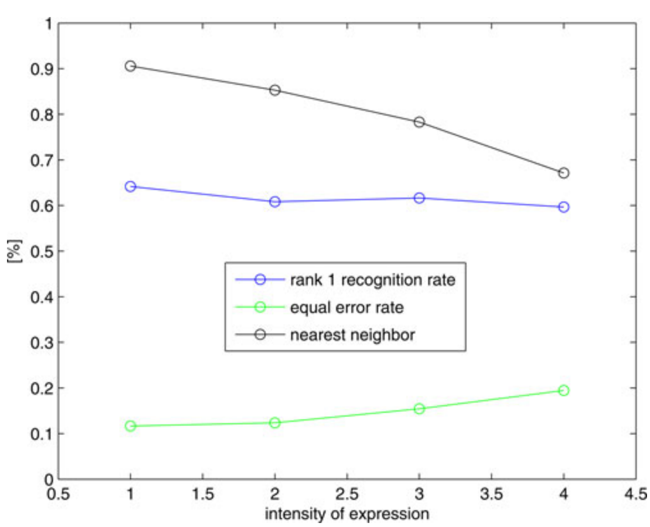

Fig. 7. R_1 RR, the equal error rate, and the nearest neighbor rate as a function of the number of expressions in the BU-3DFE database.

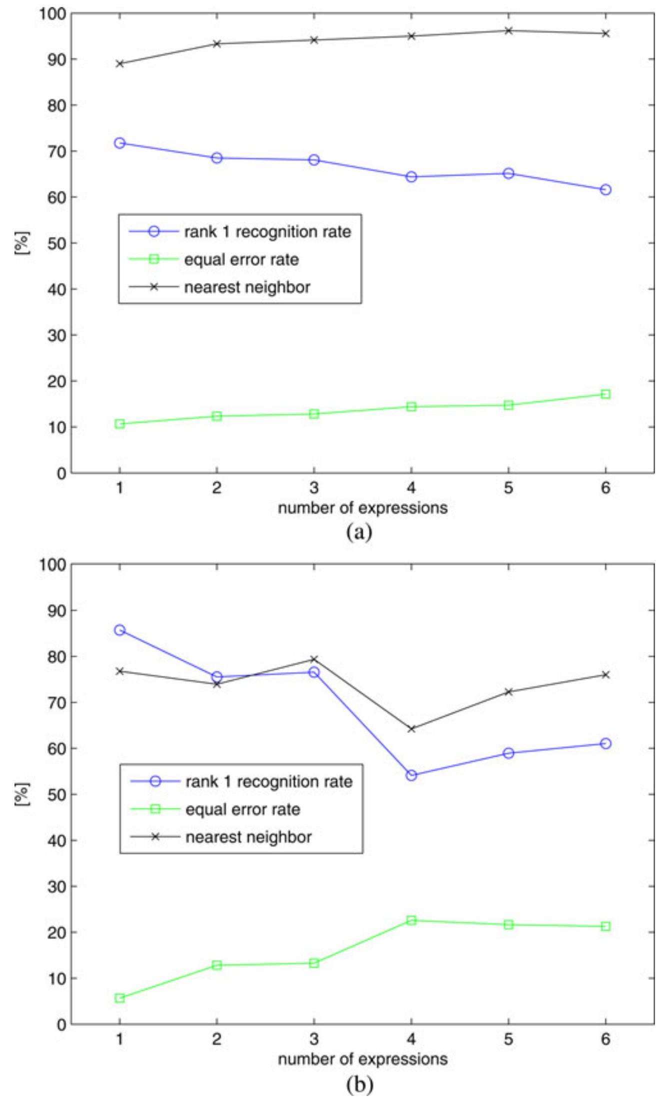

Fig. 8. R_1 RR, the equal error rate, and the nearest neighbor rate as a function of the number of different expression types in (a) BU-3DFE database and (b) Bosphorus database.

$r = -0.934$. This linear performance decrease, however, can only be seen for the R_1 RR and less, and so for the nearest neighbor rate or the equal error rate (with $r = -0.800$ and $r = -0.703$, respectively).

4) Outliers: The presence of outliers has a negative impact on the performance of the ICP baseline algorithm because of the risk to get stuck in a local optimum during optimization. Outliers can be present because of the presence of extra attributes (eyeglasses, hats, scarfs,...), a changing field of view of the 3-D scanner such that ears or chest are sometimes visible sometimes not, or because of artifacts in the acquisition. In Fig. 2, we provide an impression of the presence of outliers in the considered databases. The BU-3DFE database has the least number of outliers, which is (partly) the reason for the good performance of the baseline algorithm despite the strong expression variations (see Fig. 4 and Table III).

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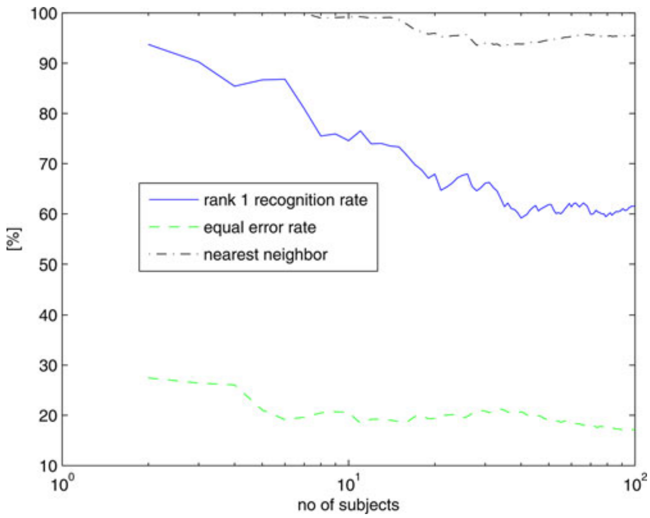

Fig. 9. R_1 RR, the equal error rate, and the nearest neighbor rate as a function of the number of subjects in the BU-3DFE database in a logarithmic plot.

5) Texture: The use of 2-D texture information combined with the 3-D shape is expected to provide better results than the use of 3-D shape information only. This expected difference is confirmed in [62]–[65], where the combination of 2-D and 3-D performs better. Using only 2-D texture information is expected to perform worse as is demonstrated in [66]. In [67], a recognition improvement is obtained by adding texture to the shape information for frontal (neutral and nonneutral) scans. However, a recognition decrease is noticed for nonfrontal scans, probably because of illumination changes in the texture information.

III. Three-Dimensional Face-Recognition Methods That Deal With Expression Variations

Because of facial muscle contractions the soft tissue of the face deforms during expression variations, which obviously has an effect on recognition performance. In this section, we review several 3-D face-recognition approaches and classify them into three main categories based on their approach to handle expression variations. Some methods build a statistical model of facial soft tissue deformations that are caused by expressions using a training dataset of expression-labeled exemplars. We termed these methods as *statistical methods*. Other methods assume the deformation because of expression variation to be isometric, meaning that the deformation preserves lengths along the surface. We call these methods the *isometric deformation modeling* approaches. The third class of methods, which are called *region-based methods*, does not assume a statistical or isometric deformation model but uses only regions that are not or not much affected by expressions. The three classes are discussed in more detail in the following sections. Their typical processing pathway is presented in Fig. 10.

A. Region-Based Methods

Historically, the first class of expression-invariant face-recognition algorithms is the region-based methods. In

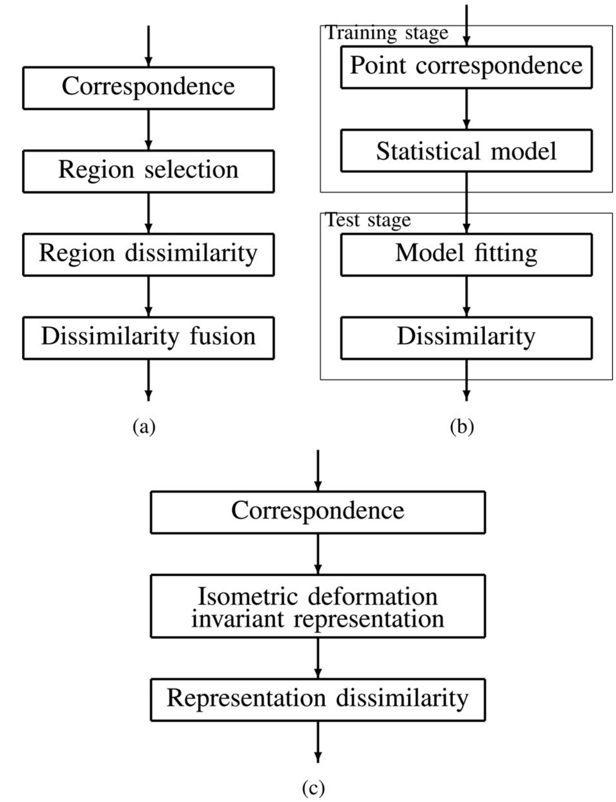

Fig. 10. (a) Typical structure of a region-based 3-D face-recognition algorithm. (b) an algorithm using a statistical model, and (c) an isometric deformation model.

Fig. 10(a), the typical structure of a region-based 3-D face-recognition algorithm is shown.

The first block contains the calculation of region correspondence, which is based on knowledge about the location of landmarks and their relation with the regions to be selected [59], [62], [68]–[72], by automatic region segmentation mostly using curvature information [55], [73]–[75], by a matching process [46], [59], [62], [63], [73], [76]–[82], or by a combination.

The second part is the selection of regions that vary less under expression deformations, which can be done by several strategies. The first and most used strategy is to select well-defined anatomic regions based on observations or on the literature. The most popular region is positioned around the nose, as in [55], [59], [62], [65], [68]–[71], [73]–[75], [83], and [81]. Another anatomic region that is used is the eyes/forehead region [59], [62], [70], [78]. The second strategy to determine expression-invariant regions is the use of local features. Convex regions [73], Gabor features [42], [65], [78], [84], [85], matched local-invariant range images [77], Haar and Pyramid wavelet features [79], and local shape pattern (LSP) features [82] appear to be less affected by expressions. This often involves a learning step using AdaBoost [42], [84], sparse representation classifier (SRC) [82], or visual codebooks [78]. The third strategy is the automatic determination of the more rigid part of the face during rigid registration as in [46], [63], [76], and [80]. Points with low registration error are considered to belong to the more rigid part of the face.

TABLE V
OVERVIEW OF THE RESULTS OF THE REGION-BASED METHODS

method	year	DB	# prob.	# temp. (subj.)	# expr.	RR	EER	FRR@0.1%FAR
Chua [76]	2000	-	6	6 (6)	4	100.0%	0.0%	0.0%
Mian [62]	2005	UND	671	277 (277)	-	100.0%	0.3%	±1.7%
[86]	2006	FRGCv1	668	275 (275)	-	100.0%	< 0.1%	0.0%
Maurer [63] (2D+3D)	2005	FRGCv2	4007	4007 (466)	-	-	2.1%	6.5%
(3D)	2005	FRGCv2	4007	4007 (466)	-	-	±3%	13.0%
Chang [55]	2006	UND	3839	449 (449)	-	95.2%	-	-
		UND	1590*	355 (355)	-	87.1%	12%	±37%
Wang [46]	2006	ZJU	320	40 (40)	4	96.9%	-	-
Mian [77] (2D+3D)	2006	FRGCv2	200*	466 (466)	-	81.0%	±3%	14.0%
(3D)	2006	FRGCv2	200*	466 (466)	-	73.0%	5%	24.0%
Faltemier [68]	2006	FRGCv2	3541	466 (466)	-	94.9%	-	-
		FRGCv2	4007	4007 (466)	-	-	3.2%	12.5%
		FRGCv2	2114	1893 (466)	-	-	2.5%	11.2%
[69]	2008	FRGCv2	3541	466 (466)	-	98.1%	-	-
		FRGCv2	4007	4007 (466)	-	-	-	6.8%
		FRGCv2	2114	1893 (466)	-	-	-	5.2%
Cook [65]	2006	FRGCv2	4007	466 (466)	-	93.2%	±1.6%	± 6.3%
[85]	2006	FRGCv2	4007	466 (466)	-	94.6%	-	-
		FRGCv2	4007	4007 (466)	-	-	-	7.7%
Xu [42]	2006	CASIA	500*	100 (100)	5	90.8%	-	-
[84]	2009	FRGCv2	2114	1893 (466)	-	-	±4.6%	29.5%
Zhong [78]	2007	FRGC	4950	4950 (466)	-	-	4.9%	
		CASIA	1845	1845 (123)	-	-	7.5%	
Lin [66] (sum rule)	2007	FRGCv2	2114	1893 (466)	-	-	±18%	69.16%
(LDA)		FRGCv2	2114	1893 (466)	-	-	±18%	68.96%
Kakadiaris [79]	2007	FRGCv2	4007	466 (466)	-	97.0%	-	-
	2007	FRGCv2	2144	1893 (466)	-	-	±1.5%	3.0%
		FRGCv2	2114	1893 (466)	-	-	-	4.7%
Queirolo [83]	2008	FRGCv2	4007	465 (465)	-	98.4%	-	-
		FRGCv2	4007	4007 (465)	-	-	-	3.5%
		FRGCv2	2144	1893 (465)	-	-	-	3.4%
Xu [71]	2008	SHREC	427	427 (61)	7	81.7%†	-	-
[84]	2009	CASIA	500*	100 (100)	5	90.0%	-	-
Nair [75]	2008	SHREC	427	427 (61)	7	82.2%†	-	-
Fabry [80]	2008	SHREC	427	427 (61)	7	90.6%†	-	-
Alyüz [59]	2008	Bosph.	1847	81 (81)	34	95.4%	-	-
Smeets [81]	2010	BU-3DFE	900	100 (100)	8	89.9%	-	-
		BU-3DFE	900	900 (100)	8	-	6.8%	-

In the third part, region dissimilarities are calculated using a variety of dissimilarity measures. The region dissimilarity is frequently set equal to the final average dissimilarity measure that is used for the matching process, when region correspondence is found by a matching process or with an additional registration for dissimilarity calculation. This is often the Euclidean distance between closest points (ICP) as in [46], [62], [63], [68], [74], and [81], but also correlation [73], number of points having a similar feature [76], surface interpenetration measure [70], and kernel correlation [80] are used. In some cases, the dissimilarity is measured with a measure different from the one used during matching, e.g., the volumetric difference [59] or Hausdorff distance [75]. Other dissimilarity measures that are computed between feature vectors are the Mahalanobis cosine [65], the mean Euclidean distance [77], the Bray–Curtis distance [71], L1 distance [79], and the structural similarity (SSIM) index [79] (which is translational insensitive with the intention to be insensitive for expressions). Dissimilarity can also be obtained using a learned classifier [42], [82], [84].

When more than one region is taken into account, fusion of the region dissimilarities is needed. This can be done at score or rank level, combining the dissimilarity scores or the ranks, respectively, after ordering of the faces based on the individual scores. Fusion is not always necessary since sometimes only one region is used [46], [71], [75], [76]. When fusing is used, authors often experiment with different fusing rules [55], [59], [62], [69], [74]. At the score level, the product rule consistently seems to be the best in [55], [62], [74], and [59], while the sum rule is used in [73], [77], [83], [85], and [81]. At the rank level, the Borda count voting scheme is used in [69].

An advantage of region-based methods is their handling of missing data, since these methods work quasi-locally. However, region-based methods do not use all available information by throwing away those parts that are affected by expressions. This leads to loss of information that could be discriminative.

In Table V, we provide an overview of the reported results of the region-based methods. The asterisk in the "# prob." column indicates that only nonneutral probes are used. The "†" in "RR" column means that the nearest neighbor rate is used instead of the R_1RR.

B. Statistical Modeling Methods

In the second class of methods, a statistical model is used. The most popular statistical model is the PCA model, which expresses a random shape $\mathcal{S}$ as the sum of the average shape $\overline{\mathcal{S}}$ of the training set and a linear combination of the principal components, which is mathematically expressed as

$$\mathcal{S}(\alpha) = \overline{\mathcal{S}} + M \cdot \alpha \tag{1}$$

with M being a matrix that contains the principal components in the columns and α the coefficients of the shape in the PCA space. In order to obtain such a statistical model, correspondences between different shapes are needed. Each shape can then be represented as a vector in an n-dimensional space. The principal components are the eigenvectors of the covariance matrix, calculated on the n-dimensional vector representations of the shapes in the training data. The eigenvector that corresponds to the largest eigenvalue describes the largest mode of variation. If all model parameters α_i of the model are retained, the shape can be fully recovered. However, when dimensionality reduction is applied, only the parameters that correspond to the largest modes of variation are preserved. PCA models are often used in 2-D face recognition [87], leading to the concept of eigenfaces. This made its application on 2.5-D range images a logic extension. Later on, PCA was also applied to 3-D scans.

In Fig. 10(b), the general structure of methods using a statistical model for expression-invariant face recognition, which consists of two main stages, i.e., a training and a test stage, is shown. The training stage involves establishing point correspondence and statistical model construction. In the test stage, the model is fit to the probe, and a dissimilarity measure is calculated.

A variety of methods are available for finding point correspondences. When the statistical model is derived from range images, pose normalization and projection onto a 2-D grid provide 2-D range images that are pixelwise in correspondence [44], [88], [89]. In statistical models that are derived from 3-D shapes, ICP often provides correspondence information, as in [90] (combined with features for initialization), [91] (on the rigid parts of the face) and [92] (with extra energy terms for regularization and larger convergence area). In [93], anatomic landmarks are detected as correspondence information.

Second, a statistical model is built using the correspondence information. A PCA shape model can deal with expressions by including faces with expression in the training data as in [44], [88], and [90]. PCA can also be used to model deformations, in this case, the deformation during expression variations. This is called "principal warps" and is done in [94] and [91]. The former combined this expression model with a PCA shape model for identity into one additive model, assuming that it is possible to transfer expressions from one face to another. When this assumption is considered to be false, it is necessary to combine the expression model and identity model into a bilinear model as in [92]. However, model fitting becomes computationally more demanding. Other statistical models use independent component analysis (ICA) [44], linear discriminant analysis (LDA) [88] or simply pointwise mean and standard deviation [93].

During validation, the model needs to be fitted to the probe. Some methods solve this by a combination of correspondence findings and projection onto the subspace obtained by the statistical model [44], [88], [90], [91], while others minimize cost functions with respect to transformation parameters and statistical model parameters [45], [92], [94].

Finally, when the model is fitted, a dissimilarity measure between probe and gallery is calculated. Popular measures are the Euclidean distance [44], [88], [92], the related RMS distance [45], the cosine distance [88], [90], [94], the Mahalanobis distance [89], and the number of matched points [93].

An important advantage of these statistical model-based methods is that the template must not be matched to every gallery image, but only to the statistical model, if dimensionality reduction has been applied. This makes statistical models generally the fastest.

On the other hand, these methods always need a training stage to construct the model. Therefore, if no sufficient representative training data are used or are available, the recognition performance will decrease. Moreover, the quality of the shape or deformation model depends on the quality of the point correspondences, which is still an active field of research for 3-D face data.

In Table VI, we summarize the results of the methods using a statistical model.

C. Isometric Deformation Modeling

The third class of algorithms makes use of an isometric deformation model in which facial surface changes during expression variations are modeled as isometric deformations. Since expression variations can be approximated by isometric transformations [97], the isometric deformation-invariant representation is approximately an expression-invariant representation. Since it is invariant for position and orientation, it is an intrinsic representation. Mathematically, an isometric deformation of a submanifold $\mathcal{M}$ in a Riemannian space $\mathcal{V}$ is a deformation that preserves the lengths of curves in $\mathcal{M}$. For recognition purposes, it is interesting to study geometric invariants during isometric deformations. According to Gauss's Theorema Egregium, the Gaussian curvature K of a surface, i.e., the product of the principal curvatures, is invariant under local isometry [98]. However, on real surfaces, curvatures are sensitive to noise, which makes the practical use of this invariant difficult. Another geometric invariant is the first fundamental form of $\mathcal{M}$, which is the inner product of the tangent vectors and is given explicitly by the Riemannian metric [99]

$$ds^2 = Edu^2 + 2Fdudv + Gdv^2. \tag{2}$$

It determines the arc length of a curve on a surface. The coefficients are given as follows [99]:

$$E = \left|\frac{\partial \mathbf{x}}{\partial \mathbf{u}}\right|^2 \tag{3}$$

$$F = \frac{\partial \mathbf{x}}{\partial \mathbf{u}} \cdot \frac{\partial \mathbf{x}}{\partial \mathbf{v}} \tag{4}$$

$$G = \left|\frac{\partial \mathbf{x}}{\partial \mathbf{v}}\right|^2. \tag{5}$$

The shortest path between two points on the surface is called the minimal geodesic, and its length is called the geodesic distance. This geometric invariant is less noise sensitive and,

TABLE VI
OVERVIEW OF THE REPORTED RESULTS OF THE NONRIGID METHODS

method	year	DB	# prob.	# temp. (subj.)	# expr.	RR	EER	FRR@0.1%FAR
Hesher [44] (PCA)	2003	FSU	37*	185 (37)	6	94%	-	-
(ICA)		FSU	37*	185 (37)	6	97%	-	-
Heseltine [88]	2004	York	1470	(230)		-	8.2%	>45%
Zhong [89]	2006	CASIA	861	369 (123)	5	96.1%	-	-
Lu [54] (ESM)	2006	UND	877	100 (100)	7	92%	±2%	±31%
(EGM)		UND	877	100 (100)	7	89%	±7.5%	±33%
(ESM)		MSU	533	90 (90)	2	94%	±5%	±47%
(EGM)		MSU	533	90 (90)	2	91.5%	±7%	±51%
Russ [90]	2006	UND	753*	202 (202)	-	82.6%	-	9%
Amberg [95]([94])	2008	SHREC	427	427 (61)	7	99.7%(98.8%)	0.2%	0.2%
		UND	953	953 (?)	-	100.0%	0.2%	-
Mpiperis [92]	2008	BU3DFE	1250	? (50)	6	86%	±12%	>40%
Al-Osaimi [96]	2009	FRGCv2	3541	466 (466)	-	96.52%	-	-
Al-Osaimi [96]	2009	FRGCv2	2114	1893 (466)	-	-	±2.7%	5.95%
Kaushik [93]	2009	BU-3DFE	695	695 (100)	6	98.92%	1.08%	

therefore, often used for isometric deformation-invariant 3-D face recognition. The geodesic distance can be calculated by the fast marching method on triangulated domains, as described in [100].

A method using an isometric deformation model usually has a structure as shown in Fig. 10(c), i.e., correspondence finding, the construction of an isometric deformation-invariant representation, and dissimilarity calculation.

First, some minimal correspondence information is required in order to construct the isometric deformation-invariant representation. In [60], [101]–[107], and [108], the nose tip is localized on the probe and gallery image either automatically or manually. This location and its relation, by definition, with the invariant representation, provide enough correspondence information. In [57], [109], and [110], 43, 25, and 7 manual landmarks are indicated, respectively. In [110], extra pseudolandmarks are found by remeshing. In [111], ICP is used for correspondence finding, and in [112], the face is fitted to a cylinder and further aligned by mesh resampling. Finally, in [113] and [114], correspondence calculation is done after construction of the isometric deformation-invariant representation, respectively, with a moment matching algorithm and in an implicit manner with a singular-value decomposition.

The mostly used isometric deformation-invariant representations are isogeodesics, curves containing points on an equal geodesic distance to a reference point (nose tip), as in [60], [102], [104], [105], [107], [108], and [115]. Vectors with geodesic distances from points in a well-defined order are related to the nose tip [111]. Those representations have the advantage that only the geodesic distances from the nose tip to all other points need to be calculated, which is efficiently done with the fast marching method for triangulated domains [100]. In [101] and [103], the depth values of points on a facial surface mesh are (near-)isometrically mapped to an isomorphic circle. A computational more demanding representation is the geodesic distance matrix, containing the geodesic distance between each pair of points as in [112]–[114], or with a limited number of points, in [57], [109], and [110]. In [113], this geodesic distance matrix is transformed into a geometrical configuration using the multidimensional scaling algorithm.

TABLE VII
OVERVIEW OF THE RESULTS OF THE ISOMETRIC DEFORMATION METHODS

	$\tilde{X}$	$\overline{X}$	S	n
region-based methods	94.6%	91.9%	7.3%	21
statistical methods	94.0%	93.7%	5.3%	13
isometric methods	94.5%	91.6%	8.5%	26

The final step is to calculate a dissimilarity between the invariant representations in order to be able to compare faces, using a dissimilarity measure on features of the representation [60], [102], [104]–[108], [110], [111], [114], a dissimilarity measure on statistical model coefficients [57], [103], [109], [112], [116], or a dissimilarity measure on the matching process of the invariant representations [113], [117], [118].

A benefit of the isometric deformation model is that it needs no training and that it has a broad applicability. As demonstrated in [97], geodesic distances between corresponding point pairs do not remain constant during expression variations. Following [103], the standard deviation of the relative change in the geodesic distance was found to be about 15%. Therefore, the isometric deformation model is an approximation only. Moreover, topological changes, like occlusions and open mouth, need special care since they disturb the correct calculation of the geodesic distances.

In Table VII, we provide an overview of the reported results of the methods using a isometric deformation model.

D. Quantitative Comparison

In this section, we perform a quantitative comparison between the different class performances. Thereto, we analyze the available RRs without taking into account the data used. The median $\tilde{X}$, the sample mean $\overline{X}$, and standard deviation S of the RRs are computed for each class and shown in Table VIII.

No statistical significant difference in performance is found between any pair of classes. The hypothesis of equal median could not be rejected for any pair using the Wilcoxon rank

TABLE VIII
QUANTITATIVE COMPARISON

method	year	DB	# prob.	# temp. (subj.)	# expr.	RR	EER	FRR@0.1%FAR
Bronstein [113]	2005	-	220	65 (30)	10	100.0%	1.9%	±7.5%
[117]	2005	-	104	? (4)	7	98.0%	12.4%	-
[119]	2006	UND	180	30 (30)	6	100.0%	3.1%	±24%
Pan [101]	2005	FRGCv1	943	943 (276)	-	95%	2.83%	-
Samir [53]	2006	FSU	300	50 (50)	6	59%	-	-
		FSU	300	250 (50)	6	92%	-	-
		UND	270	470 (162)	-	90.4%	±2%	±14%
Berretti [60]	2006	Gavab	366	61 (61)	7	87.8%	-	-
		Gavab	183*	61 (61)	3	82.0%	-	-
[72]	2008	Gavab	427	427 (61)	7	99.5%	-	-
Ouji [111]	2006	ECL-IV	400	? (50)	8	92.7%	±12%	25%
Feng [102]	2007	UND	-	222 (222)	-	95%	-	-
Li [57]	2007	Gavab	120	30 (30)	7	94.2%	-	-
		Gavab	150	150 (30)	7	97.0%	-	-
		FRGCv2	150	30 (30)	6	85.4%	-	-
		FRGCv2	180	180 (30)	6	95.6%	-	-
Li [110]	2009	Gavab+FRGCv2	600	120 (120)	5	94.7%	-	-
Mpiperis [103] (color)	2007	BU3DFE	1500	100 (100)	7	80.3%	9.8%	25%
(depth)	2007	BU3DFE	1500	100 (100)	7	84.4%	12.0%	25%
Gupta [120]	2007	-	663	105 (105)	2	94.7%	1.3%	3.5%
Jahanbin [104] (LDA)	2008	-	813	10 (109)	-	-	2.6%	±12%
(SVM)	2008	-	813	10 (109)	-	-	2.8%	25%
Li [105]	2008	CASIA	300	100 (100)	4	90.3%	-	-
terHaar [107]([106])	2009	SHREC	427	427 (61)	7	92.5% (91.1%)	-	-
		UND	953	953 (?)	-	97.6%	-	-
Smeets [114]	2009	BU3DFE	900	100 (100)	3	-	13.4%	71.07%
Miao [108]	2010	FRGCv2	100	50 (50)	2	93.64%	-	-
		FRGCv2	100	100 (50)	2	-	±12%	±26%
Tang [112]	2010	BJUT-3D	450	150 (150)	3	95.3%	-	-
		FRGCv2	350	350 (350)	3	95.04%	-	-

sum test (region based versus statistical: $p = 0.62$; region based versus isometric: $p = 0.91$; and statistical versus isometric: $p = 0.60$).

The main limitation of this metaanalysis, however, is that the algorithms' performances are obtained on different datasets. It would therefore be better to analyze results on a standard dataset, but not enough samples are available for this. Second, the specific implementation of a certain method has an important influence on the method's performance. It would therefore be interesting to implement a baseline method for each strategy. Finally, nonparametric tests, as the one used in this metaanalysis, are known to lack statistical power with small sample sizes. Therefore, the current metaanalysis can only give limited insights. However, it does allow reflecting about the development of both methodologies and their implementations, as well as the construction of future databases.

IV. Discussion of the Face-Recognition Methods

During the development of 3-D face-recognition algorithms, several design choices have to be made, like the representation of the 3-D face, the way to establish the correspondence information and the dissimilarity measure. They all have an influence on recognition performance, speed of the algorithm, implementation time, applicability to real situations, and so on. Here, we discuss these fundamental problems in 3-D face recognition for which design choices are crucial.

A. *Face Representations*

All the face-recognition algorithms that are discussed in this paper use a database containing range images, meshes, or point clouds. This representation mainly depends on the way the acquisition device outputs data. However, many of the face-recognition algorithms use another internal data representation of the faces for probe-template comparison or as an intermediate representation. We discuss three representations (landmarks, curves, surfaces) that are all extrinsic. Intrinsic representations, which are independent of the reference frame, can be extracted from these basic extrinsic representations.

A first type of representation consists of a sparse set of landmarks. Originally, a landmark literally means a geographic feature that is used by explorers and others to find their way back or through an area. In modern usage, a landmark includes anything that is easily recognizable. In cephalometry, i.e., the measurement of the human head by imaging, or in anthropometry, in general, those landmarks play a crucial role [121], [122]. For 3-D facial expression methods, those landmark representations are used in [120] and [57]. The main disadvantage of this representation is its sparseness, implying that some useful shape information is not captured in the representation. On the other hand, by using landmarks, the fundamental problem of correspondence is easier to solve (see the text).

The second way of representation of faces are contour curves and profiles, as shown in Fig. 11. Contour curves are closed, nonintersecting curves of different lengths [see Fig. 11(c)–(f)]. Profile curves have a starting and an end point [see Fig. 11(a) and Fig. 11(b)]. Mostly, the starting point is in the middle of the face,

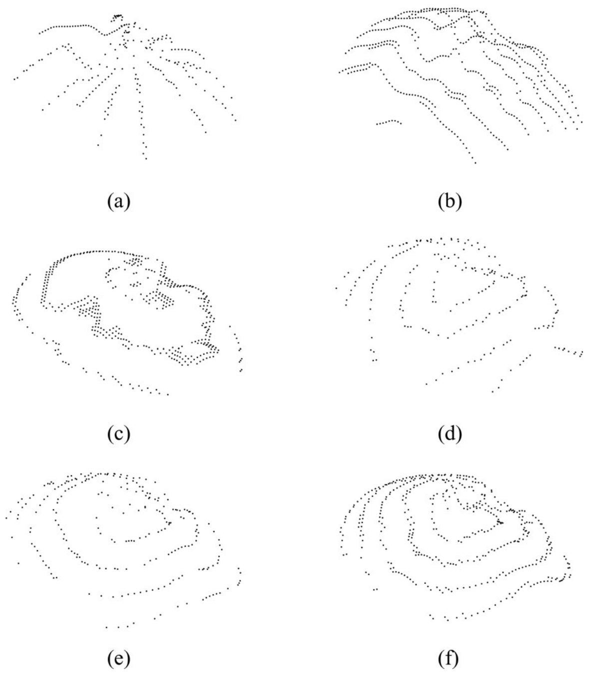

Fig. 11. Points on profile curves with (a) curve parts under the same angle or (b) same x-value and (c) points lying on iso-depth curves and on isoradius curves obtained by intersection with (d) cylinder or (e) sphere, and (f) isogeodesics.

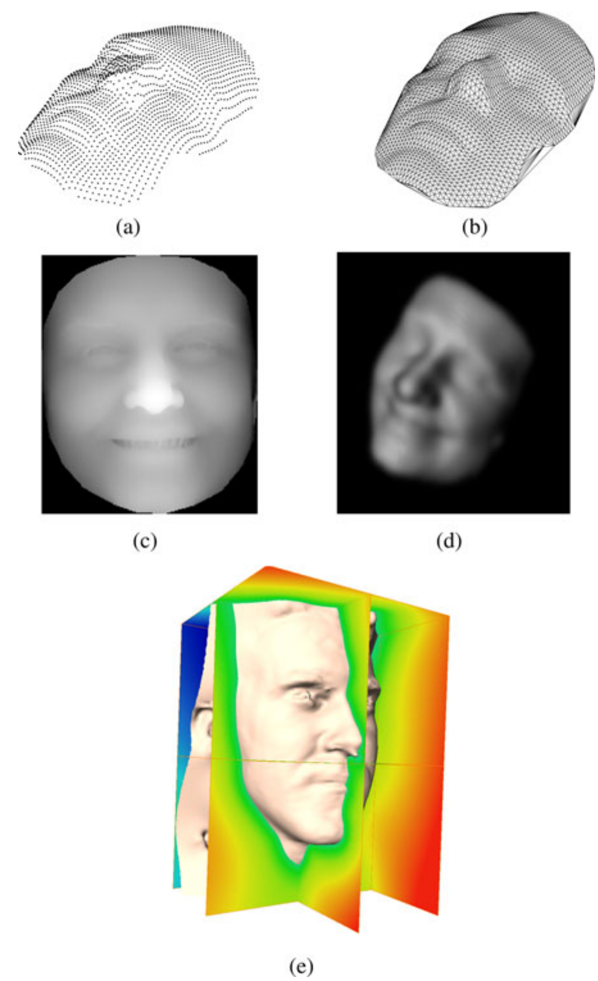

Fig. 12. Possible surface representations of 3-D faces are (a) dense point cloud, (b) mesh, (c) the range image, (d) kernel density estimate, and (e) distance map.

while the end point is at the edge of the face. Contour curves can be subdivided into isodepth curves and isogeodesics. Isodepth curves are obtained by translating a plane through an object in one direction. The intersections of the object surface and the plane are closed contours and form isodepth curves. In [104] and [53], iso-depth curves are used as face representation. All points on an isogeodesic curve have an equal geodesic distance to a reference point. According to isometric models, isogeodesics are more or less invariant for expression variations. In [60], [102]–[105], isogeodesics are, therefore, used for expression-invariant face recognition. Curve representations are less sparse than landmarks; however, some facial shape information is still not captured. Often, by use of such curves, the relative weight of the reference point, mostly the nose tip, is higher than points on, e.g., the cheeks. This is mostly an advantage since the nose region contains distinctive shape information as shown in [55].

The third type for representation of faces are surfaces, as shown in Fig. 12. A review of surface representations is given in [123] and [124]. Most surface representations that are used for 3-D face-recognition methods are explicit. Dense point clouds are the most simple representation of surfaces [see Fig. 12(a)]. However, they are frequently used because of the ease to transform it into another representation. They are used in [113] and [54]. A mesh, i.e., a cloud of points that are connected by edges, can be constructed given a point cloud [see Fig. 12(b)]. The most powerful algorithm to deal with this problem, i.e., the power crust algorithm, is described in [125]. Meshes are used in [57] and [56] and have the advantage of incorporating knowledge about the connectivity between points. This is useful for the calculation of geodesic distances, which can be calculated on a mesh using the fast marching method on triangulated domains [100]. Another frequently used explicit surface representation is range images, e.g., in [44], [83], and [88]; see Fig. 12(c). They can be easily captured with a laser scanner or especially calculated as intermediate surface representation [53]. Another interesting representation is the point-cloud-based kernel density estimate used in [80]; see Fig. 12(d). Implicit surface representation is far less used for 3-D face recognition, although some positive arguments are stated in [123]. The only used implicit representation is the distance map in [126]; see Fig. 12(e).

B. *Correspondences*

The second fundamental research question in 3-D face recognition is the correspondence problem.

The most simple way of finding correspondences is the manual indication of landmarks as done in [57] and [120]. The main advantage is reliability because of the user intelligence that can be used. However, the indication of landmarks is a tedious and timeconsuming task, and therefore, only a relative small set of corresponding points is obtained.

Starting from a set of manual landmarks, heuristic rules can be used to generate more corresponding points.

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TABLE IX
MOST COMMON DISSIMILARITY MEASURES

Dissimilarity measure	definition
Euclidean distance	$D(p,q) = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2}$
Normalized Euclidean distance	$D(p,q) = \sqrt{\sum_{i=1}^{n}\frac{(p_i-q_i)^2}{\sigma_i^2}}$
Mahalanobis distance	$D(p,q) = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{(p_i-q_j)^2}{\Sigma_{ij}^2}}$
Root mean square distance	$D(p,q) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i - q_i)^2}$
Cosine distance	$D(p,q) = 1 - \frac{\sum_{i=1}^{n} p_i q_i}{\sqrt{\sum_{i=1}^{n} p_i^2}\sqrt{\sum_{i=1}^{n} q_i^2}}$

Dense correspondences can be determined using rigid and nonrigid alignment of facial surfaces. The standard algorithm for rigid surface registration is the ICP algorithm, which iteratively finds correspondences using the nearest neighbor principle and calculates a rigid transformation aligning these corresponding points. It is used in [45], [46], [55], [59], [62], [63], [69], [75], [79], [90], and [95]. Besides ICP, other rigid registration methods are used, such as higher order moment matching in [116] and mean shift in [80].

C. Dissimilarity Measures

Face-recognition algorithms require a dissimilarity measure, a scalar value on the basis of which a verification/identification decision is made. In Table IX, we list the most common dissimilarity measures. The vectors p_i and q_i typically represent 3-D coordinates of corresponding points.

In [127], a psychological study reveals that the Cosine distance in face space (PCA) bears a closer relation to how humans perceive similarity than the Euclidean distance in face space.

V. CONCLUSION AND FUTURE CHALLENGES

A. Conclusion

In this study, an overview of the most important existing public 3-D face databases containing expressions has been provided. The availability of these databases worked as a catalyst for the development of (expression-invariant) 3-D face-recognition algorithms. However, since these algorithms have been tested on different databases, it is important to quantify the complexity of these databases when comparing one algorithm with another.

In order to quantify this complexity, in the context of face recognition, the use of the ICP algorithm as the baseline face-recognition technique to compare the databases has been proposed. Based on these results, the use of the FRGC v2 database as reference database has been recommended to evaluate the overall performance of (expression-invariant) 3-D face-recognition algorithms, since it shows the highest complexity expressed in ROC and CMC curves. The BU-3DFE database, on the other hand, is the most appropriate database to evaluate algorithms for robustness against expression variations. In an attempt to quantify the most influential factors in a database, first, these factors have been determined, and their influences on the performance of the ICP baseline algorithm have been measured. From these experiments, it is clear that large rotations deteriorate the performance of the baseline algorithm. Moreover, an increasing number of expressions and an increasing expression strength decreases the recognition performance during identification, as well as during verification. Performance differences for different types of expressions have also been observed.

Furthermore, a metaanalysis of 3-D expression-invariant face-recognition algorithms has been performed. Methods that deal with expression variations were subdivided into three groups. Region-based methods perform face recognition by only taking parts of the face into account that are more or less rigid during expressions. Isometrical deformation models use the invariance of geodesic distances between corresponding points. Statistical methods construct an additive or combined PCA decomposition either to model expressions separately or by including nonneutral faces in the training set, respectively. For each category, strengths and disadvantages were listed. It appeared that there is no global intercategory performance difference. A thorough and fair comparison, however, requires a standardized database to validate 3-D face-recognition algorithms on, for which we recommend to use the FRGC v2 database.

B. Future Challenges

One challenge will be the reduction in computational complexity, since the processing of the ever growing size of databases is proportional to the square of the database size and, thus, takes a considerable amount of time. For example, if it takes 1 s for a face-to-face comparison, validation of the FRGC v2 database requires 186 days. Parallel, cluster-based processing and GPU implementation provide a possible solution. Another data-related challenge is 3-D face acquisition with affordable and reliable equipment. This leads also to questions of minimum quality. How does the performance of 3-D face-recognition algorithms degrades with the decreasing quality of the data? An important aspect here is the limited capture range of 3-D face scanners, which, often in combination with self-occlusion, obligates 3-D face-recognition methods to deal with partial data. Some initial work has been done here [128], [129].

Although much research has been done on 3-D face recognition under expression variations, other intrashape deformations, mainly time-related changes, are not yet tackled in the current research. Ageing and weight variation manifest themselves in changes of the facial soft tissue envelope. Some work on age-invariant face recognition has been done [130]. However, the main challenge there is building appropriate databases to validate robustness against age variations. In addition, purposeful facial shape modification for identity spoofing becomes another challenge. Unfortunately, data to validate robustness against spoofing are not available.

With respect to 3-D face-recognition methodology, performance can be further increased by fusing different methods, different classes of methods [81], and/or different modalities. The challenges of such multibiometrics for person identification are discussed in [131]. The correspondence problem, which is often a key component in 3-D face-recognition algorithms, is still an active field of research, and 3-D face recognition will benefit from the improvement in solving this problem. In addition, we believe that solving the problem of expression-invariant 3-D face recognition could benefit from the dual problem of 3-D face expression recognition, and vice versa.

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