Block Based Face Recognition Approach Robust to Nose Alterations

Neslihan Kose, Nesli Erdogmus and Jean-Luc Dugelay
Multimedia Department, EURECOM
Sophia-Antipolis, France
{neslihan.kose, nesli.erdogmus, jean-luc.dugelay}@eurecom.fr

Abstract

Face recognition that is robust to alterations applied on face via plastic surgery or prosthetic make-up can be still considered as a new topic. In this paper, a block based face analysis approach is proposed which provides a fairly good recognition performance together with the advantage of robustness to such kind of alterations. For this study, a simulated nose alteration face database is used which is prepared using FRGC v1.0. Since this is a 3D database, the approach can be tested both in 2D and 3D, which is one of the contributions of this study. Furthermore, differently from previous works, baseline results for the original database are reported. The impact which is purely due to the applied nose alterations is measured using both the proposed approach and the standard techniques which are based on holistic description for comparison. The results indicate that although both 2D and 3D modalities lose precision due to alterations, the proposed approach is superior in terms of both the recognition performance and robustness to alterations compared to standard techniques.

1. Introduction

Plastic surgery is considered to be a new challenge in face recognition when compared to pose, expression or illumination variations [1]. The number of people resorting to plastic surgery for correction of feature defects or cosmetic reasons has been increased a lot in recent years. Therefore researchers started to work on measuring and preventing the impact of facial alterations on recognition.

To the best of our knowledge, the impact of plastic surgeries on face recognition was first analysed by Singh et al. in [3, 4] where the effect of plastic surgery is evaluated on several recognition algorithms. In our previous study [1], three shortcomings in the studies [3, 4] are identified as:

- Single image is provided before the plastic surgery procedure; therefore recognition experiment in case of no surgical operation, which aims to measure the baseline performance, had to be conducted on a separate database with different subjects. For face recognition algorithms, the accuracy can vary widely depending on the difficulty of the database. Hence an authentic comparison is not possible.
- In [4], the before and after images differ not only as a result of the procedure, but also due to expressions, makeup and facial hair variations as illustrated in [1]. This leads to an additional decrease in performances which prevents the true measurement of the plastic surgery effect.
- Since this is an image database, analyses are restricted to 2D. However, 3D face recognition gains popularity as it offers superiority over to its 2D counterpart by being intrinsically robust against illumination and pose variations. For this reason, the impact of the facial alterations on 3D algorithms should also be investigated.

In [1], these limitations are eliminated by creating a synthetic database using FRGC v1.0 [5] for which nose regions are exchanged between subjects in the same database. In this way, a 2D+3D database is obtained for nose alterations and since the conditions and the subjects are identical for the original and the simulated databases, measuring the exact impact of nose alterations is possible.

Our previous study [1] focuses on the nose modifications and analyze their effects on success rates of several face recognition methods both in 2D and 3D face recognition using the simulated nose alteration database.

In this paper, we focus on developing a new approach which reduces the impact of nose alterations on recognition performances. The proposed approach is based on local description. Principal Component Analysis (PCA) [6], Linear Discriminant Analysis (LDA) [6] and Circular Local Binary Pattern (CLBP) [7] are standard techniques in face recognition. These techniques are applied generally over the whole image to extract image features as in the studies [1, 3, 4]. In this study, these techniques are applied over image blocks to extract block features. Dissimilarity between an image pair is computed using the dissimilarities which are previously computed for each block pair of these images in the most optimum way to maximize the recognition performances. This study aims to reduce the performance decrease caused by nose alterations.

1.1. Related Work

Studies which address the problem of preventing the impact of face alterations are very limited. An evolutionary granular approach is proposed in [8] for matching a post-surgery face image with a pre-surgery face image and 15% improvement in identification performance is reported compared to other face recognition methods. Furthermore, two new methods, FARO and FACE, based on fractals and a localized version of correlation index, respectively, are implemented in [9] which claims that the performance of these two algorithms compare favourably against standard face recognition such as PCA and LDA in case of plastic surgery changes. Singh et al. adopted the near set theory to classify facial images that have previously undergone some feature modifications in [10].

The rest of the paper is organized as follows: Section 2 gives brief information for the simulation of nose alterations. Section 3 describes the proposed approach. Section 4 gives the experimental results to show the effect of nose alterations in 2D and 3D face recognition. In this section, the results are reported using both the proposed approach and the standard techniques which are based on holistic description for comparison purposes. Finally, the conclusions are provided in Section 5.

2. The Simulation of Nose Alterations

According to the statistics published by The American Society for Aesthetic Plastic Surgery in 2010 [2], nose reshaping (rhinoplasty) is the second most common surgical operation on face. Plastic surgery is just one of several ways to change the appearance of the nose. The nose region can be altered using plastic surgery, prosthetic appliances or makeup and it can be made bigger, smaller, wider or thinner. In [1], in order to simulate these changes, noses in the FRGC v1.0 database, which consists of 943 multimodal samples from 275 subjects, are replaced by randomly chosen ones from different subjects. This process provides the simulated database of the same size.

A metamorphosis technique for 3D plastic surgery simulation was proposed in [11], where three morphing operations: augmentation, cutting and lacerating were simulated. Later in [12], an automatic virtual plastic surgery system was presented which similarly to our approach, replaced an individual's facial features with corresponding features of another individual and fused the replaced features with the original face, but only in 2D.

In [1], the simulation of nose alterations is explained in details. In this part, brief information is given to explain the characteristics of the database that is used also in this study.

Firstly, nose regions of all facial scans are automatically segmented in a similar manner to [13] where an annotated generic face model is deformed to fit the target models and the annotations are transferred. Next, nose deformations are applied using TPS method [14] in 3D. Prior to warping, the target model is aligned with the source model using 4 of 5 landmark points around the nose (Figure 1), excluding the nose tip. A linear transformation that includes rotation, translation and isotropic scaling is computed in a least square sense, based on the two sets of landmarks and

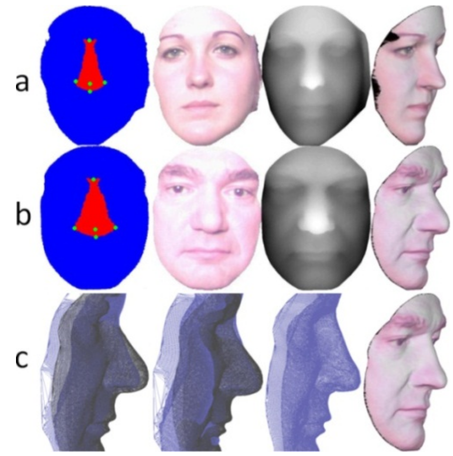

Figure 1. (a) Nose region with landmark points, color map, depth map and profile view for the target model (b) Same images for the source model (c) Two models superimposed before and after alignment, resulting mesh after warping and profile view for the synthesized model. This figure is taken from [1].

applied onto the source model. Subsequently, using all 5 point pairs a coarse TPS approximation is computed. In the final step, for one-fifth of the vertices on the target nose, the closest vertices on the source nose are found and coupled to be utilized in a second and denser TPS warping, which results in the source nose completely transforming into the target nose. The proposed method is illustrated in Figure 1.

In order to evaluate the visual plausibility of the created database, an online survey was conducted, for which the participants were asked to classify the randomly displayed facial images (with or without texture) as original or simulated. According to a total number of 81 participations, success rate is found to be 60.68% for the images displayed with texture. For the ones without texture, the performances deteriorate as expected (58.77%) since the texture gives a better hint about originality. Being very close to the average performance of a random classifier, this result indicates very low distinguishability, and hence a highly realistic look for the simulated noses. These results show that the simulated nose alteration database is a realistic database.

In the rest of this paper, the original databases in 2D and 3D will be referred as DB-o2 and DB-o3, while the simulated nose alteration databases will be referred as DB-s2 and DB-s3. Furthermore, when the key techniques PCA, LDA and CLBP are applied over the whole image to extract image features, it will be referred as the holistic approach whereas; when the same techniques are applied over the image blocks to extract block features as a part of our study in this paper, it will be referred as the proposed approach for the sake of clarity.

3. The Proposed Approach

The proposed approach analyses images by dividing them according to a regular square grid. Initially, cropping of all texture and range images (depth maps) in DB-o and

DB-s is done. Then, all cropped images are resized with the parameter [300 300] since in our case, all these images in both DB-o and DB-s have pixel size more than [300 300]. After resizing, they are divided into 36 blocks each of which has size [50 50] (Figure 2). These parameters should be adjusted according to the size of selected databases.

In our study, the techniques PCA, LDA, and CLBP are used only to extract features of the image blocks. For each image pair, using these extracted features, dissimilarities between blocks of the first image and corresponding blocks of the second image are computed, separately. This process provides 36 dissimilarity results for one image pair. Distribution of these dissimilarity results is analyzed for both DB-o and DB-s. According to our analysis, the blocks which deteriorate the recognition performances are decided not to be involved in resultant dissimilarity computation between the image pairs by applying a special technique which is explained in the next paragraphs.

Figure 3 shows an example to our analysis by using an original image in gallery (Image#1), another image of the same person for original vs. original comparison (Image#2) and a synthetic image which is in fact Image#2 after nose alteration for original vs. synthetic comparison (Image#3). The figure shows dissimilarity results computed for each of 36 blocks. PCA is applied to extract the block features. Dissimilarity results between the blocks of Image#1 and Image#2 are computed for original vs. original comparison (Or. vs. Or. in Figure 3). Dissimilarity results between the blocks of Image#1 and Image#3 are computed for original vs. synthetic comparison (Or. vs. S. in Figure 3). From Figure 3, it is clear that dissimilarity results for the two comparisons are similar at most of the block numbers except the ones which have undergone nose alteration. For instance, very high dissimilarity is obtained for Or. vs. S. compared to Or. vs. Or. comparison at Block#15 which represents the nose region affected from nose alteration. Also Figure 3 shows that the lowest dissimilarities are observed at the blocks which represents just the skin part (e.g. Block#18) and higher dissimilarities are observed usually at the dense-textured blocks (e.g. Block#8). According to these analysis for Or. vs. Or. and Or. vs. S. comparison cases, we developed our approach.

In the proposed approach, after dissimilarities are computed for each block pair, respectively, they are sorted from minimum to maximum. D_i represents the i^{th} minimum dissimilarity result inside the total 36 dissimilarity results.

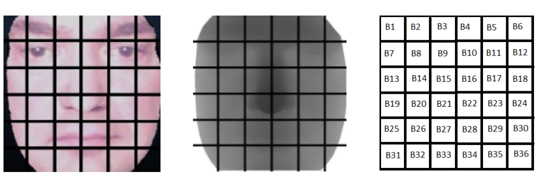

Figure 2. (a) Texture image divided into 36 blocks (b) Depth map divided into 36 blocks. (c) Image showing the ordering of blocks (B_I represents Block #I).

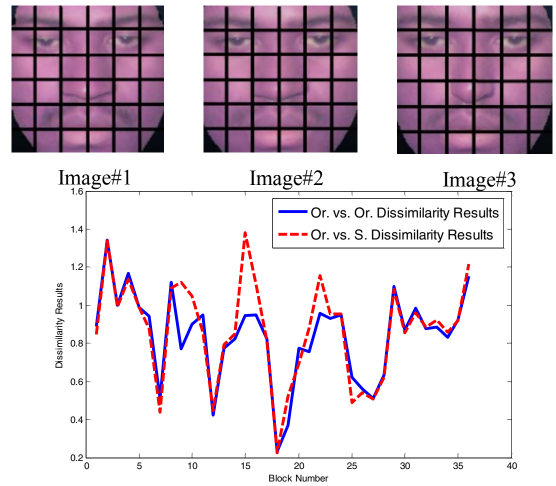

Figure 3. Dissimilarity Results obtained for original vs. original comparison between Image#1 and Image#2 and original vs. synthetic comparison between Image#1 and Image#3.

Equation 1 shows how the results are obtained inside the proposed approach.

$$RD(k) = \frac{1}{k}\sum_{i=1}^{k} D_i\,, \qquad k = 1, \ldots, 36 \qquad (1)$$

For the first computation (k=1), only the block pair with minimum dissimilarity (D_1) is involved in the resultant dissimilarity computation between an image pair, which is represented as *RD* in Eq. 1. For next computations (k>1), each time, the next minimum dissimilarity is added to the array and the resultant dissimilarity is computed as mean of the dissimilarities in this array. This means that at the last computation (k=36), the dissimilarity results computed for all block pairs ($D_1,\ldots,D_{36}$) are used in Eq. 1 to compute the resultant dissimilarity between an image pair. The resultant dissimilarities are computed for each image pair and then recognition performances are evaluated from these results.

Figure 4 shows the 36 identification rates which are computed by using the depth maps in our database for one non-overlapping training and testing partitioning. In this study, RD is assumed as the dissimilarity between an image pair and the distance matrix is obtained using the dissimilarities that are computed for all image pairs. From the distance matrix, rank-1 identification rates are computed for increasing k values. The x axis in this figure represents the number of block pairs involved in resultant dissimilarity computation between image pairs (k in Eq. 1). Three outcomes can be extracted from Figure 4:

- In case significant number of block pairs are not involved in the resultant dissimilarity computation (k<15), a rapid decline is observed in performances.
- In case the block pairs with higher dissimilarities are not involved in the resultant dissimilarity computation (15<k<36), better performance can be observed even for DB-o compared to the case for which all block pairs are used (k=36). (Best performance for DB-o is observed at k=23 for the example in Figure 4.)

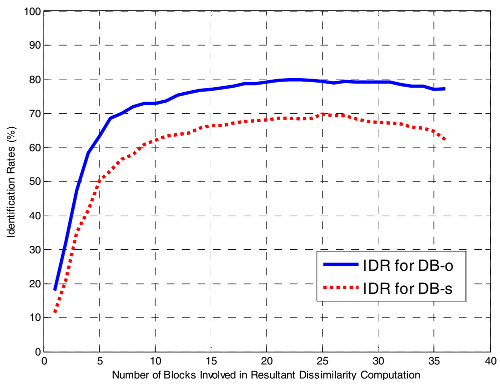

Figure 4. An example showing the identification rates computed at each of 36 successive computations using depth maps

- It is obvious that the increase in the performance (*(max(IR(k))-IR(36)) / IR(36)*; *IR* represents Identification Rates) is much more for DB-s compared to DB-o.

The proposed approach is mainly based on these outcomes. Due to the impact of facial alterations, the increase in the performance is observed as always higher for DB-s under the same conditions for DB-o and DB-s. Therefore, in this study the maximum identification rate obtained after successive computations (the rate at k=23 for DB-o and at k=25 for DB-s for the example in Figure 4) is selected as the resultant performance rate of the system. Based on the first outcome, in the proposed approach, computations are started using the first 15 minimum dissimilarities instead of using only the first minimum one in order to reduce the computation time. Note that in this method, we do not eliminate exactly the altered blocks, we eliminate the blocks with higher dissimilarities. Therefore there is no need to know which part of the face has plastic surgery and the method can be applied for any operation.

Table 1 shows the identification rates obtained for DB-o and DB-s using the example in Figure 4 for three cases. PCA is used to extract features. Case 1 is the case for which dissimilarities of all block pairs ($D_1,\ldots,D_{36}$) are used to compute the rate with block based face analysis (rate at k=36). Case 2 is the proposed approach, for which maximum rate obtained after successive computations is selected as the rate of system (maximum rate at 15<k<36). Finally, Case 3 is the case for which standard PCA (based on holistic description) is used to compute the rate.

Table 1 shows the superiority of the proposed approach in terms of both recognition performances and robustness to nose alterations. The identification rates computed with standard PCA (Case 3) are reported to make a comparison between the standard and the proposed approach. The same training-test partitioning is used for all cases. From the table, it is clear that block based analysis of images (both Case 1&2) improves the results significantly compared to Case 3, which is a holistic approach. However, using the proposed approach, for which only the blocks that maximizes recognition performances are used (Case 2), it

Table 1. Rank-1 identification accuracies obtained for three cases using the same data of the example in Figure 4.

Algorithm PCA	DB-o	DB-s	Performance Decrease
Case1	77.32%	62.37%	19.34%
Case2	**79.90%**	**69.85%**	**12.58%**
Case3	58.51%	45.88%	21.59%

is clear that the best performance rates are obtained for both DB-s and DB-o with the advantage of the most robust result to alterations, which is the main target of this study.

4. Experimental Evaluation

In this part, the results of the proposed method are compared with the results of standard techniques used in the studies [1, 3, 4], in which the impact of facial alterations on recognition performances is measured.

Initially, all four databases, DB-o2, DB-o3, DB-s2 and DB-s3 are partitioned in non-overlapping training and testing datasets. This is done by randomly selecting 40% of the subjects and assigning their samples to the training set, while the rest is used for testing, similarly to the studies in [1, 4]. The partitioning is repeated 10 times and verification and identification rates are computed over these 10 trials.

For verification tests, the verification rates at 0.001 FAR are reported. For identification tests, the first sample of each individual in the test set is used as gallery and the rest as probes. The rank-1 recognition rates are reported.

The effect of the applied nose alterations on face recognition performances is evaluated with two different scenarios in both 2D and 3D which are determined according to the study of Singh et al. [4] for comparison.

- **Experiment 1 – Performance on the original database**: It is important to compute performances on the original datasets in terms of having a baseline. In this way, the impact of the applied changes can be measured accurately. For this purpose, 2D and 3D algorithms are evaluated on DB-o where the dissimilarities are calculated between each original image pair.
- **Experiment 2 – Performance on the simulated database:** In this scenario, the similarity scores between every DB-o and DB-s sample pairs are calculated and used to evaluate recognition performances. For the training set, for each subject selected, half of the corresponding images are taken from DB-o and the rest from DB-s. This experiment is identical to Experiment 1, except the probe images are now replaced by their modified versions.

Results of Experiment 1 and 2 are reported using both the proposed approach and the holistic approach, in which the key techniques (PCA, LDA, CLBP) are applied over the whole image which are resized as [50 50]. This selection of the resizing parameter for the holistic approach in this study is based on the following reason:

- The key techniques are applied on plastic surgery database in [4] and results that are close to the reported results in [4] are obtained with this resizing parameter.

4.1. Evaluation on 2D Face Recognition

In this part, three key methods, PCA, LDA, and CLBP, are applied over the image blocks for the proposed approach; whereas they are applied over the whole image for the holistic approach, which is in fact the approach generally used for standard techniques. PCA and LDA are appearance-based approaches. CLBP is a texture-based algorithm for describing local structures.

The plastic surgery database in [4] has images after several types of surgery operations such as forehead surgery, ear surgery, eyelid surgery, nose surgery, face lift etc. In this part, the proposed approach is tested also using this real plastic surgery database to compare our results with the reported results in [4].However, since this database includes only one image before the plastic surgery, it is not possible to compute exact baseline performances. Hence using this database, it is also not possible to show the robustness of our approach to plastic surgery due to the lack of baseline scores. Therefore in Table 2, only the success of our approach in terms of recognition performance is shown.

The first column of Table 2 shows the results reported in [4], second column shows the results we obtained using the same techniques just to verify the parameters we selected for each technique are appropriate or not, and last column shows the results obtained with the proposed approach. Since the results in column 1 and 2 are consistent; the same parameters are selected to be used in this study to make an authentic comparison between the proposed approach and the holistic approach. Inside the PCA, LDA and CLBP methods used in [1, 3, 4], only the CLBP applied in [1] is not based on holistic description. However, in this study, CLBP based on holistic description [7] is selected to be used to make the comparison just between the proposed and the holistic approach. From Table 2, performance increase with the proposed approach is obvious for all methods.

The rank-1 recognition rates and the verification rates at 0.001 FAR are given in Table 3 and 4, respectively, for both the proposed and holistic approach. The training-test partitioning are the same to make an exact comparison.

The relative difference between results of Experiment 1 and 2 shows robustness of the methods to nose alterations. According to the results in Table 3 and 4, best performance is obtained using CLBP method for both identification and verification. It is also more robust to nose alterations compared to PCA and LDA with both of the approaches.

Table 2. Rank-1 identification accuracies for 2D FR algorithms for Experiment 2 on Real Plastic Surgery Database (P. A is proposed approach, H.A is holistic approach)

Algorithm	Exp. 2 (Results in [4])	Exp. 2 (H. A.)	Exp.2 (P. A)
PCA	29.1%	29.01%	39.94%
LDA	38.6%	36.14%	44.24%
CLBP	47.8%	46.87%	51.28%

Table 3. Rank-1 identification accuracies for 2D FR using two approaches for Experiment 1 and 2

Algorithms	Holistic Approach		Proposed Approach	
	Exp. 1	Exp. 2	Exp. 1	Exp. 2
PCA	44.60%	31.62%	79.24%	64.62%
Perf. Decrease	29.10%		18.45%	
LDA	69.90%	55.67%	80.36%	68.33%
Perf. Decrease	20.36%		14.97%	
CLBP	77.08%	70.05%	81.27%	76.33%
Perf. Decrease	9.12%		6.08%	

Table 4. Verification rates at 0.001 FAR for 2D FR using two approaches for Experiment 1 and 2

Algorithms	Holistic Approach		Proposed Approach	
	Exp. 1	Exp. 2	Exp. 1	Exp. 2
PCA	31.75%	21.06%	69.29%	52.75%
Perf. Decrease	33.67%		23.87%	
LDA	55.54%	41.60%	70.27%	57.86%
Perf. Decrease	25.10%		17.66%	
CLBP	60.74%	53.30%	72.39%	66.26%
Perf. Decrease	12.25%		8.47%	

This shows that CLBP is much more appropriate than PCA and LDA in case of nose alterations as also concluded in [1]. Robustness of LDA is observed to be higher than PCA, for both verification and identification.

The effect of the proposed approach in terms of the increase in recognition performances is most obvious for PCA. Performance is almost doubled for both identification and verification. On the other hand, there is also an increase in the performance for CLBP with the proposed approach, however it is less compared to PCA and LDA. From Table 3 and 4, it is also clear that using the proposed approach, the decrease in the performance due to facial alterations is lower compared to the results obtained with the holistic approach for all three techniques. This proves that the proposed approach both increases the recognition performances and provides more robust results to facial alterations compared to the holistic approach.

4.2. Evaluation on 3D Face Recognition

For the evaluation on 3D face recognition, 2 algorithms are selected where the facial surfaces are represented as depth maps. Depth maps can be involved in most of the existing 2D techniques, including subspace methods. In this part, similar to the 2D evaluations, PCA and LDA are used. The achieved rank-1 identification rates and the verification rates at 0.001 FAR on DB-o3 and DB-s3 are given in Table 5 and Table 6.

For both identification and verification, using both of the approaches, LDA provides better performing and more robust result compared to PCA on depth maps. Similar to analysis on texture images, again the proposed approach provides both better performances and also more robust results compared to the holistic approach. This proves the

Table 5. Rank-1 identification accuracies for 3D FR using two approaches for Experiment 1 and 2

Algorithms	Holistic Approach Exp. 1	Holistic Approach Exp. 2	Proposed Approach Exp. 1	Proposed Approach Exp. 2
PCA	62.37%	47.46%	81.05%	69.58%
Perf. Decrease	23.91%		14.15%	
LDA	66.48%	56.55%	83.32%	75.12%
Perf. Decrease	14.94%		9.84%	

Table 6. Verification rates at 0.001 FAR for 3D FR using two approaches for Experiment 1 and 2

Algorithms	Holistic Approach Exp. 1	Holistic Approach Exp. 2	Proposed Approach Exp. 1	Proposed Approach Exp. 2
PCA	47.91%	31.86%	71.24%	54.34%
Perf. Decrease	33.50%		23.72%	
LDA	54.56%	39.61%	72.49%	60.35%
Perf. Decrease	27.40%		16.75%	

superiority of our approach also on depth maps. From the analysis on both texture and range images, it is observed that in verification, performance decrease is much more visible for all the methods. Also, with the holistic approach, much better results are obtained on range images compared to texture images for PCA. With the proposed approach, results on texture and range images are closer for PCA.

5. Conclusion

In this study, a synthetic nose alteration database is used which is prepared from FRGC v1.0. It is used to evaluate the performances of the proposed approach and compare the results with the standard recognition methods.

The novelty of this study is that the analyses are not restricted to 2D, the effect of the applied modifications can be determined also in 3D. Also, since it is possible to measure the original performances on FRGC v1.0, an authentic comparison between pre- and post-alteration performances can be provided, which is an advantage of this study when compared to the previous ones.

The results in [1, 3, 4] show that the standard recognition methods are not robust to the variations caused by nose alterations, especially for the verification case. Robustness to nose alterations is also observed to be method dependent. Robust algorithms are necessary to mitigate the effects of facial alterations. Therefore, in this paper, a new approach is proposed which provides more robust results compared to the standard methods. It is simply a block based face analysis method, for which only the blocks of images that maximize recognition performance are used in dissimilarity computation between image pairs by applying a special technique. Our future research direction is to measure the efficiency of nose alterations for spoofing purposes.

Acknowledgment

This work has been partly performed by the TABULA RASA project 7th Framework Research Programme of the European Union (EU), grant agreement number: 257289. The authors would like to thank the EU for the financial support and the partners within the consortium for a fruitful collaboration. For more information about the TABULA RASA consortium please visit http://www.tabularasa-euproject.org.

References

[1] N. Erdogmus, N. Kose, J.-L. Dugelay. Impact Analysis of Nose Alterations on 2D and 3D Face Recognition. IEEE Int. Workshop on Multimedia Signal Processing 2012, Canada, Sept. 2012.

[2] The American Society for Aesthetic Plastic Surgery. Cosmetic Surgery National Databank Statistics, 2010. http://www.surgery.org/sites/default/files/Stats2010.pdf .

[3] R. Singh, M. Vatsa. Effect of Plastic Surgery on Face Recognition: A Preliminary Study. IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, pp.72-77, June 2009.

[4] R. Singh, M. Vatsa et al. Plastic Surgery: A New Dimension to Face Recognition. IEEE Transactions on Information Forensics and Security, 5(3):441-448, 2010.

[5] P. J. Phillips, P. J. Flynn et al. Overview of the face recognition grand challenge. IEEE Computer Society Conf. on Comp. Vision and Pattern Recognition, 1: 947-954, 2005.

[6] P. N. Bellhumer, J. Hespanha et al. Eigenfaces vs. fisherfaces: Recognition using class specific linear projection. IEEE Transactions on Pattern Analysis and Machine Intelligence, 17(7):711–720, 1997.

[7] T. Ojala, M. Pietikainen, and T. Maenpaa. Multiresolution Gray-scale and Rotation Invariant Texture Classification with Local Binary Patterns. IEEE Transactions on Pattern Analysis and Machine Intelligence, 24(7):971–987, 2002.

[8] H. S. Bhatt, S. Bharadwaj, R. Singh et al. Evolutionary granular approach for recognizing faces altered due to plastic surgery. IEEE International Conference on Automatic Face & Gesture Recognition and Workshops, pp.720-725, 2011.

[9] M. De Marsico, M. Nappi et al. Robust Face Recognition after Plastic Surgery Using Local Region Analysis. Lecture Notes in Computer Science - Image Analysis and Recognition, pp.191-200, Springer Berlin/Heidelberg, 2011.

[10] K. R. Singh, R. S. Khedgaonkar, and S. P. Gawande. A New Approach to Local Plastic Surgery Face Recognition Using Near Sets. International Journal of Engineering Science and Technology, NCICT Special Issue, pp.71-75, 2011.

[11] T.-Y. Lee, Y.-N. Sum et al. Three-dimensional facial model reconstruction and plastic surgery simulation. IEEE Transactions on Information Technology in Biomedicine, 3(3):214-220, 1999.

[12] S.A. Rabi, and P. Aarabi. Face Fusion: An Automatic Method for Virtual Plastic Surgery. International Conference on Information Fusion, pp.1-7, 2006.

[13] I.A. Kakadiaris, G. Passalis et al. Three-Dimensional Face Recognition in the Presence of Facial Expressions: An Annotated Deformable Model Approach. IEEE Trans. on Pattern Analysis and Machine Intelligence, 29(4), pp.640-649, 2007.

[14] F. L. Bookstein. Principal warps: Thin-Plate Splines and Decomposition of Deformations. IEEE Trans. on Pattern Analysis and Machine Intelligence, 11(6):567–585, 1989.