UNDERSTANDING THE DISCRIMINATION POWER OF FACIAL REGIONS IN FORENSIC CASEWORK

Pedro Tome[a], Luis Blázquez[a], Ruben Vera-Rodriguez[a], Julian Fierrez[a], Javier Ortega-Garcia[a], Nicomedes Expósito[b] and Patricio Lestón[b]

[a]Biometric Recognition Group - ATVS, Escuela Politecnica Superior
Universidad Autonoma de Madrid
Avda. Francisco Tomas y Valiente, 11 - Campus de Cantoblanco - 28049 Madrid, Spain
{pedro.tome, luis.blazquez, ruben.vera, julian.fierrez, javier.ortega}@uam.es
[b]Dirección General de la Guardia Civil - DGGC Madrid, Spain
{nexposito, pleston}@guardiacivil.es

ABSTRACT

This paper focuses on automatic facial regions extraction for forensic applications. Forensic examiners compare different facial areas of face images obtained from both uncontrolled and controlled environments taken from the suspect. In this work, we study and compare the discriminative capabilities of 15 facial regions considered in forensic practice such as full face, nose, eye, eyebrow, mouth, etc. This study is useful because it can statistically support the current practice of forensic facial comparison. It is also of interest to biometrics because a more robust general-purpose face recognition system can be built by fusing the similarity scores obtained from the comparison of different individual parts of the face. To analyse the discrimination power of each facial region, we have randomly defined three population subsets of 200 European subjects (male, female and mixed) from MORPH database. First facial landmarks are automatically located, checked and corrected and then 15 forensic facial regions are extracted and considered for the study. In all cases, the performance of the full face (faceISOV region) is higher than the one achieved for the rest of facial regions. It is very interesting to note that the nose region has a very significant discrimination efficiency by itself and similar to the full face performance.

***Index Terms*—** Forensic, biometrics, face recognition, facial regions, forensic casework.

1. INTRODUCTION

Automatic face recognition has been extensively researched over the past two decades. This growth is due to its easy acquisition and its important role in a growing number of application domains, including access control, video surveillance, and its wide use in government issued identity documents (e.g., passport and driving's license) [1].

An area where these kinds of systems have obtained an increased emphasis is the forensic field [2, 3]. Forensic science analyses data collected by law enforcement agencies in order to prove or disapprove the guilt of a suspect with high confidence under the legal system.

While DNA and fingerprint forensic identification are two of the most reliable and available identification methods in forensic science, automatic face recognition technology needs to improve the set of available tools to determine a person's identity, particularly from video surveillance imagery. Such progress for forensic face recognition is one of the goals of the FBI's Next Generation Identification program [4].

Automatic face recognition systems are generally designed to match images of full faces. However, in practise, forensic examiners focuses carry out a manual inspection of the face images, focussing their attention not only on full face but also on individual traits. They carry out an exhaustive morphological comparison, analysing the intra-variability of a face, trait by trait on nose, mouth, eyebrows, etc., even examining soft traits such as marks, moles, wrinkles, etc. On the other hand, there are several studies [5, 6, 7, 8] based on realistic scenarios trying to understand the effect of the different variability factors in this field.

As Jain et al. decribe as future work in [9, 2, 10], facial regions-based system for matching and retrieval would be of great value to forensic investigators.

There are some previous works where region-based face recognition is studied [11, 12, 13, 14, 15, 16] but these papers do not focus their attention in the regions usualy considered by forensic experts. In this work, we have extracted facial components (called from now facial regions) following forensic protocols from law enforcement agencies, allowing us to study the discriminative power of different facial regions individually. In particular we address in this paper the problem of finding the most discriminative areas of the face for recognition.

Understanding the discrimination power of different facial regions on a wide population has some remarkable benefits, for example: *i*) allowing investigators to work only with particular regions of the face, *ii*) preventing that incomplete, noisy, and missing regions degrade the recognition accuracy. Further, a better understanding of facial regions-based face recognition should facilitate the study of individuality models.

In summary, the main contribution of the paper is an experimental study of the discriminative power of different forensic facial regions on a wide population using forensic protocols. Additionally, we propose a novel framework for facial regions extraction useful for controlled and uncontrolled scenarios.

The rest of the paper is organized as follows. In Section 2, we provide an overview of the automatic facial region extraction procedure. Section 3 presents the analysis of the extracted facial regions defining the database used, the experimental protocol followed, the feature extraction and classification used and the experimental results achieved. We conclude in Section 4 with a

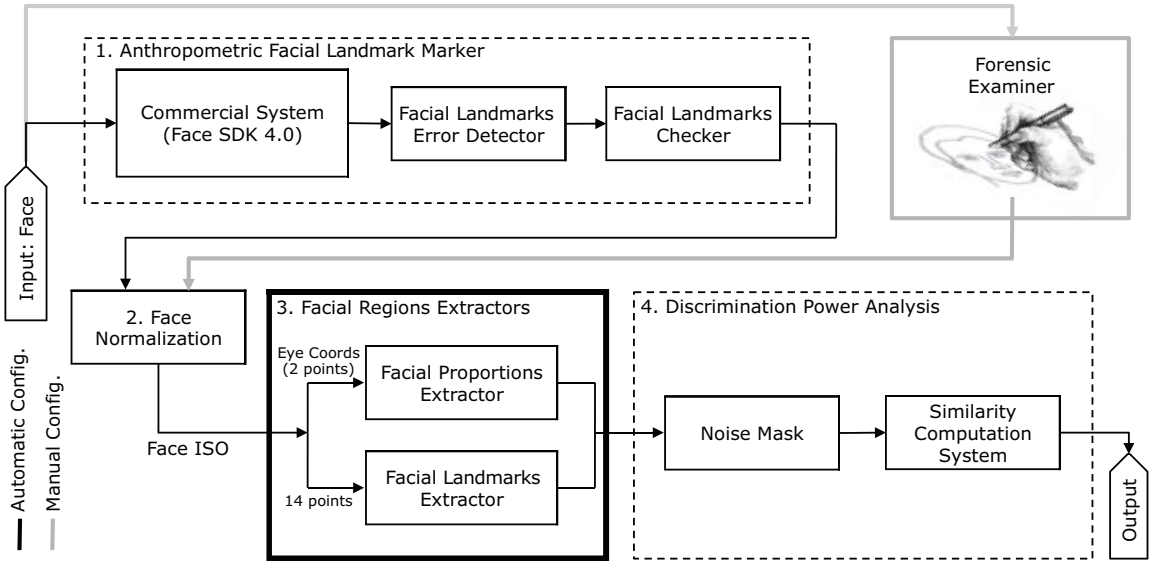

Figure 1: Experimental framework.

discussion and summary of our work.

2. FACIAL REGIONS EXTRACTION

This section describes the experimental framework developed to extract the different forensic facial regions analysed in this work.

The traditional inspection procedure of the law enforcement agencies carried out by forensic examiners is mainly based on manual and individual skills of the human examiners using some general image processing tools. Automatic approaches of image processing could help the examiners to reduce the human subjective decisions, reaching higher precisions. In this sense, we have developed a useful tool able to extract different facial regions as summarized in Fig. 1.

The presented experimental framework has two different configurations in order to find the facial landmarks for extraction of the facial regions: automatic and manual . Automatic configuration uses a commercial system [1] that provides 65 facial points of which only 13 are used. These 13 facial landmarks plus a new point that indicate the top of the head (defined by us) (see Fig. 2) are used as inputs to a facial landmarks error detector developed by us based on distances, angles and symmetries between these points. This system allows us to know which facial landmark is correctly located and which of them needs to be corrected. On the other hand, the location of these facial landmarks could be done manually by a forensic examiner.

After a correct facial landmark location, faces are normalized based on the ISO standard [17] with an *Interpupillary Pixel Distance* (IPD) of 75 pixels. Therefore, facial regions can be extracted with a standard size for all faces.

In our approach we have implement two different facial region extractors: *i*) based on human facial proportions, and *ii*) based on facial landmarks. The first one extracts the facial area of interest of the face (eyebrows, eyes, nose, mouth, etc.) using just the two eyes coordinates, following simple facial proportions rule [18, 19]. The mentioned extractor would be of interest in challenging uncontrolled scenarios where landmarks are very difficul to be extracted automatically. On the other hand, the second extractor, based on facial landmarks correctly located, allows to extract the facial regions with high precision.

The experimental framework implemented extracts of 15 different facial regions as can be seen in Fig. 2. The election of these 15 regions is based on protocols from Spanish Guardia Civil [20] and NFI [21], two of the most important national forensic science laboratories in Spain and Netherlands, respectively.

3. FACIAL REGIONS ANALYSIS

This section decribes how facial regions extracted from a face are analysed in order to evaluate their discriminative power. Firstly, the database and the experimental protocol adopted for this work are presented. Then, the feature extraction and classification will be described and finally, the experimental results will be detailed.

3.1. Database

The experiments are carried out on a subset of the MORPH Non-Commercial Release database [22]. MORPH contains 55.000 frontal face images from more than 13.000 subjects, acquired from 2003 to late 2007. The distribution of ages ranges from 16 to 77 with an average age of 33. The average number of images per individual is 4 and the average time between pictures is 164 days, with the minimum being 1 day and the maximum being 1.681 days. The MORPH database is divided in 5 subsets named: *i*) African, *ii*) European, *iii*) Asian, *iv*) Hispanic and *v*) Other.

The subset "European" comprises 2.704 subjects (2.070 males plus 634 females) and has been selected for these experiments. Fig. 2 shows an example in our dataset together with their extracted regions.

3.2. Experimental Protocol

For the experimental work of this paper we discarded those subjects with less than three images and chose three images per subject with the smallest gap between acquisitions in order to

[1] Luxand, Inc. http://www.luxand.com.

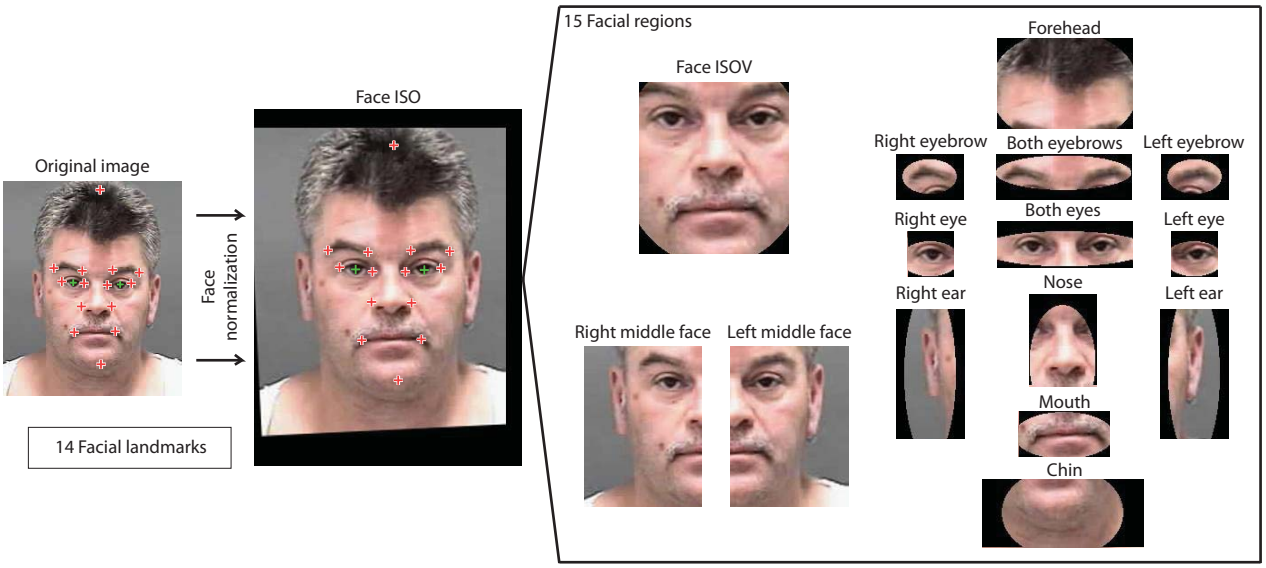

Figure 2: Facial regions extraction.

reduce the time lapse effect.

Then using this selection, three population sets were randomly chosen in order to analyse the discrimination power of each facial region on different populations: *i*) 200*female*, *ii*) 200*male*, and *iii*) 200*mix* (100 male+100 female).

Each population subset of 200 subjects with 3 face images each is then divided into: *i*) a training set comprising the first sample (enrolment template); and *ii*) an evaluation set comprised of the other two images available for each subject.

3.3. Feature Extraction and Classification

Regarding feature extraction and classification, a system based on PCA-SVM was adopted to compute the discrimination power between different facial regions. Different noise masks were applied to each facial region (Fig 2) (e.g. 75×101 (width $\times$ height) for nose region). PCA was applied to each facial region over the training set retaining 96% of variance. This leads to a system where the original image space (e.g. of 7.575 dimensions for nose region) is reduced to 200 dimensions. Similarity scores are computed in this PCA vector space using a SVM classifier with linear kernel.

3.4. Experimental Results

This section describes the experimental analysis of individual features of each facial region and their discrimination power (represented by EER) over the different 3 population datasets. Results are shown using ROC curves with EERs (in %).

The discrimination power of each defined forensic facial region for the three studied population datasets is presented in Fig. 3. As can be seen, doing a global analysis, faceISOV region reaches the highest performance compared to the other facial regions, followed by the nose and middle faces regions. It is worth highlighting that the faceISOV and middle faces include other facial regions considered. However, the nose region does not, hence it is important to remark that the nose region has a very high and important discrimination power with respect to the other regions of the face. Ranking the remaining facial parts regarding their discrimination power, the eye regions come next, followed by eyebrows, mouth and chin. The worst results were obtained for the chin, which could be explained due to difficulty to locate the corresponding landmark. As it was expected, ears achieved worse results due to the common occlusion by hair and the pose. It is important to note that mouth region achieves poor performance, it could be due to variability having a not neutral expression: open, closed, smiling, etc.

As can be seen in Fig. 3 (middle and bottom), faceISOV for male and female populations has more or less the same performance, but in general discriminative results for the male population were better than female, due to less variability.

4. CONCLUSIONS

In the present work, an experimental framework for the extraction of different facial regions of a face has been presented and used to understand their discrimination power. The discrimination efficiency of each facial region has been studied considering three different populations obtained from the MORPH database. In all cases, the performance of the full face named faceISOV region is higher than the one achieved by the rest of facial regions. In a real forensic scenario, partial faces are considered very often for recognition due to occlusions or other factors, hence this individualized study is very useful in order to give some insight into the expected degradation when working with partial faces. Furthermore, the nose region has a very significant discrimination efficiency by itself and similar to full face performance. There are notable differences between male and female performances on different facial regions and in general men achieve better discriminative reults for their facial regions compared to women, most likely due to less variability of appearance. This work highlights the benefits of adequate analysis of facial regions from a face in order to better understand the facial intra-variability.

5. ACKNOWLEDGEMENT

P. Tome is supported by a FPU Fellowship from Univ. Autonoma de Madrid. This work has been partially supported by contract with Spanish Guardia Civil and projects

BBfor2 (FP7-ITN-238803), Bio-Challenge (TEC2009-11186), Bio-Shield (TEC2012-34881), Contexts (S2009/TIC-1485), TeraSense (CSD2008-00068) and "Cátedra UAM-Telefónica".

6. REFERENCES

[1] Anil K. Jain, Arun A. Ross, and Karthik Nandakumar, *Introduction to Biometrics*, Springer Science+Business Media, LLC, 2011.

[2] Anil K. Jain, Brendan Klare, and Unsang Park, "Face recognition: Some challenges in forensics.," in *FG*. 2011, pp. 726–733, IEEE.

[3] D. Meuwly and R. Veldhuis, "Forensic biometrics: From two communities to one discipline," in *Biometrics Special Interest Group (BIOSIG), 2012 BIOSIG - Proceedings of the International Conference of the*, sept. 2012, pp. 1 –12.

[4] Next Generation Identification, "http://www.fbi.gov/about-us/cjis/fingerprints_biometrics/ngi/ngi2," .

[5] Xiaozheng Zhang and Yongsheng Gao, "Face recognition across pose: A review.," *Pattern Recognition*, pp. 2876–2896, 2009.

[6] Pedro Tome, Julian Fierrez, M. C. Fairhurst, and Javier Ortega-Garcia, "Acquisition scenario analysis for face recognition at a distance," in *6th International Symposium on Visual Computing (ISVC)*, November-December 2010.

[7] Stan Z. Li and Anil K. Jain, Eds., *Handbook of Face Recognition*, 2nd Edition. Springer, 2011.

[8] Pedro Tome, Ruben Vera-Rodriguez, Julian Fierrez, and Javier Ortega-Garcia, "Variability compensation using nap for unconstrained face recognition," in *Proc. 10th International Conference on Practical Applications of Agents and Multi-Agent Systems (PAAMS12)*. March 2012, vol. 151, pp. 129–139, Springer.

[9] Anil K. Jain, Brendan Klare, and Unsang Park, "Face matching and retrieval in forensics applications," *IEEE MultiMedia*, vol. 19, no. 1, pp. 20, 2012.

[10] Kathryn Bonnen, Brendan Klare, and Anil K. Jain, "Component-based representation in automated face recognition," *IEEE Transactions on Information Forensics and Security*, vol. 8, no. 1, pp. 239–253, 2013.

[11] Massimo Tistarelli, "Active/space-variant object recognition," *Image and Vision Computing*, vol. 13, no. 3, pp. 215–226, 1995.

[12] Bernd Heisele, Thomas Serre, and T. Poggio, "A component-based framework for face detection and identification," *Int. J. Computer Vision*, vol. 74, no. 2, pp. 167–181, Aug. 2007.

[13] Fayin Li, Harry Wechsler, and Massimo Tistarelli, "Robust fusion using boosting and transduction for component-based face recognition," in *10th International Conference on Control, Automation, Robotics and Vision, ICARCV 2008, Hanoi, Vietnam, 17-20 December 2008, Proceedings*. 2008, pp. 434–439, IEEE.

[14] Shalini Gupta, Mia K. Markey, and Alan C. Bovik, "Anthropometric 3d face recognition," *Int. J. Comput. Vision*, vol. 90, no. 3, pp. 331–349, Dec. 2010.

[15] Tauseef Ali, Pedro Tome, Julian Fierrez, Ruben Vera-Rodriguez, Luuk Spreeuwers, and Raymond Veldhuis, "A study of identification performance of facial regions from cctv images," in *5th International Workshop on Computational Forensics, IWCF 2012*, November 2012.

[16] Omar Ocegueda, Shishir K. Shah, and Ioannis A. Kakadiaris, "Which parts of the face give out your identity?," in *CVPR*. 2011, pp. 641–648, IEEE.

[17] ISO/IEC JTC 1/SC 37 N 504, "Biometric data interchange formats part 5: Face image," in *International Organization for Standardization*, 2004.

[18] Y. Jefferson, "Facial beauty-establishing a universal standard," *IJO*, vol. 15, no. 1, pp. 9, 2004.

[19] Hatice Gunes and Massimo Piccardi, "Assessing facial beauty through proportion analysis by image processing and supervised learning.," *International Journal of Man-Machine Studies*, vol. 64, no. 12, pp. 1184–1199, 2006.

[20] Spanish Guardia Civil (DGGC), "http://www.guardiacivil.es/," .

[21] Netherlands Forensic Institute (NFI), "http://www.forensicinstitute.nl," .

[22] K. Ricanek and T. Tesafaye, "Morph: a longitudinal image database of normal adult age-progression," in *Automatic Face and Gesture Recognition, 2006. FGR 2006. 7th International Conference on*, april 2006, pp. 341 –345.

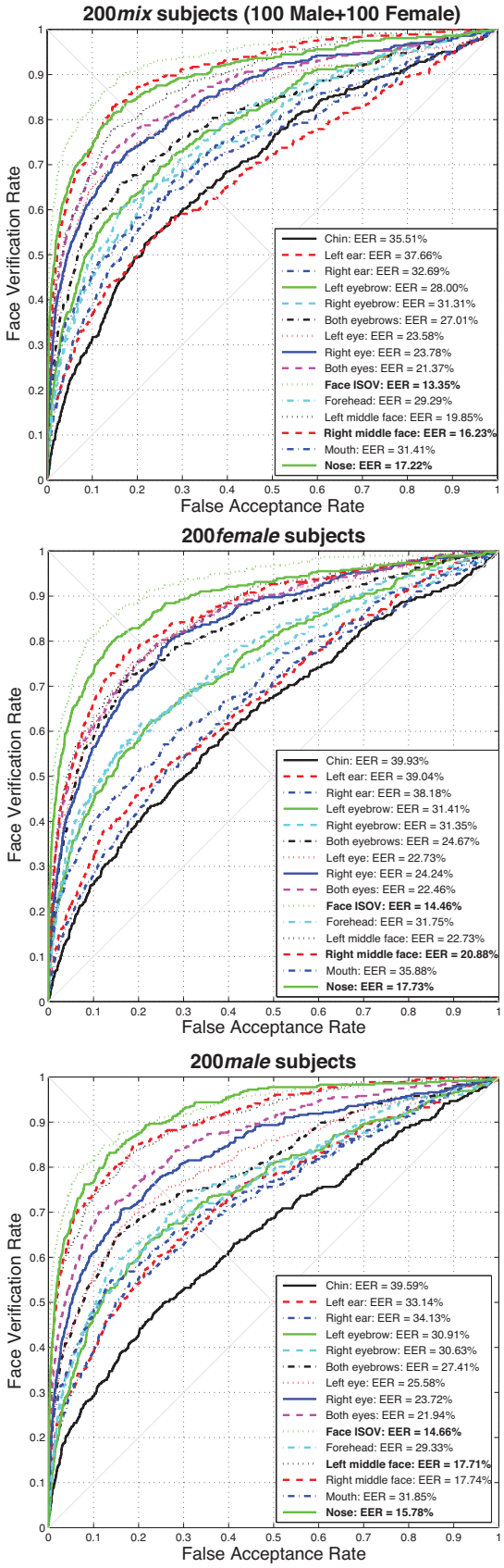

Figure 3: ROC curves showing verification performance of different facial regions (highlighting the best three regions) obtained for the three population sets: 200*mix* (top), 200*female* (middle), and 200*male* (bottom). See one example of the different regions in Fig. 2.