

Unconstrained Periocular Recognition: Using Generative Deep Learning Frameworks for Attribute Normalization

Luiz A. Zanlorensi^{1,2}, Hugo Proença^{2,3} and David Menotti¹

¹Federal University of Paraná, Curitiba, Brazil

²University of Beira Interior, Covilhã, Portugal

³IT: Instituto de Telecomunicações, Portugal

Presenter: Luiz A. Zanlorensi

ARS-01 – Image Video Biometric Analysis
ICIP, 2020

1 Introduction

- Periocular Recognition
- Unconstrained Environments
- Motivation

2 Methodology

- Proposed Method
- Databases
- Att-GAN Training Process
- Evaluation

3 Results

- Qualitative Results
- Quantitative Results
- Result Analysis

4 Final Considerations

- Discussion and Conclusions

Eye regions

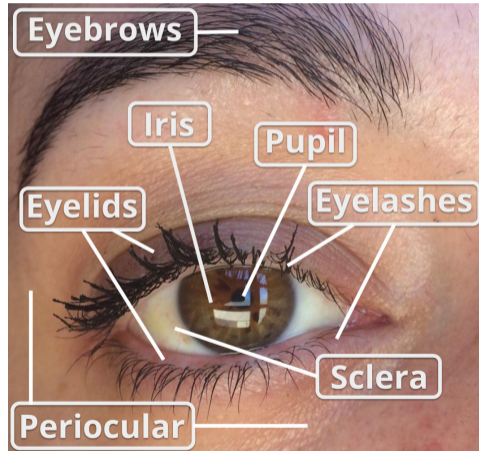


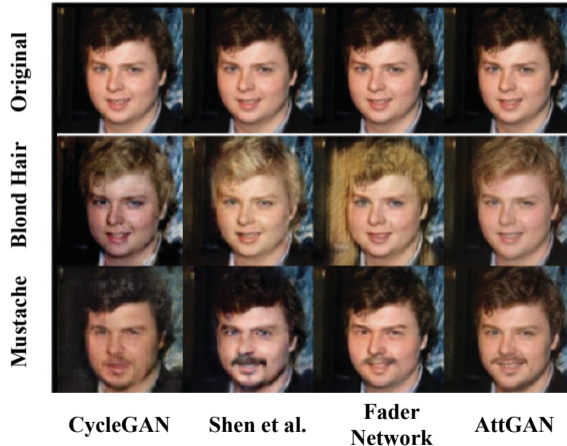
Image from [Zanlorensi et al., 2019].

Problem

- Ocular biometric systems under unconstrained environments:
 - Image: blur, motion blur, lighting, occlusion, specular reflection;
 - Subject: Eye gaze, off-angle, eyeglasses, contact lenses, makeup;
 - Feature extraction quality;
 - High intra-class variability:
- Samples:

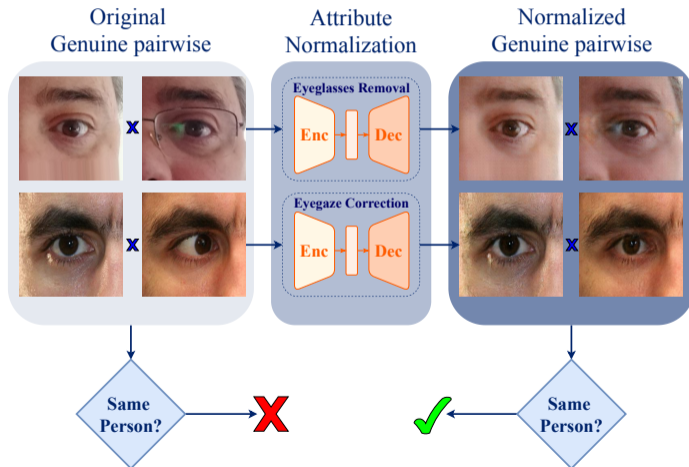


Automatic Image Editing Frameworks - Deep Learning



Adapted from [He et al., 2019].

Proposed Method

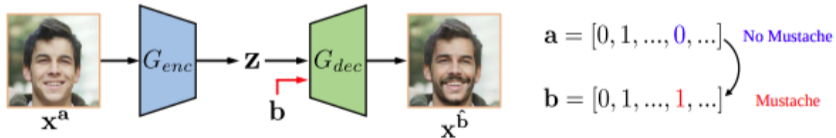


Databases

- UFPR-Eyeglasses (Eyeglasses):
 - 2270 images of both eyes (4540) from 83 subjects;
 - Images collected by the participant himself using a mobile app through 3 sections;
 - Iris bounding boxes manually annotated;
 - Images normalized regarding rotation and scale;
 - Variability factors: illumination, occlusion, distance, reflection, and eyeglasses;
- UBIPr (Eye gaze):
 - 10250 eye images from 344 subjects;
 - Variability factors: distance, scale, occlusion, pose, eye gaze, and eyeglasses;

Attribute GAN training

- Training data:
 - Eyeglasses: Entire UBIPr dataset;
 - Eye gaze: First half of the subjects from the UBIPr dataset;
- The training only used information about Eyeglasses and Eye gaze;
- Simplified process for training and test:



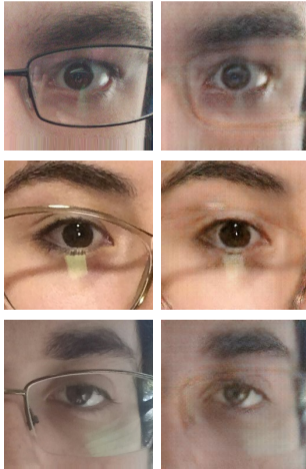
Adapted from [He et al., 2019].

Evaluation

- Protocol:
 - Verification - Open-world: AUC and Decidability;
 - Pairwise with different attributes;
 - All against all comparison;
 - UFPR-Eyeglasses pairs: 3,072 genuine x 274,464 impostors;
 - UBIPr pairs: 22,012 genuine x 6,246,232 impostors;
- Benchmark:
 - Handcrafted features:
 - [Park et al., 2011]: LBP, HOG, SIFT;
 - [Ahmed et al., 2017]: MB-TLBP;
 - LBP, LPQ, HOG, SIFT;
 - Deep learning - based-models:
 - [Luz et al., 2018]: VGG-16
 - [Zanlorensi et al., 2020]: ResNet-50
 - Matching: Cosine distance;

Samples of the normalized images by the Att-GAN model

UFPR-Eyeglasses



UBIPr

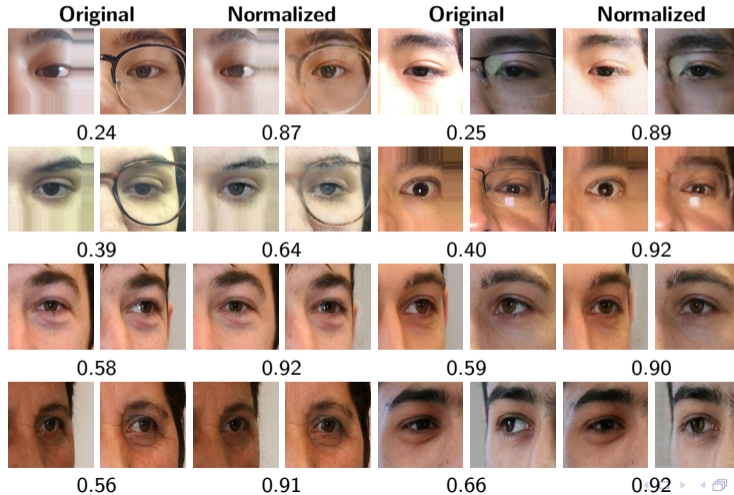


Quantitative Results

Benchmarks - Agnostic Evaluation

Method - Features	Att. Norm.	UFPR-Eyeglasses		UBIPr	
		AUC (%)	Decidability	AUC (%)	Decidability
Ahmed et al. [Ahmed et al., 2017]	✓	73.0 73.2	0.77 0.79	84.9 85.2	1.16 1.17
Park et al. [Park et al., 2011]	✓	78.8 85.2	1.11 1.43	89.6 87.8	1.73 1.62
LBP + LPQ + HOG + SIFT	✓	75.9 87.2	0.92 1.58	90.2 90.0	1.71 1.77
Luz et al. [Luz et al., 2018]	✓	85.9 89.0	1.57 1.81	98.3 98.1	3.64 3.50
Zanlorensi et al. [Zanlorensi et al., 2020]	✓	92.2 92.9	2.09 2.16	99.2 99.4	4.00 4.14

Pairwise matching score analysis



Discussion and Conclusions





- Attribute normalization scheme (preprocessing) to reduce the intra-class variability;
- Our proof-of-concept was conducted in two datasets and five different baseline;
- The results corroborated our hypothesis that the attribute normalization can reduce the intra-class variabilities, without compromising the discriminability between classes;



Acknowledgments

- National Council for Scientific and Technological Development (CNPq);
- Coordination for the Improvement of Higher Education Personnel (CAPES);
- FCT/MEC and FEDER - PT2020;
- We also gratefully acknowledge the support of NVIDIA Corporation with the donation of the Titan Xp GPU used for this research.

Thank you!

e-mail: lazjunior@inf.ufpr.br

-  Ahmed, N. U., Cvetkovic, S., Siddiqi, E. H., Nikiforov, A., and Nikiforov, I. (2017).
Combining iris and periocular biometric for matching visible spectrum eye images.
Pattern Recognition Letters, 91:11–16.
-  He, Z., Zuo, W., Kan, M., Shan, S., and Chen, X. (2019).
Attgan: Facial attribute editing by only changing what you want.
IEEE Transactions on Image Processing, 28(11):5464–5478.
-  Luz, E., Moreira, G., Zanlorensi Junior, L. A., and Menotti, D. (2018).
Deep periocular representation aiming video surveillance.
Pattern Recognition Letters, 114:2–12.
-  Park, U., Jillela, R. R., Ross, A., and Jain, A. K. (2011).
Periocular biometrics in the visible spectrum.
IEEE Transactions on Information Forensics and Security, 6(1):96–106.

-  Zanlorensi, L. A., Laroca, R., Luz, E., Britto Jr., A. S., Oliveira, L. S., and Menotti, D. (2019).
Ocular recognition databases and competitions: A survey.
arXiv preprint, arXiv:1911.09646:1–20.
-  Zanlorensi, L. A., Lucio, D. R., Britto Jr., A. S., Proença, H., and Menotti, D. (2020).
Deep representations for cross-spectral ocular biometrics.
IET Biometrics, 9:68–77.