The Impact of Preprocessing on Deep Representations for Iris Recognition on Unconstrained Environments

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Introduction Iris Recognition

2 Methodology

- Image Preprocessing
- Feature Extraction
- Dataset and Matching
- 3 Protocol, Results and Discussion







Introduction

Methodology Protocol, Results and Discussion Future Work and Unpublished results

Iris Recognition

Eye regions





Image from NICE.II dataset [Proença and Alexandre, 2012].



Iris Recognition

Iris recognition steps:

- Image acquisition;
- Preprocessing:



- Feature extraction;
- Matching;





Image Preprocessing Feature Extraction Dataset and Matching

Image Preprocessing

Segmentation: Winner of the NICE.I contest [Tan et al., 2010].



Normalization: Rubber sheet model [Daugman, 1993].



Image Preprocessing Feature Extraction Dataset and Matching

Image Preprocessing







Image Preprocessing Feature Extraction Dataset and Matching

Recognition System





Original Image

Preprocessing



Deep features extraction



Matching





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CNN models

- VGG16: convolution, activation(ReLu), pooling and fully connected layers.
- ResNet-50: residual information.
- Architecture modification: fully-connected layer with 256 neurons.



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CNN models training

- Transfer learning from the face domain (VGGFace) with fine-tuning (do not freezing any weights).
- Data augmentation rotation.
- 30 epochs: 10 with lr = 0.001 and 20 with lr = 0.0005.
- SGD optimizer;
- Feature extractor training SoftMax (identification)



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Data Augmentation







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Dataset

• NICE.II official contest database and protocol:

- Training: 1000 images from 171 classes;
- Testing: 1000 images from 150 classes;



- 31



Protocol and Matching

- Verification protocol (open world):
 - All against All:
 - 4,634 intra-class pairs;
 - 494,866 inter-class pairs;
- Metrics:
 - EER (Equal Error Rate): FAR = FRR;
 - Decidability: how well separated are intra- and inter-classes;
- Cosine distance metric;





Experiments Analysis

- CNN models: VGG16 and ResNet50;
- Normalization: 8:1, 4:2 and Non-Norm;
- Data Augmentation;
- Segmentation;
- Delineation;
- 30 repetitions;
- t-test for statistical difference;





Data Augmentation

Network	Norm.	DA	EER (%)	Decidability
VGG16	8:1		26.19 ± 1.95	1.3140 ± 0.1246
VGG16	8:1	\checkmark	23.63 ± 1.33	1.4712 ± 0.0881
ResNet-50	8:1		24.38 ± 1.41	1.4297 ± 0.0916
ResNet-50	8:1	\checkmark	19.18 ± 0.75	1.7988 ± 0.0552
VGG16	4:2		24.77 ± 1.42	1.4127 ± 0.1001
VGG16	4:2	\checkmark	18.74 ± 0.89	1.8527 ± 0.0712
ResNet-50	4:2		22.78 ± 1.22	1.5307 ± 0.0853
ResNet-50	4:2	\checkmark	17.11 ± 0.53	1.9822 ± 0.0482
VGG16	Non-Norm		$\textbf{23.32} \pm \textbf{1.10}$	1.4891 ± 0.0740
VGG16	Non-Norm	\checkmark	$\textbf{17.49} \pm \textbf{0.90}$	1.9529 ± 0.0760
ResNet-50	Non-Norm		21.51 ± 0.97	1.6119 ± 0.0677
ResNet-50	Non-Norm	\checkmark	$\textbf{13.98} \pm \textbf{0.55}$	$\textbf{2.2480} \pm \textbf{0.0528}$



*white rows represent that there is statistical difference between: Models,



Segmentation for noise removal

Network	Norm.	Seg.	EER (%)	Decidability
VGG16	8:1	\checkmark	22.58 ± 1.07	1.5437 ± 0.0697
VGG16	8:1		$\textbf{23.63} \pm \textbf{1.33}$	1.4712 ± 0.0881
ResNet-50	8:1	\checkmark	$\textbf{20.68} \pm \textbf{1.39}$	1.6801 ± 0.1071
ResNet-50	8:1		19.18 ± 0.75	1.7988 ± 0.0552
VGG16	4:2	\checkmark	18.00 ± 0.93	1.9055 ± 0.0750
VGG16	4:2		18.74 ± 0.89	1.8527 ± 0.0712
ResNet-50	4:2	\checkmark	17.44 ± 0.85	1.9450 ± 0.0803
ResNet-50	4:2		17.11 ± 0.53	1.9822 ± 0.0482
VGG16	Non-Norm	\checkmark	$\textbf{17.48} \pm \textbf{0.68}$	1.9439 ± 0.0589
VGG16	Non-Norm		17.49 ± 0.90	1.9529 ± 0.0760
ResNet-50	Non-Norm	\checkmark	14.89 ± 0.78	2.1781 ± 0.0794
ResNet-50	Non-Norm		13.98 ± 0.55	2.2480 ± 0.0528



*painted rows represent that there is no statistical difference



315

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Delineation



Delineated

Non-delineated (Bounding box)

Method	Delineated	EER (%)	Decidability
VGG16 VGG16	\checkmark	$\begin{array}{c} 17.49 \pm 0.90 \\ 17.52 \pm 0.98 \end{array}$	$\begin{array}{c} 1.9529 \pm 0.0760 \\ 1.9652 \pm 0.0790 \end{array}$
Resnet-50 Resnet-50	\checkmark	$\begin{array}{c} 13.98 \pm 0.55 \\ 14.26 \pm 0.47 \end{array}$	$\begin{array}{c} 2.2480 \pm 0.0528 \\ 2.2304 \pm 0.0542 \end{array}$





The state of the art comparison (Unpublished results)

Results on the NICE.II contest dataset.

Method	EER (%)	Decidability
Wang et al.[Wang et al., 2012]	19.00	1.8213
Silva et al.[Silva et al., 2018] (Best Model)	14.56	2.2200
Proposed ResNet-50	13.98	2.2480
Proposed ResNet-50 ensemble (5 models)	9.53	2.8132
Proposed ResNet-50 ensemble (10 models)	9.27	2.8538
Proposed ResNet-50 ensemble (20 models)	9.21	2.8643
Proposed ResNet-50 ensemble (30 models)	9.15	2.8725

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3



Conclusion

- Data Augmentation by rotation significantly improved the results;
- Non-normalized iris achieved a better result;
- ResNet-50 reported better result than VGG16;
- Delineated and Non-delineated images reported no statistical difference.





Future work - Other databases

Database	Spectrum	Classes/Images	Resolution
CASIA-Lamp	NIR	819/16212	$\begin{array}{c} 640 \times 480 \\ 640 \times 480 \end{array}$
CASIA-Thousand	NIR	2000/20000	
UbirisV2	VIS	522/11102	$\begin{array}{c} 400 \times 300 \\ 2322 \times 4128 \text{ to } 640 \times 480 \\ 3264 \times 2448 \text{ to } 640 \times 480 \\ 240 \times 160 \\ 300 \times 200 \end{array}$
MICHE DB	VIS(3 sensors)	184/3732	
CSIP	VIS(10 sensors)	100/2004	
VISOB	VIS(3 sensors)	1100/158136	
MobBio	VIS	210/1680	





Thank you!

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