Gaze-angle Impact on Iris Segmentation using CNNs

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Introduction and Problem Statement

Introduction

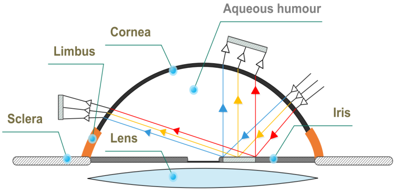
- Iris images captured by emerging stand-off iris recognition systems are more subject to off-angle distortions.
- Showing superior performance, convolutional neural networks are increasing being used for iris segmentation.

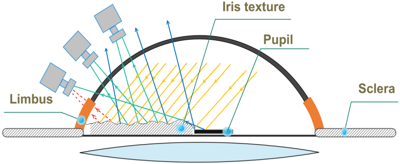
Problem Statement

- There is a significant lack of information about how these distortions affect the performance of such models.
- Having such knowledge available, we can figure out the proper segmentation strategy when dealing with iris images captured from different angles.
- It might turn out that CNN training has to be done specifically for a certain gaze angle (eye-gaze estimation algorithms required).
- Alternatively, it would be of advantage to improve the generalization capability of the networks, and thus eliminate the need for any further processing stages.

Eye Structures Effect on Iris Segmentation

- 3D structure of iris.
- Limbus occlusion.
- Perspective and refraction distortion.
- Missing iris boundary in extreme angles.





Experimental framework

Database: A database containing 4400 left eye iris images belonging to 40 subjects (captured from -50°(N50) to +50°(P50), with a 10° step) is used.

We divided the database into two parts (training and testing datasets).

Segmentation evaluation and measures: Nice1 (NICE protocol)[1]

$$nice1 = \frac{1}{c \times r} \sum_{c'} \sum_{r'} O(c', r') \otimes C(c', r') \quad (1)$$

Fully convolutional neural networks (FCNs): Two different FCN architectures:

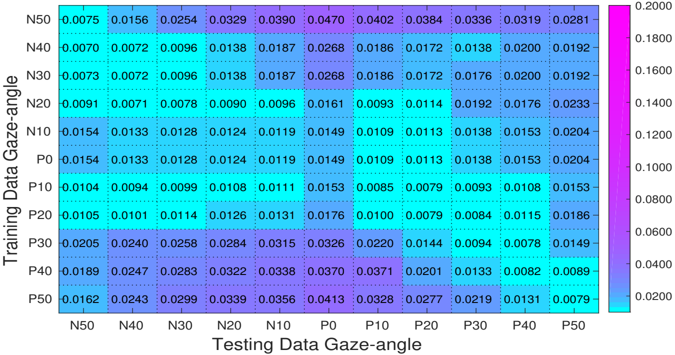
- A basic fully convolutional encoder-decoder network termed "SegNet"[1] .
- A Fully convolutional network termed "RefineNet"[2].

[1] http://nice1.di.ubi.pt/

Is Gaze-angle Specific Training Required

Experiments

- We trained the networks on iris images with identical gaze-angle (200 images per gaze-angle as in our training dataset).
- Then we conduct segmentation on the whole test dataset, differentiating and grouping results into the different gaze-angles available (first using SegNet).



Training \ Testing	N50	N40	N30	N20	N10	P0	P10	P20	P30	P40	P50
N50	0.0075	0.0156	0.0254	0.0329	0.0390	0.0470	0.0402	0.0384	0.0336	0.0319	0.0281
N40	0.0070	0.0072	0.0096	0.0138	0.0187	0.0268	0.0186	0.0172	0.0138	0.0200	0.0192
N30	0.0073	0.0072	0.0096	0.0138	0.0187	0.0268	0.0186	0.0172	0.0176	0.0200	0.0192
N20	0.0091	0.0071	0.0078	0.0090	0.0096	0.0161	0.0093	0.0114	0.0192	0.0176	0.0233
N10	0.0154	0.0133	0.0128	0.0124	0.0119	0.0149	0.0109	0.0113	0.0138	0.0153	0.0204
P0	0.0154	0.0133	0.0128	0.0124	0.0119	0.0149	0.0109	0.0113	0.0138	0.0153	0.0204
P10	0.0104	0.0094	0.0099	0.0108	0.0111	0.0153	0.0085	0.0079	0.0093	0.0108	0.0153
P20	0.0105	0.0101	0.0114	0.0126	0.0131	0.0176	0.0100	0.0079	0.0084	0.0115	0.0186
P30	0.0205	0.0240	0.0258	0.0284	0.0315	0.0326	0.0220	0.0144	0.0094	0.0078	0.0149
P40	0.0189	0.0247	0.0283	0.0322	0.0338	0.0370	0.0371	0.0201	0.0133	0.0082	0.0089
P50	0.0162	0.0243	0.0299	0.0339	0.0356	0.0413	0.0328	0.0277	0.0219	0.0131	0.0079

Experiments

- We repeated the same experiments using RefineNet.

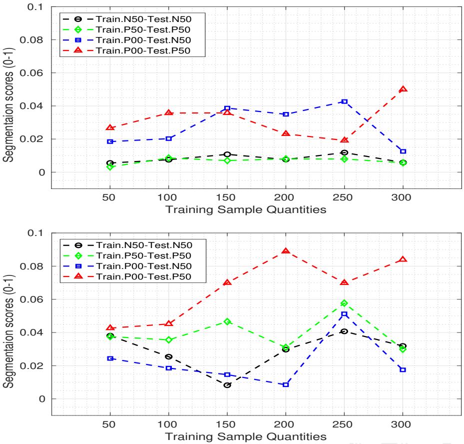
Training Data Gaze-angle (rows) / Testing Data Gaze-angle (columns)

	N50	N40	N30	N20	N10	P0	P10	P20	P30	P40	P50
N50	0.0245	0.0292	0.0380	0.0457	0.0507	0.0537	0.0487	0.0463	0.0456	0.0512	0.0679
N40	0.0163	0.0140	0.0160	0.0188	0.0221	0.0334	0.0216	0.0221	0.0334	0.0455	0.0670
N30	0.0396	0.0368	0.0378	0.0400	0.0415	0.0701	0.0439	0.0481	0.0542	0.0639	0.0730
N20	0.0206	0.0171	0.0169	0.0182	0.0184	0.0336	0.0188	0.0223	0.0376	0.0591	0.0782
N10	0.0226	0.0221	0.0227	0.0250	0.0259	0.0253	0.0256	0.0260	0.0334	0.0427	0.0557
P0	0.0178	0.0144	0.0142	0.0153	0.0152	0.0224	0.0148	0.0178	0.0292	0.0507	0.0816
P10	0.0138	0.0123	0.0134	0.0153	0.0165	0.0187	0.0150	0.0167	0.0268	0.0507	0.0828
P20	0.0154	0.0144	0.0159	0.0183	0.0199	0.0196	0.0183	0.0182	0.0222	0.0341	0.0493
P30	0.0143	0.0121	0.0145	0.0169	0.0185	0.0218	0.0157	0.0164	0.0245	0.0371	0.0545
P40	0.0150	0.0167	0.0231	0.0279	0.0345	0.0413	0.0299	0.0272	0.0283	0.0361	0.0490
P50	0.0124	0.0171	0.0250	0.0318	0.0360	0.0392	0.0308	0.0276	0.0230	0.0227	0.0295

Impact of the Size of Training Set

Experiments

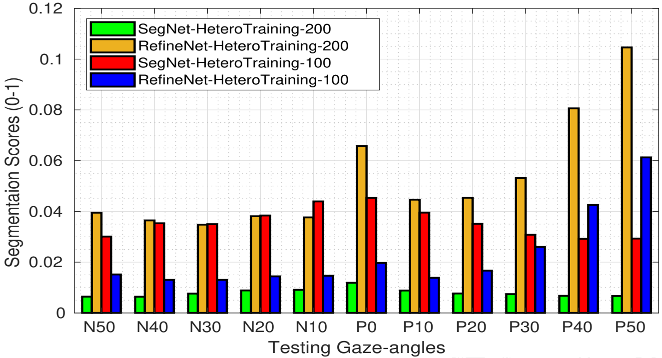
- We trained the networks with: 50, 100, 150, 200, 250, and 300 pcs of N50 and P50 gaze-angle images respectively, testing on the remaining images.
- We also trained networks with increasing quantities of frontal images (P0), and then tested on the same N50 and P50 gaze-angle images.



Does Heterogeneous Training Helps, What is the Optimal Quantity

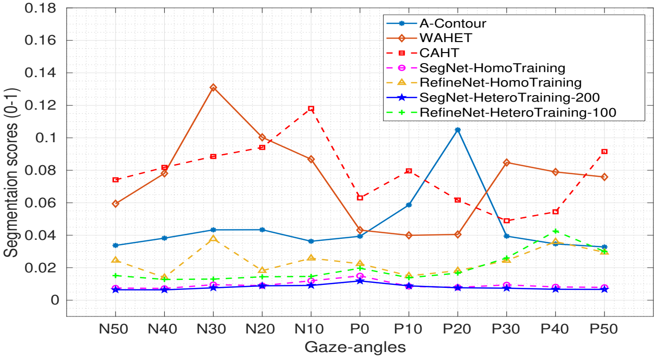
Experiments

- We trained the networks with all (200 samples per gaze-angle), and half quantity (100 samples per gaze-angle) in our training set, and then tested the networks on all images in the testing data.



Experiments

- We compared the corresponding segmentation results to those obtained by applying 3 classical iris segmentation algorithms: active contours-GrabCut (A-Contour) [3], contrast-adjusted Hough transform (Caht) [4], and weighted adaptive hough and ellipsopolar transform (Wahet) [5].



End

Thank you, Remarks?

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