Mobile NIR Iris Recognition: Identifying Problems and Solutions

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Problem Statement: Mobile NIR Iris

The spread of biometric applications in mobile devices handled leads to:

- untrained users
- larger extent of rotation

This in turn will lead to:

- harder segmentation task
- more segmentation errors
- worse biometric recognition
- more retries (user is rejected)

What we did about it

1. Analyse the problem
   - Use new near-infrared iris dataset (*protMI* available online)
   - Analyse the rotation observed in images and
   - Analyse the impact on segmentation and biometric recognition
2. Give a first solution to the problem (of segmentation):
   - Use CNN for segmentation
   - Provide a manually annotated ground truth segmentation (available online) – required to train the CNN

Problem Statement: CNN and recognition

- CNNs are very good at identifying pixels with iris information.
- Iris recognition systems require a parameterization of the iris boundaries.

What we did about it:

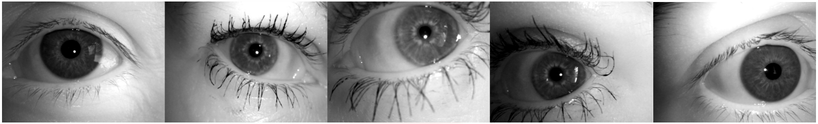
1. Propose a method to parameterize the CNN segmentation.
2. Analyse and compare the CNN based segmentation with traditional methods (USIT base available online).

Database—Protect Multimodel DB (iris subset)

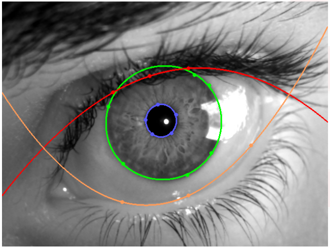
Recording device: Irishield device connected to a mobile phone (Samsung S8)

- Irishield MK212OU, optimal distance: 5cm, Focal depth: 6mm
- Illumination: NIR light
- Images:
  - 640x480, 8-bit grayscale, ISO 19794-6 conform
  - 1008 Images from 28 users
  - 21 excluded (due to algorithmic problems)

Database—Examples and Groundtruth



Sample images from the Protect Multimodal DB.



Groundtruth: Inner and outer iris boundaries and delimination of upper and lower eyelid.

Groundtruth of the database:

- Single human segmentor.
- Elliptical pupillary and sclera boundaries
- Polynomial eyelid boundaries
- Excluded 21 image: Too much rotation for the eyelids to be deliminated with polynomials.

Rotation in the Database

Setup:

- Minimize errors (use groundtruth)
- Adjust rotation compensation and minimize EER

Due to movment induced by sup/inf rectus and sub/inf oblique muscles the eye can rotate in the eysocket, range of movement is roughly $\pm 10^\circ$ (or ± 16bit).

Everything more is a rotation introduced by users of the mobile devices.

Rotation in the Database – Results I

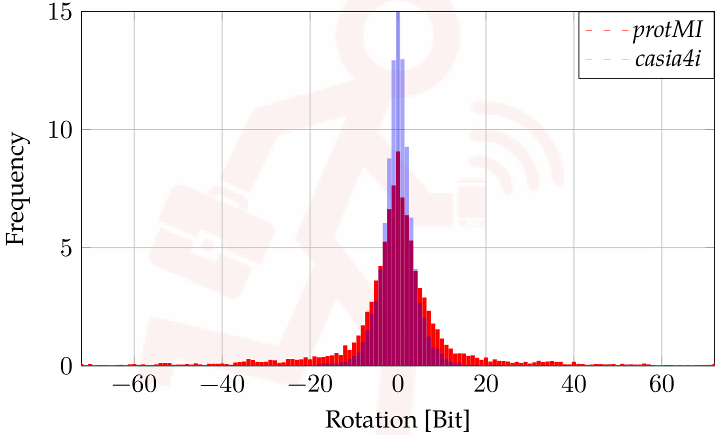
Experiment to find the rotation in the protMI *database.*

rotation [±bit]	EER [%]	$OP_{0.01}$ [%]
16	8.74	50.48
24	6.49	49.56
32	5.12	49.07
40	4.53	48.74
48	4.10	48.43
56	3.96	48.26
64	3.96	48.26
72	3.96	48.26

- ±56 bit rotation or ±40° (baseline is ±10°)

Rotation in the Database – Results II

Frequency of Rotation on the protMI *compared to the* casia4i *database.*



- Overlap of ~74%
- ~26% of users have higher rotation

CNN based Iris Segmentation

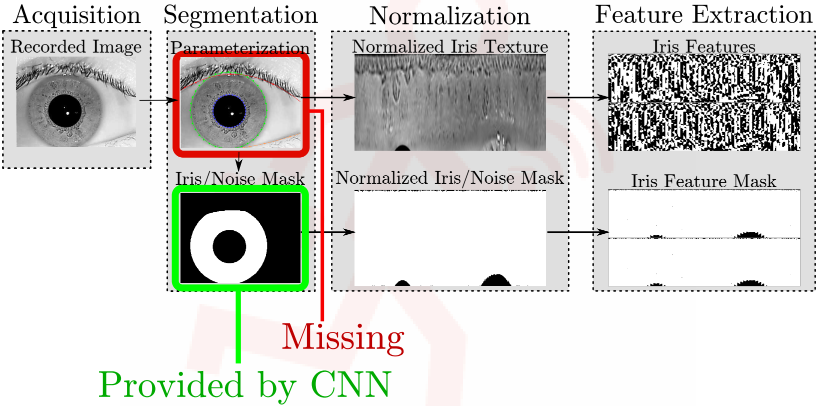
Average segmentation scores per dataset.

CNN	Database	E1	E2	$\mathcal{F}1$
RefineNet	*casia4i*	0.009	0.011	0.984
	casiaA	0.005	0.012	0.972
	iitd	0.015	0.018	0.974
	protMI	0.044	0.151	0.746
iFCEDN	*casia4i*	0.021	0.028	0.962
	casiaA	0.007	0.020	0.966
	iitd	0.018	0.022	0.970
	protMI	0.008	0.024	0.952

E1,E2 Type 1 (E1) and type 2 (E2) errors (as used in the noisy iris challenge evaluation)—lower is better

$\mathcal{F}1$ The $\mathcal{F}1$-measure is the harmonic mean between precision and recall—higher is better

Recognition and CNN Segmentation I



Problem with the Recognition pipeline and CNN Segmentations

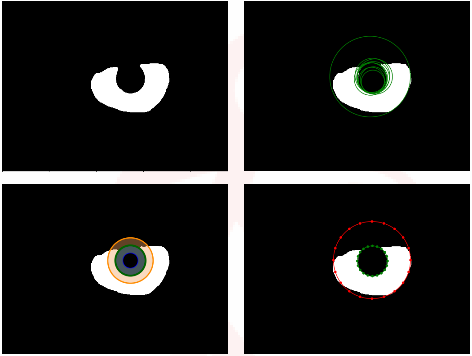
Parameterization of CNN Segmentation

CNN Segmentation

Pupillary c^p Candidates

Pupillary c^p, $A_i(c^p)$ and $A_o(c^p)$

Final Parameterization



Outline of the parameterization process.

$$V^p(c) = \frac{N(A_o(c)) - N(A_i(c))}{N(\widehat{A_o(c)})}$$

$$V^l(c, c^p) = \max\left(0, \frac{N(A_i(c)) - N(A_o(c))}{N(\widehat{A_i(c)})} - \frac{\sqrt{(c_x - c_x^p)^2 + (c_y - c_y^p)^2}}{c_r}\right)$$

Recognition and CNN Segmentation II

Comparison of different feature extraction and segmentation methods under a rotation of $\pm 56bit$.

feat.	seg.	EER [%]	$OP_{0.01}$[%]	ME
lg	*Groundtruth*	3.96	48.26	2015
lg	*CNNHT*	7.41	50.02	0
lg	*WAHET*	11.33	62.08	0
lg	*CAHT*	22.64	63.44	441500
qsw	*Groundtruth*	3.87	49.60	2015
qsw	*CNNHT*	7.36	52.03	0
qsw	*WAHET*	11.39	58.84	0
qsw	*CAHT*	23.15	49.43	441500
— OSIRIS —		15.05	99.74	0

Conclusion

- Large amount of rotation: ±56 bit (±40°)
  - Traditional segmentations have problems: EER $3\times$ higher than groundtruth)
  - Expensive to compensate
- CNN segmentation
  - Good segmentation performance ($\mathcal{F}$-measure: 0.952)
  - Proposed parameterization works
  - CNN+parameterization improves on traditional methods: EER $2\times$ higher than groundtruth)
- ***There is still room for improvement***

Reproducible research

- Database: http://projectprotect.eu/dataset
- Groundtruth: http://wavelab.at/sources/Hofbauer18b
- USIT: http://wavelab.at/sources/USIT