EIID / Advanced Image Analysis (EIID/AIA)

Machine and Deep Learning (ML/DL)

2020-2021, 2nd semester

EIID/AIA standard project

and

Multidisciplinary project

Iris Segmentation and Recognition

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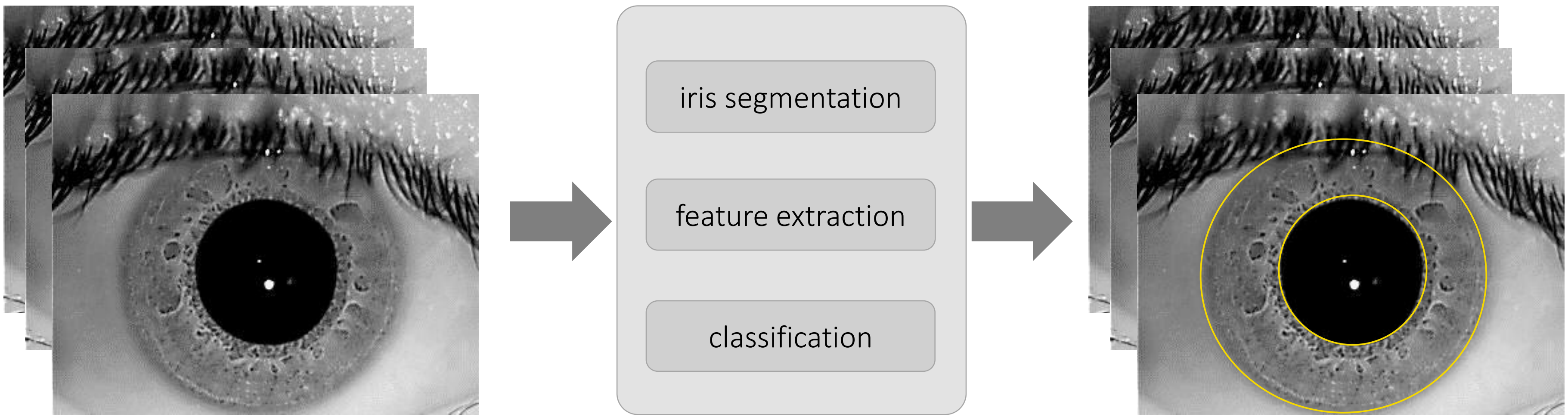
Motivations

- **iris recognition** is an important **biometric** identification method
  - classical systems assume ideal environmental conditions and cooperative users
    - when such conditions do not hold, their biometrics can be negatively affected
- iris **segmentation** is a critical part in iris recognition systems
  - errors in this initial stage are propagated to subsequent processing stages

Goal

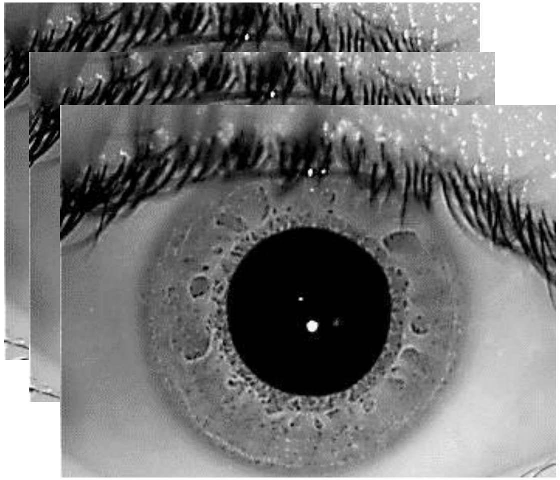
- implement a reusable module for *automated* **Iris Segmentation and Recognition**
  - `if(EIID/AIA standard project)`: implement only segmentation



input images IR system segmentation + recognition

Materials

- **IITD** dataset ($2{,}240$ images)
  - 320×240 pixels
  - 224 subjects (distinct folders), 10 images per subject



iris images (8-bit)

`/dataset/images`

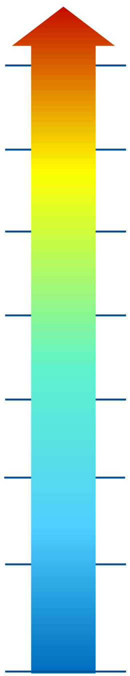
manual segmentations

`/dataset/groundtruths`

Performance evaluation (Segmentation)

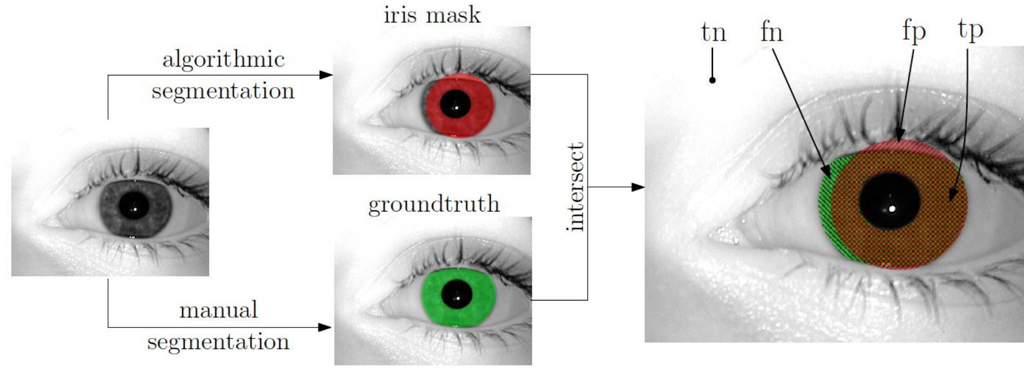
- average F1-score ($F1$)

$$F1 = \frac{2 \cdot Recall \cdot Precision}{Recall + Precision}$$



0.92	*state-of-the-art*
0.90	publication level
0.88	excellent
0.86	good
0.84	fair
0.82	adequate
0.80	fairly adequate
⋮	⋮

$$P = \frac{tp}{tp + fp} \qquad R = \frac{tp}{tp + fn}$$



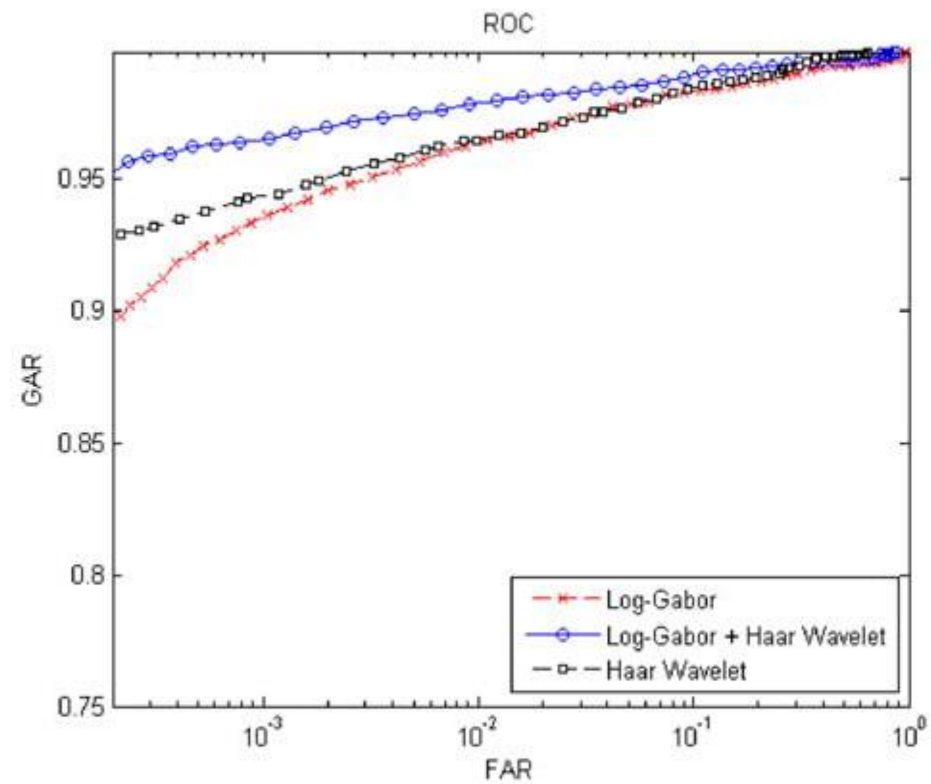
tp : pixels $\neq 0$ in the output and in the groundtruth

fp: pixels $\neq 0$ in the output and $= 0$ in the groundtruth

fn: pixels $= 0$ in the output and $\neq 0$ in the groundtruth

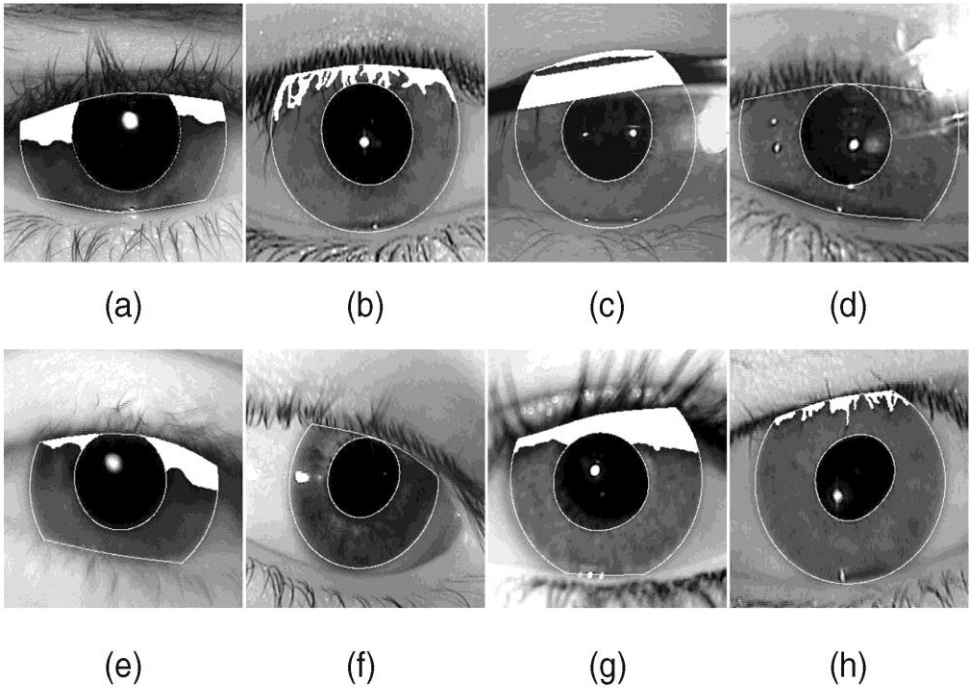
Performance evaluation (Recognition)

- **ROC curves**
  - Genuine Acceptance Rate (GAR) vs. False Acceptance Rate (FAR), 100% equivalent to True Positive Rate (TPR) vs. False Positive Rate (FPR)
  - see blue curve on the right as reference
- **Equal Error Rate** (EER)
- **Decidability Index** (DI)
- see "*Comparison and combination of iris matchers for reliable personal authentication*" in `/literature`



Challenges

- partially occluded eyes
- different viewpoints
- some blurry images
- **many classes (224)**
- **few images per-class (10)**
- low resolution images



Hints

- **segmentation**
  - edge-based + geometrical approaches
  - `if(multidisciplinary project)`: you can refine it using machine learning
- **feature extraction**
  - Haar wavelets, Gabor wavelets
  - features from autoencoders
- **ML**
  - feature / classifier combination
  - clustering approaches
- **DL**
  - 2-step (e.g. segmentation with U-Net + image classification with ResNet)
  - end-to-end: joint segmentation and classification with two branches (e.g. Mask R-CNN)
  - use other datasets to pre-train (pre-fine-tune) the network

Constraints (multidisciplinary project)

- **split the data** *class-wise* into a **training** and a **test set**
  - training set = first 50% of the images, class-wise
  - test set = second 50% of the images, class-wise
  - no random split (this way different groups will adopt the same fixed split)
  - train your ML/DL models on the training set, evaluate performance on the test set
- **ML**: test several models and find your own (possibly novel) method
  - ...it is *not* okay to train/test only one model because 'it just works'
- **DL**: it is ok to implement and/or fine-tune an architecture found on the web...
  - ...if it works on the first attempt, at least try something different, like different hyperparameters and slight modifications of the architecture

If you want to do more (optional)

- use other datasets to pre-train
- use autoencoders to boost feature extraction and ML