Improved Post-mortem Iris Recognition with DCNN-based Image Segmentation

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Post-mortem iris recognition

Current state-of-the-art

- **fairly well evaluated**, efforts by two main groups: WUT-NASK/Notre Dame (Trokielewicz, Czajka, Maciejewicz) and ORNL (Bolme, Boehnen)
- Presentation Attack Detection (PAD) method proposed

  (Trokielewicz *et al.*, BTAS 2018)

- **no methods improving post-mortem recognition accuracy**
- post-mortem-specific segmentation method proposed, but **without recognition pipeline integration**

  (Trokielewicz *et al.*, IWBF 2018)

Contributions

- an end-to-end iris localization and image segmentation model that can be used as a drop-in replacement for OSIRIS' segmentation (or any other method)
- experiments showing a considerable improvement in the performance of a hybrid method employing the proposed segmentation and iris encoding done with OSIRIS
- source codes and neural network models' weights
- a new dataset of cadaver iris images collected from 42 subjects over a time period of up to 369 hours post-mortem

Databases of iris images

Post-mortem datasets

Training data:

- **Warsaw-BioBase-Postmortem-Iris-v1.1**, 574 near-infrared (NIR) and 1023 visible light (VIS) images from 17 cadavers over a period of up to 34 days

  (Trokielewicz *et al.*, BTAS 2016)

- **Warsaw-BioBase-Postmortem-Iris-v2**, an extension of v1.1, 626 NIR and 764 VIS images from 20 more subjects

  (Trokielewicz *et al.*, IEEE TIFS 2018)

Testing data:

- **Warsaw-BioBase-Postmortem-Iris-v3**, a new set of images collected for this study, adding data from 40 subjects with 1094 NIR and 785 VIS images, over up to 369 hours

Databases of iris images

Additional datasets for evaluation

Challenging dataset:

- **Warsaw-Disease-Iris-v1**, collected mostly from elderly ophthalmology patients, including subjects with ophthalmic conditions (subset of 552 images of 77 eyes is used)

  (Trokielewicz *et al.*, CYBCONF 2015)

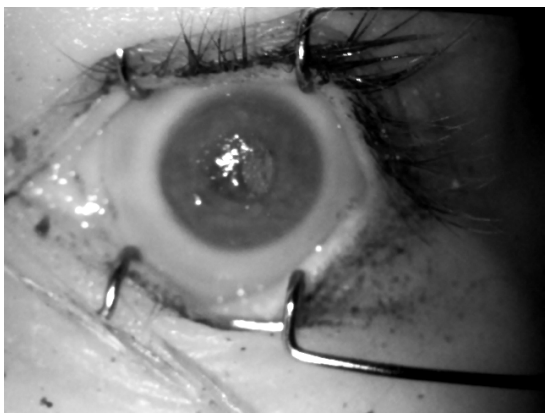
Easy dataset:

- **BioSec baseline corpus** – a well-known iris image database containing data collected from healthy subjects (subset of 1200 NIR images of 150 eyes is used)

  (Fierrez *et al.*, Pattern Recognition, 2007)

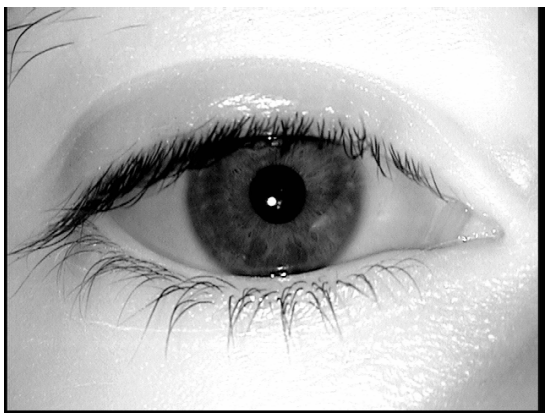
Databases of iris images

Selected samples



(a) Postmortem-Iris-v3

(b) Disease-Iris-v1



(c) BioSec

Baseline iris recognition method

OSIRIS

The method:

- open-source, developed within the BioSecure project (EU)
- follows the original Daugman concept

Recognition pipeline:

- coarse iris segmentation with circular Hough transform and active contour refinement
- iris normalization onto a dimensionless polar coordinate rectangle
- filtering with Gabor wavelets at multiple scales (3)
- calculation of the binary iris code using phase quantization
- yields fractional Hamming distance as a dissimilarity metric

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Baseline iris recognition method

OSIRIS

Score normalization

- proposed by Daugman (IEEE TSMC paper, 2007)
- penalizes comparison scores based on small number of commonly unmasked bits
- typically shifts the ROC to the left and downwards

$$HD_{norm} = 0.5 - (0.5 - HD_{raw})\sqrt{\frac{n}{N}}$$

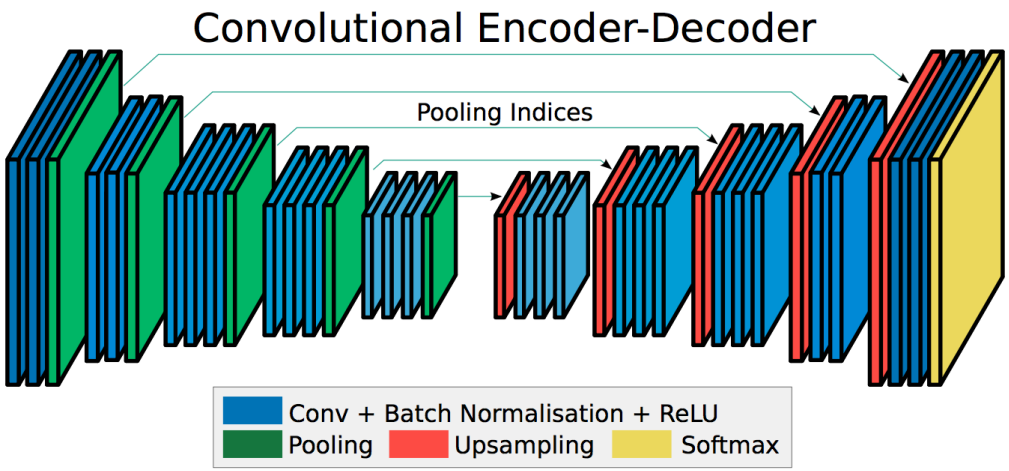
where:
n – number of bits that were available for comparison

N – typical number of bits compared between two irises, estimated for a particular database; here calculated separately for each experiment; max number of bits in OSIRIS code is 1536

Data-driven segmentation models

A starting point:

- Trokielewicz, Czajka, Maciejewicz (IWBF 2018)
  Data-Driven Segmentation of Post-mortem Iris Images
- trained and evaluated on Warsaw-Postmortem-v1 dataset, average IoU=86%, better than OSIRIS' IoU=78%



source: Badrinarayanan et al., "SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation", IEEE Trans. Pattern Anal. Mach. Intell., 2017

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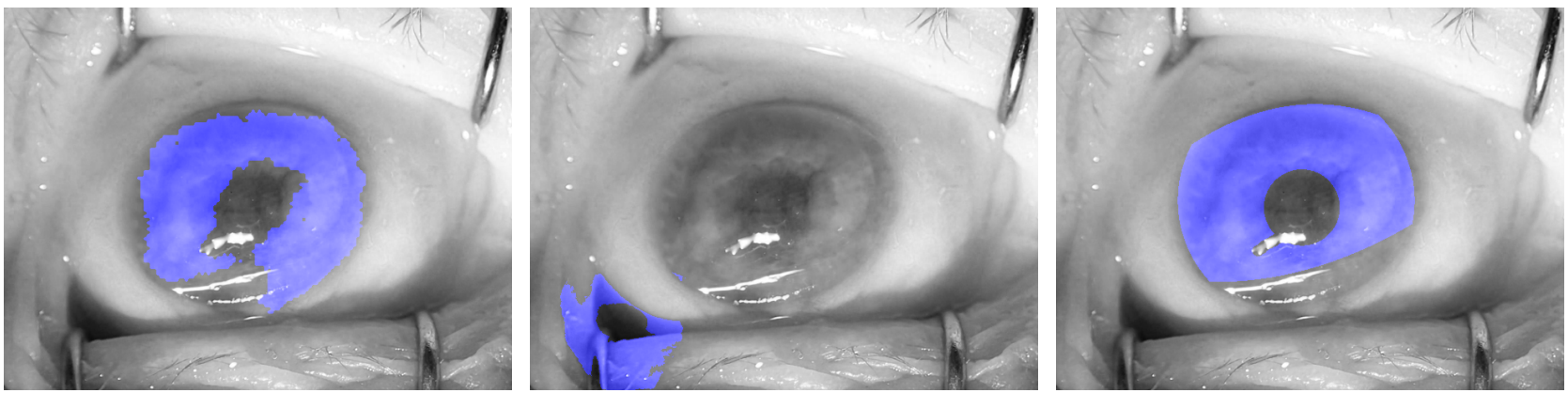


(a) DCNN-based (b) OSIRIS (c) Ground truth

Data-driven segmentation models

Old model:

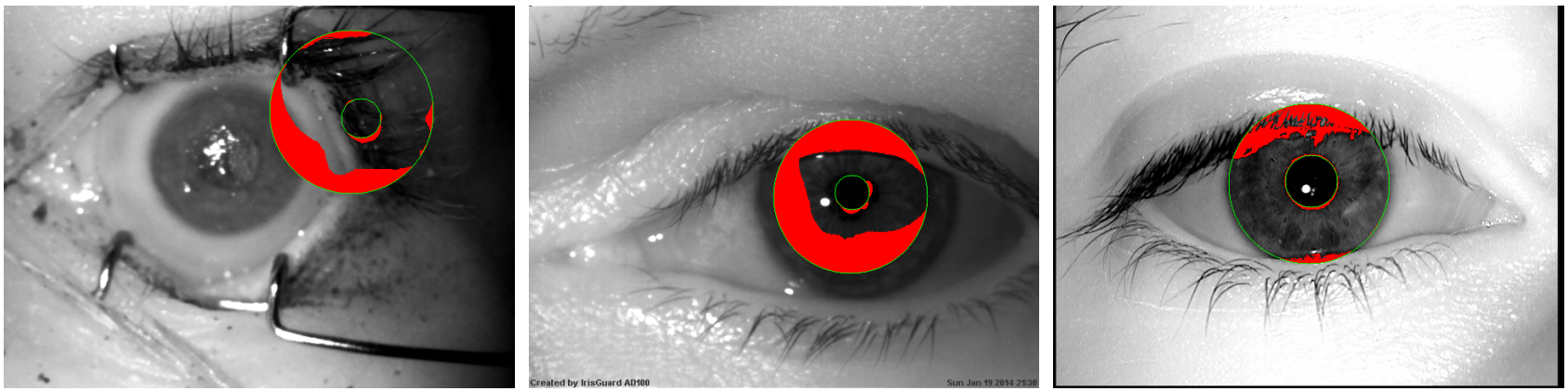
- ***fine***: trained with data from the Postmortem-Iris-v1 database with **fine-grained ground truth masks** denoting only the clearly visible iris portions, 120×160 predictions

New models:

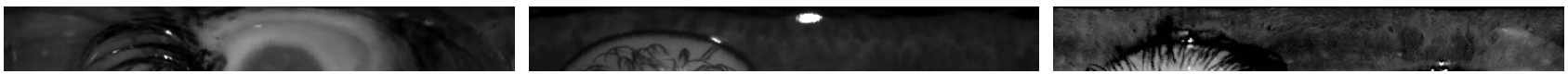
- ***fine v2highres***, trained with data from Postmortem-Iris-v1 and NIR samples from Postmortem-Iris-v2 for twice as many epochs (120 vs 60), also with **fine-grained ground truth masks**, 240×320 predictions
- ***coarse*** trained with both NIR and VIS data from v1 and v2 of the Postmortem-Iris for 120 epochs, but with **coarse ground truth masks**, denoting only the inner and outer iris boundary and eyelids, 240×320 predictions

OSIRIS segmentation and normalization

Segmentation results (samples shown before):



Normalized images:

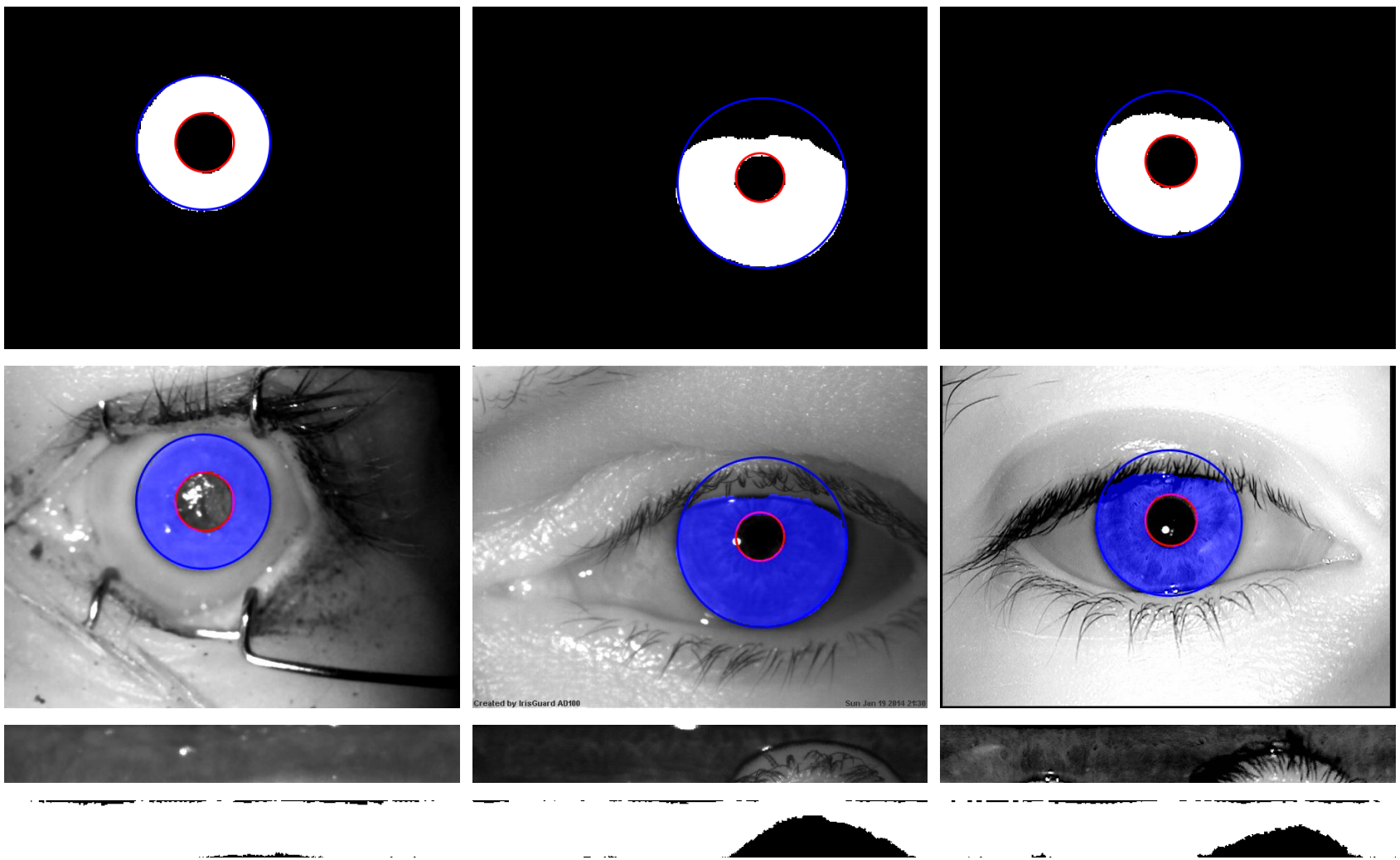


Normalized masks:

(a) Postmortem-Iris-v3 (b) Disease-Iris-v1 (c) BioSec

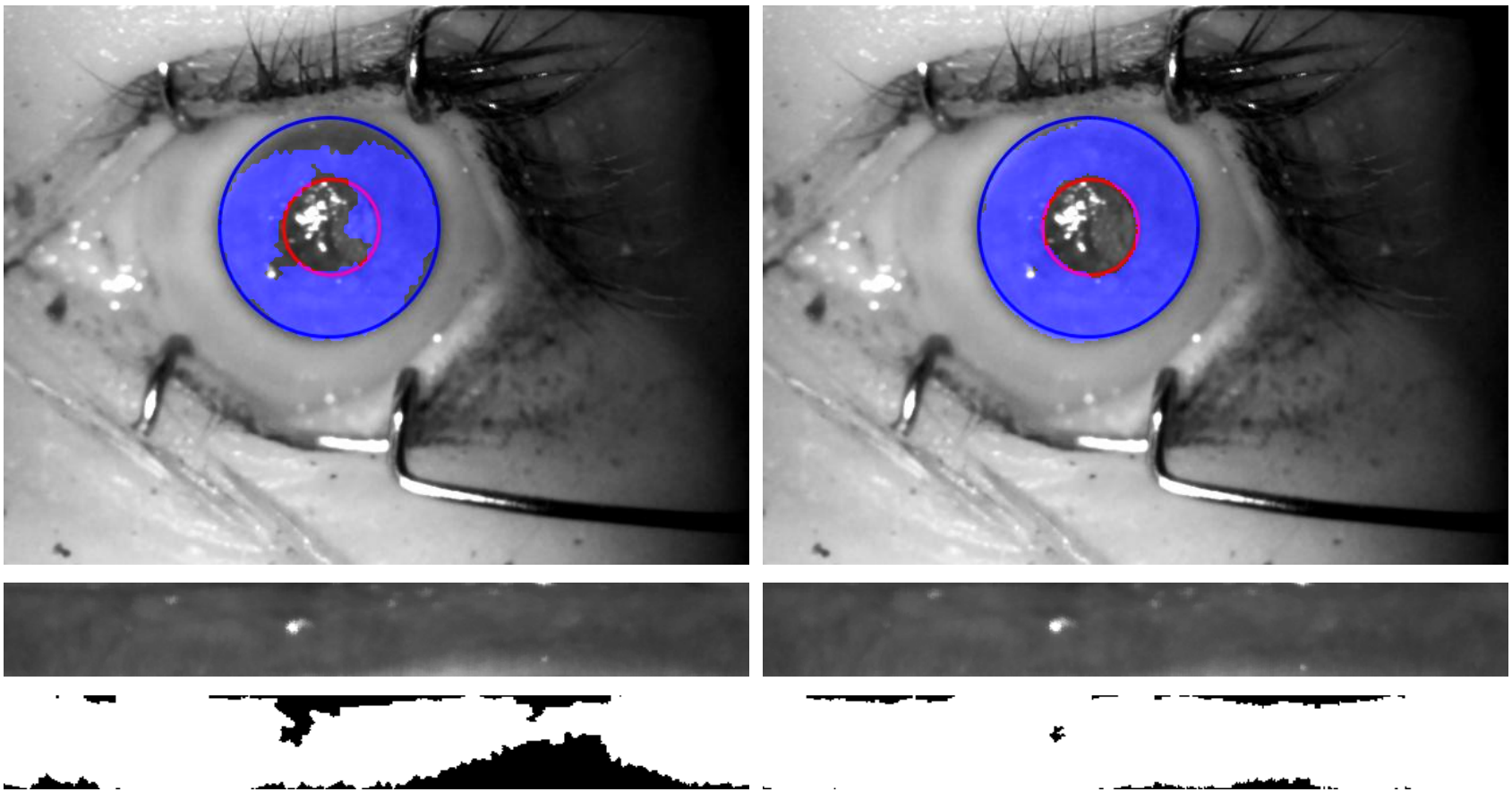
DCNN segmentation and normalization

using predictions from the *coarse* model and circular Hough transform



DCNN segmentation and normalization

using circle params from the *coarse* and masks from *fine* models (post-mortem only)



(a) fine (very selective)

(b) fine v2highres (less aggressive)

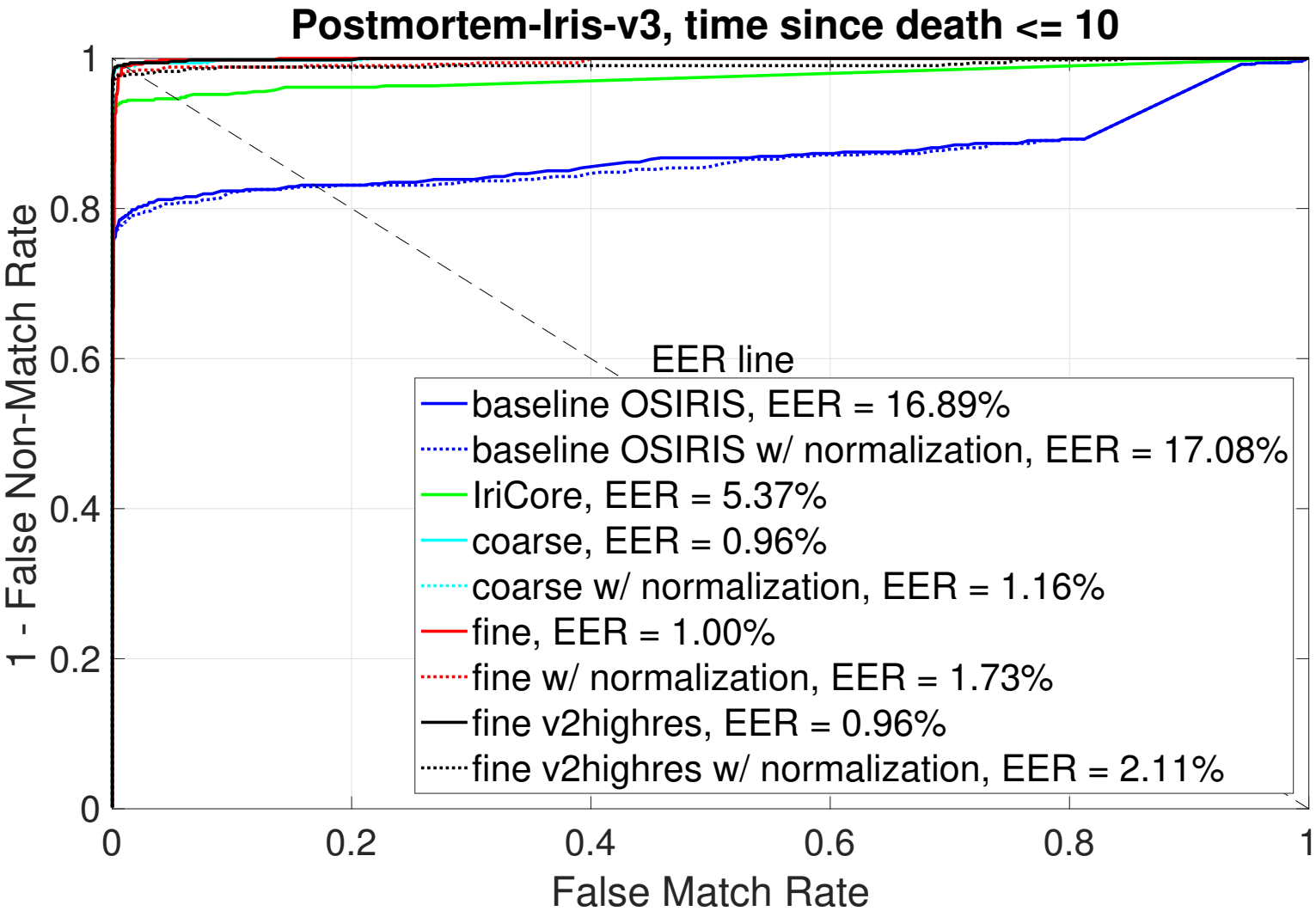
Comparison score generation

- **baseline (unmodified) OSIRIS** scores obtained for all possible genuine and impostor pairs for three test databases
- for post mortem data: segmentation results obtained from three DCNN models are injected into the OSIRIS pipeline
- for disease and healthy data: only the *coarse* model and the stock OSIRIS are evaluated

- **IriCore** commercial matcher employed as an additional method for comparison (undisclosed recognition methodology)
- chosen as best performing method in our previous post-mortem research

Results

post-mortem irises



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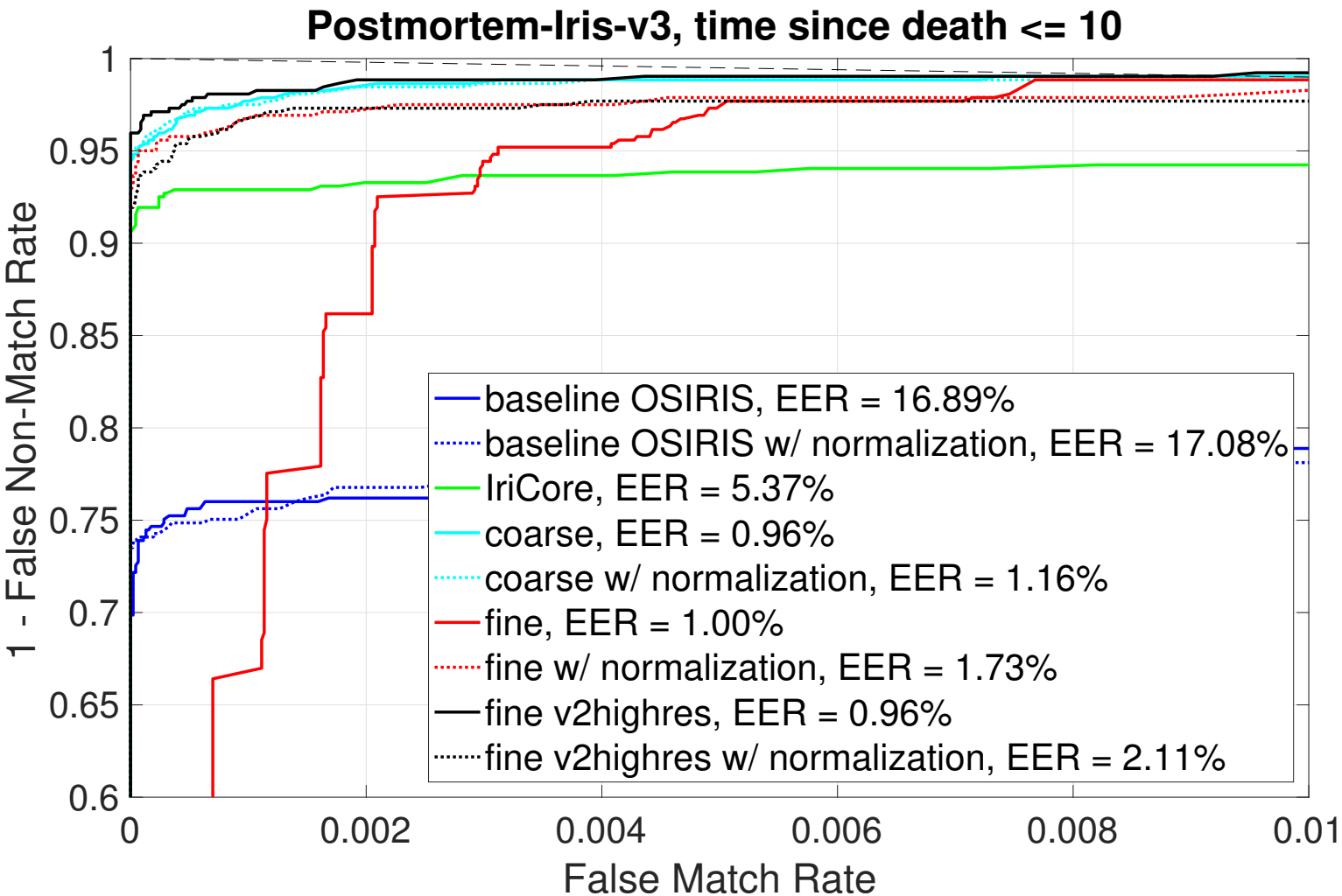

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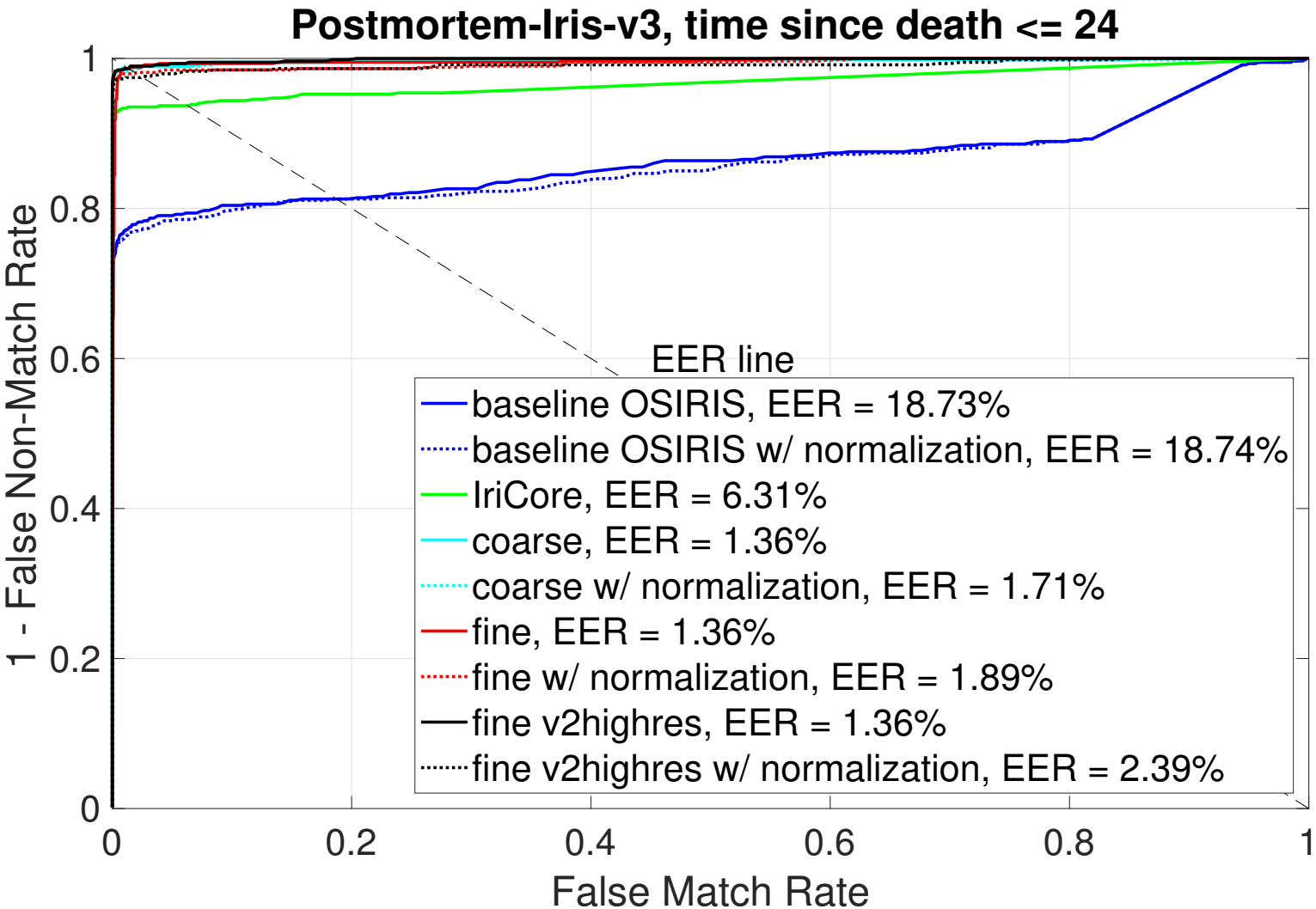
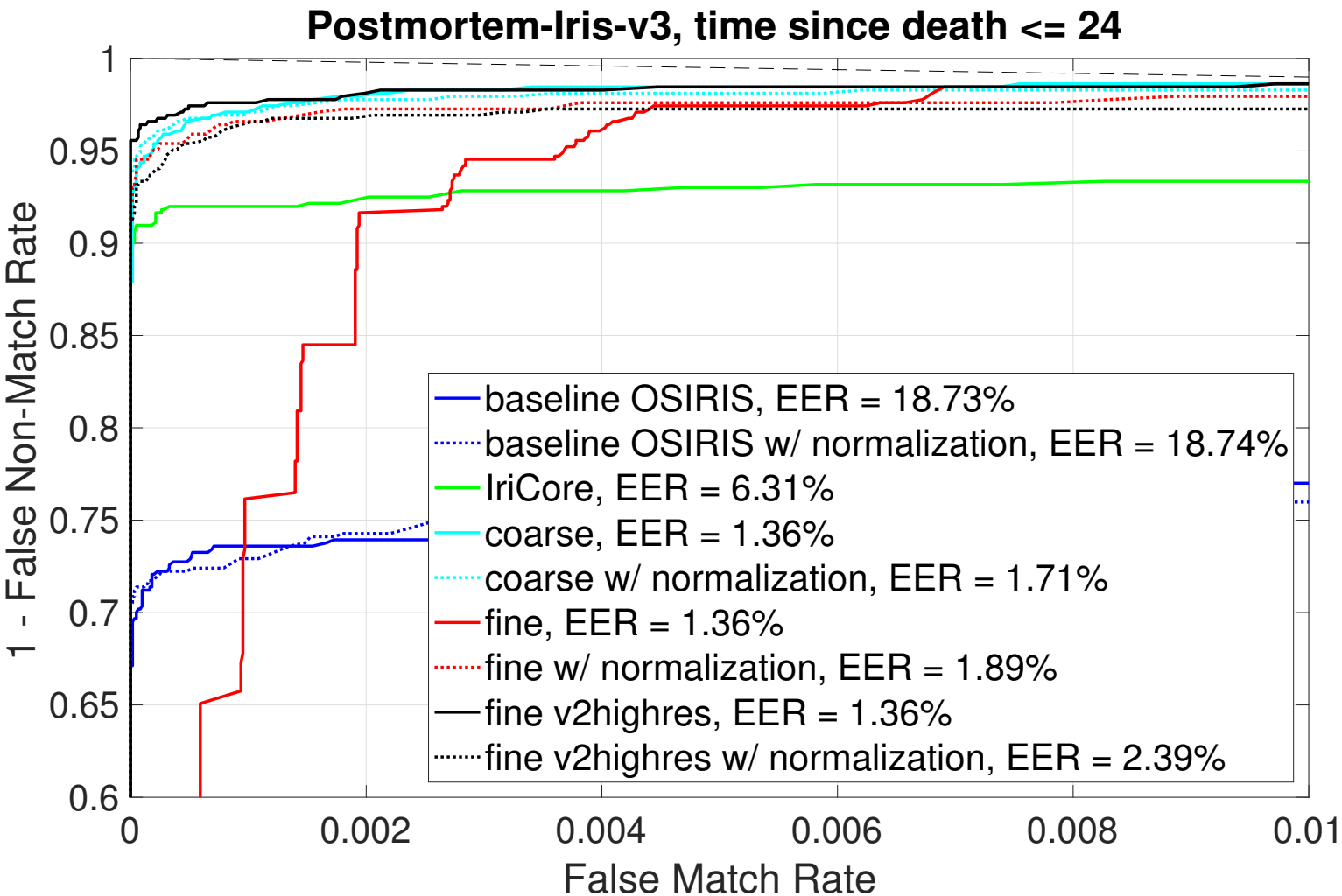


Results

post-mortem irises (close-up)



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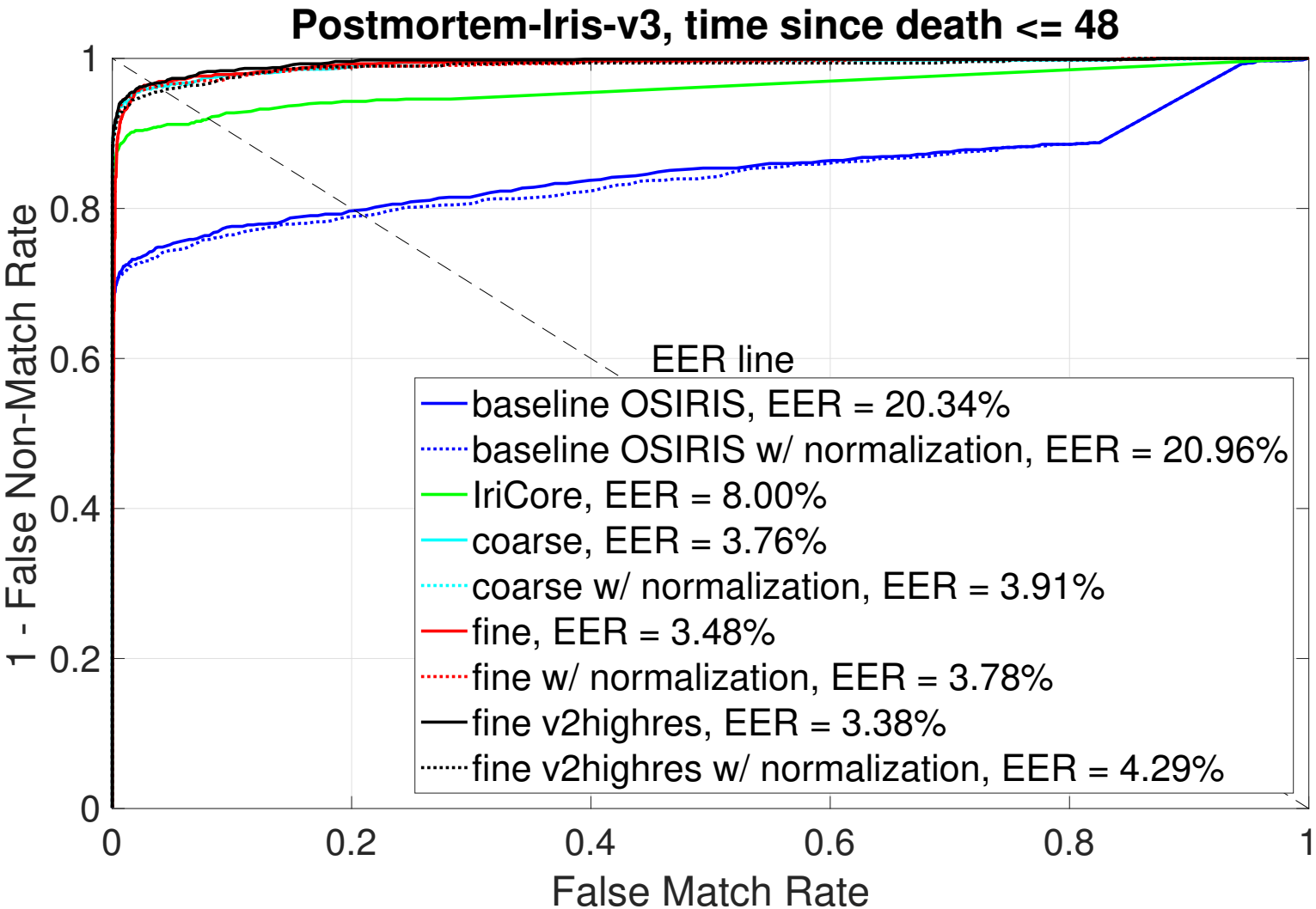

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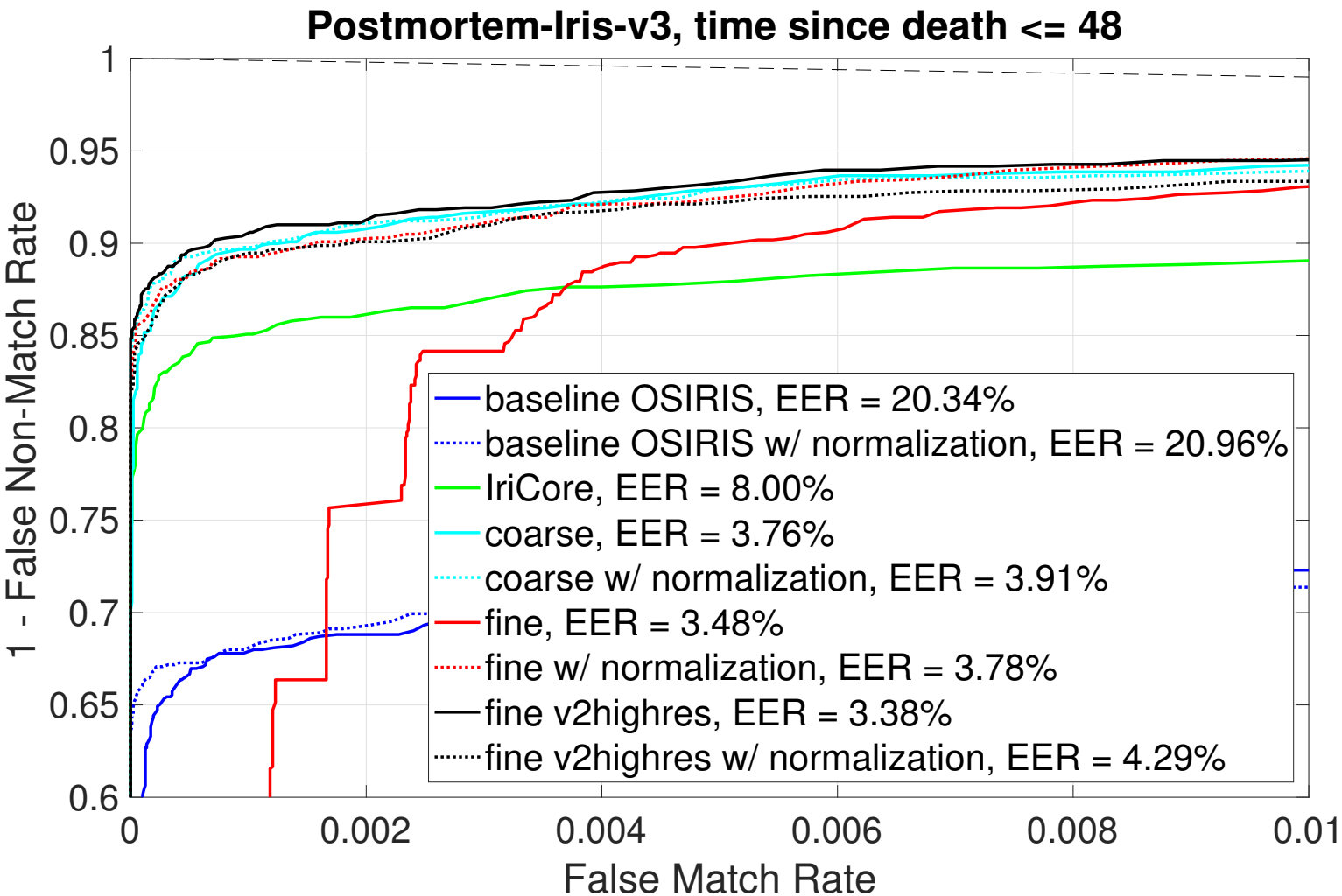

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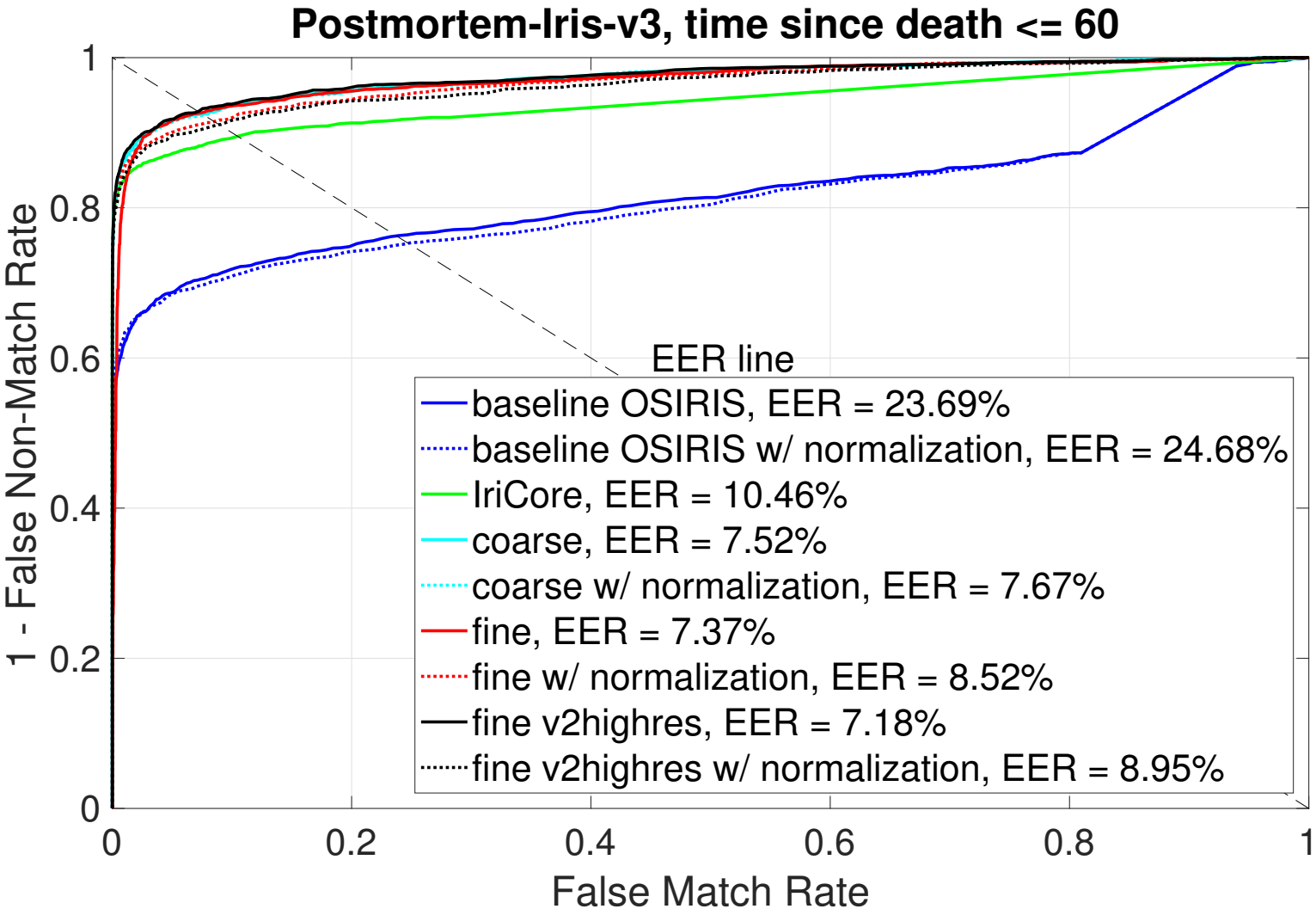

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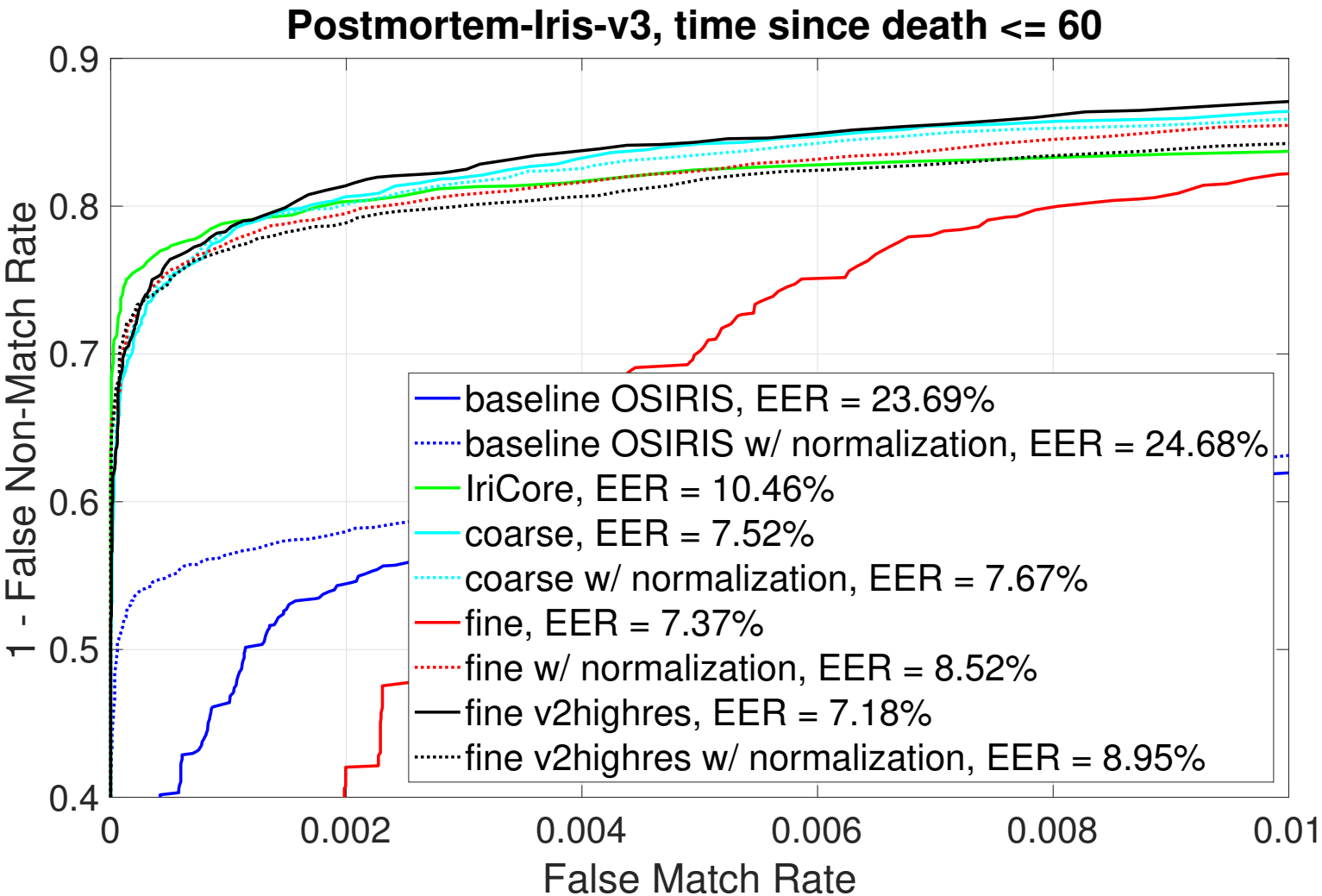

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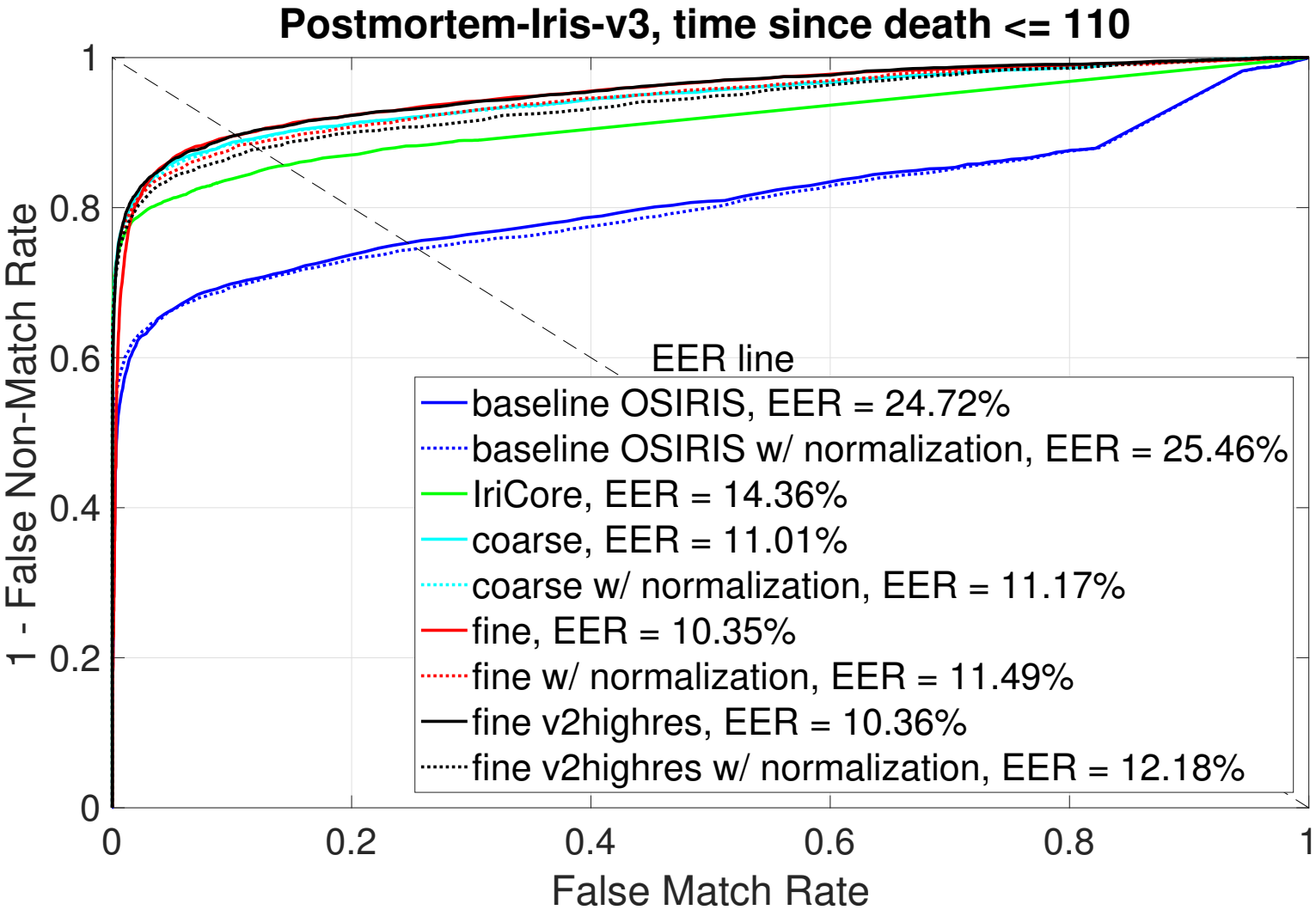

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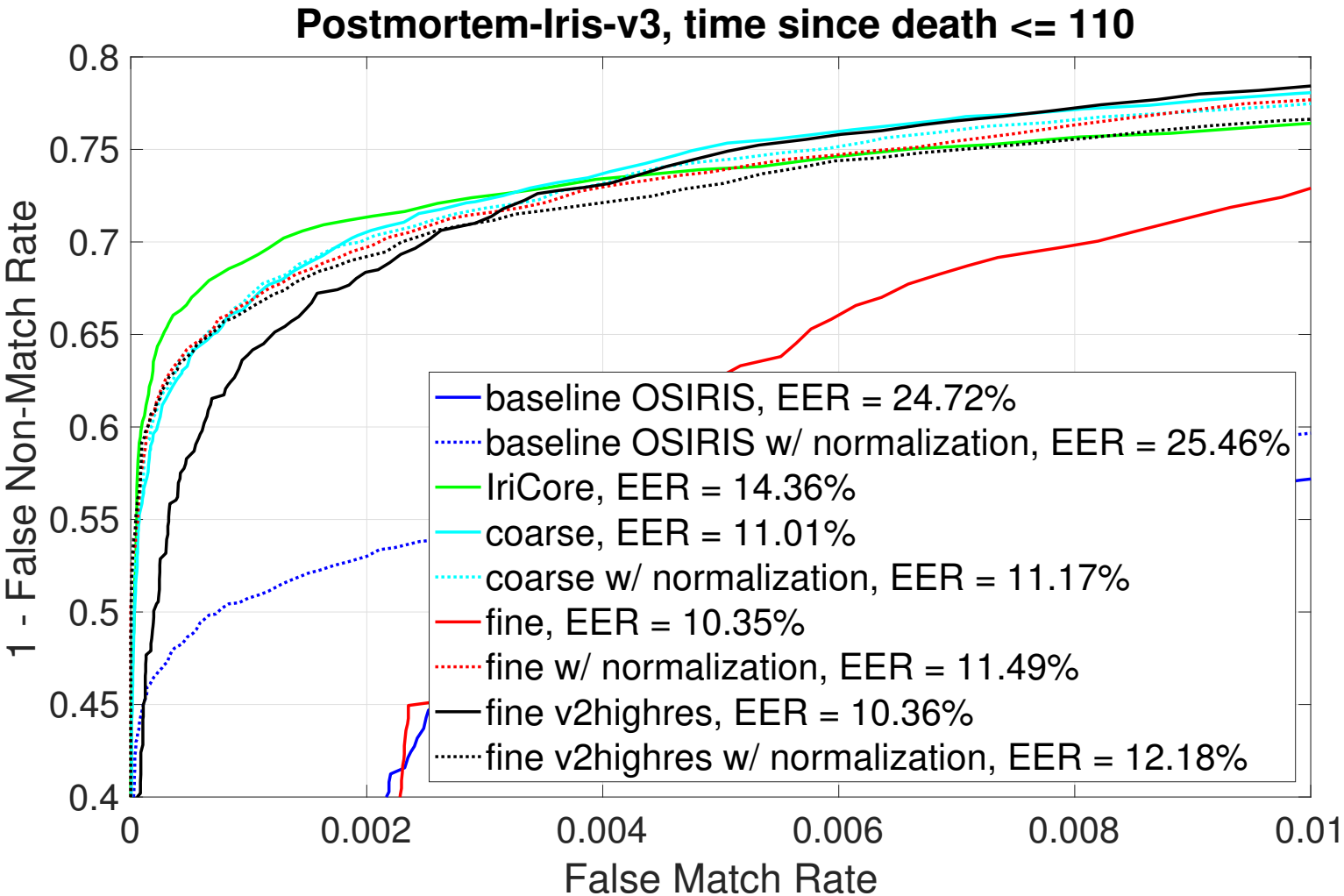

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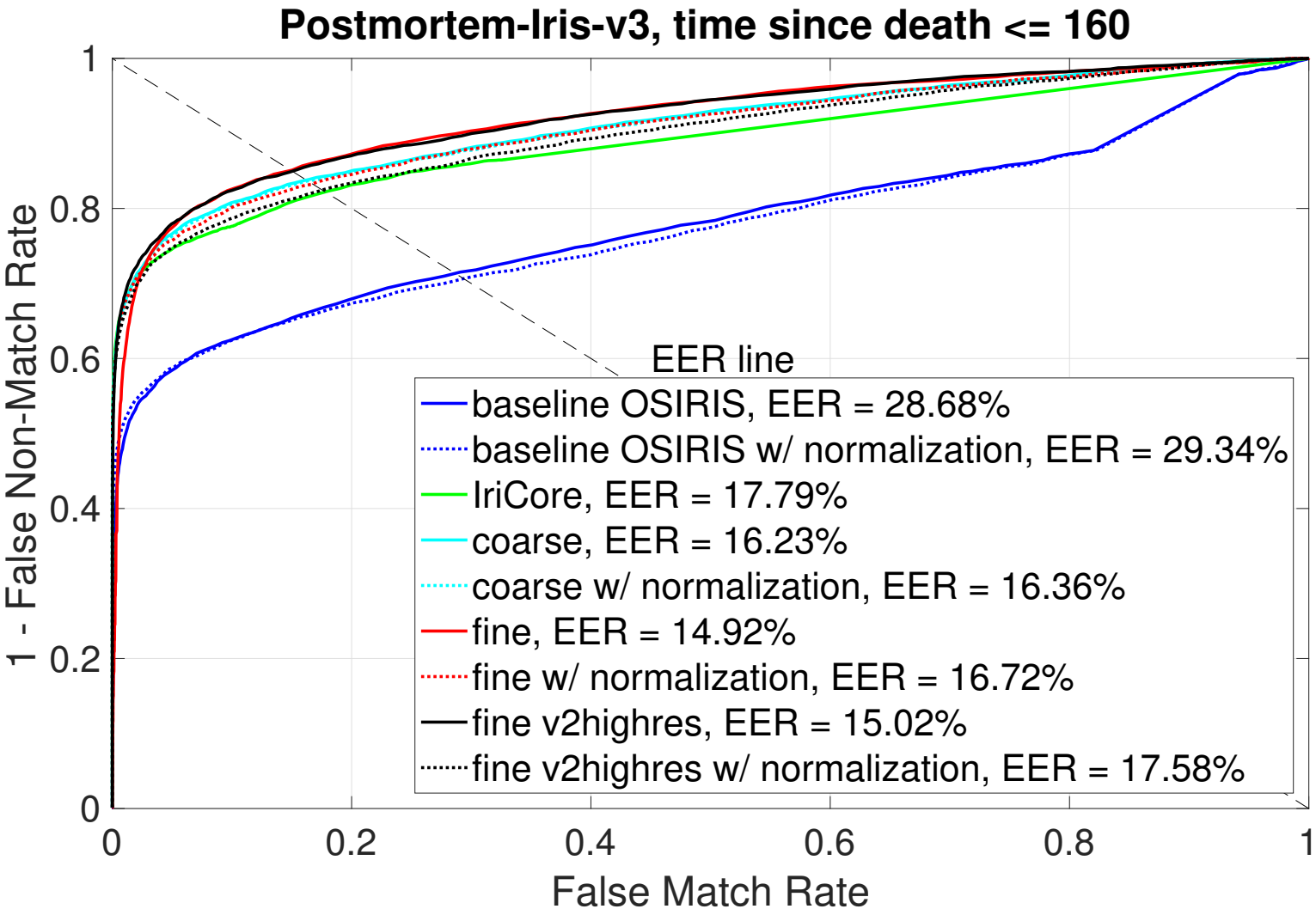

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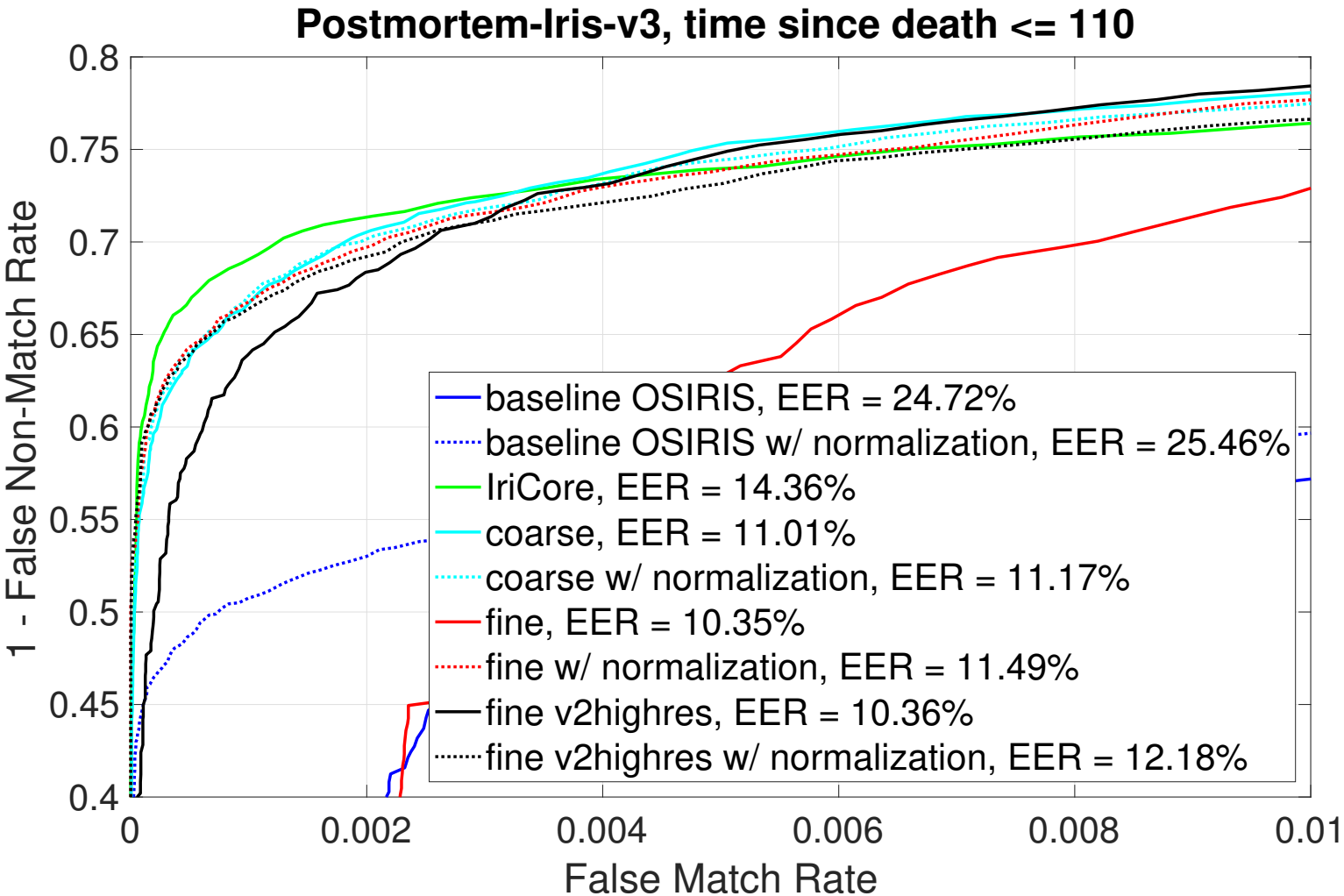

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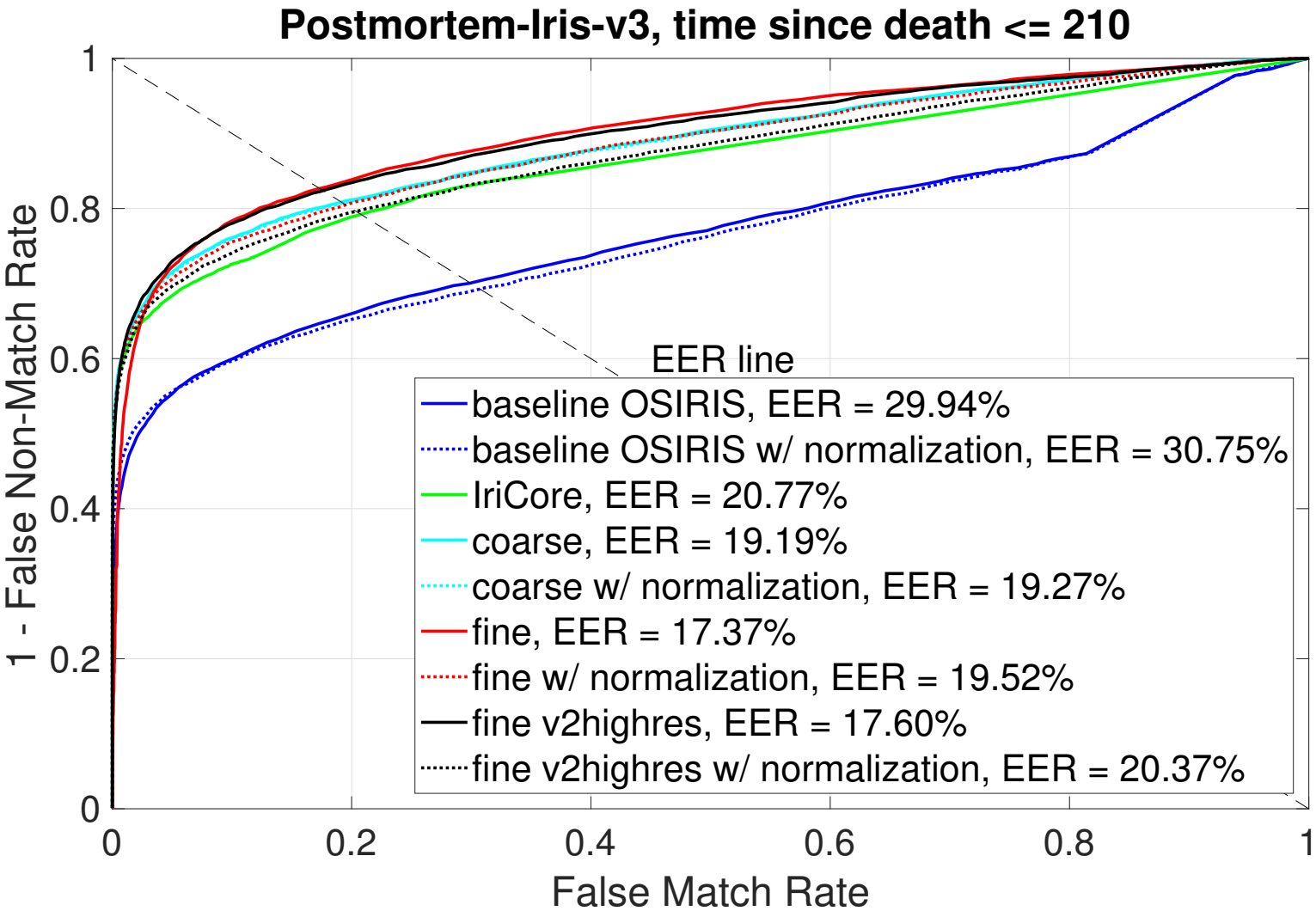

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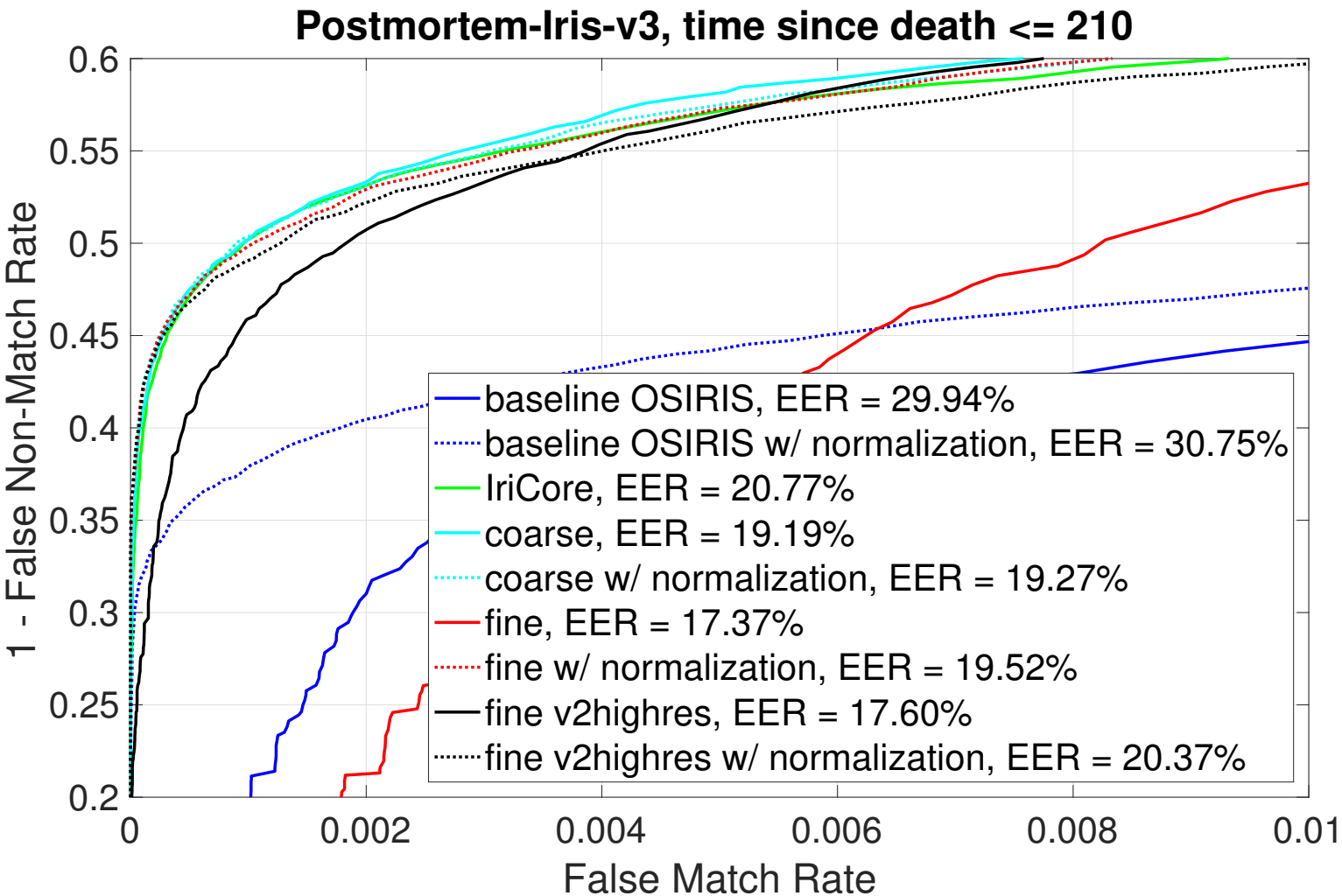
post-mortem irises (close-up)



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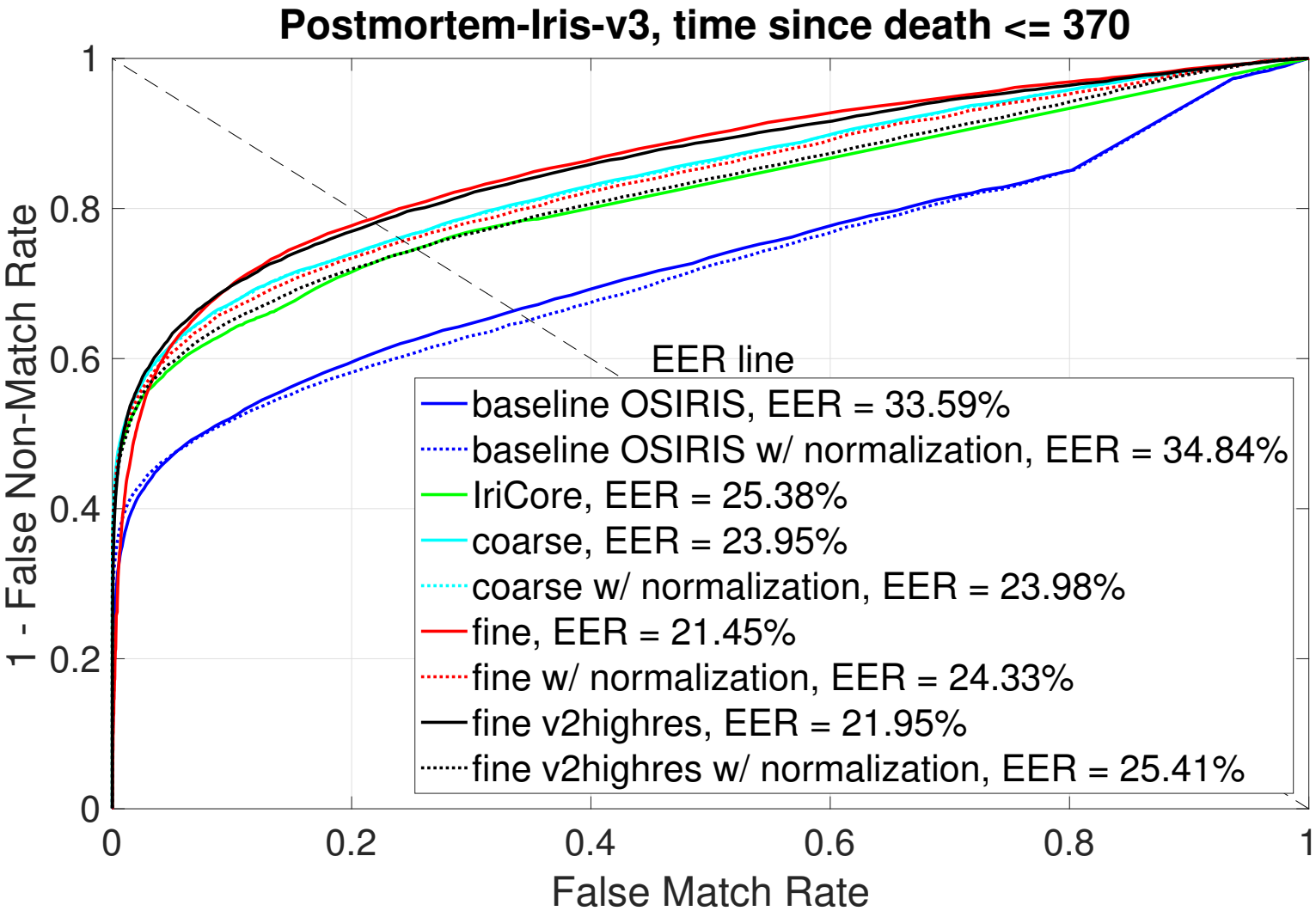

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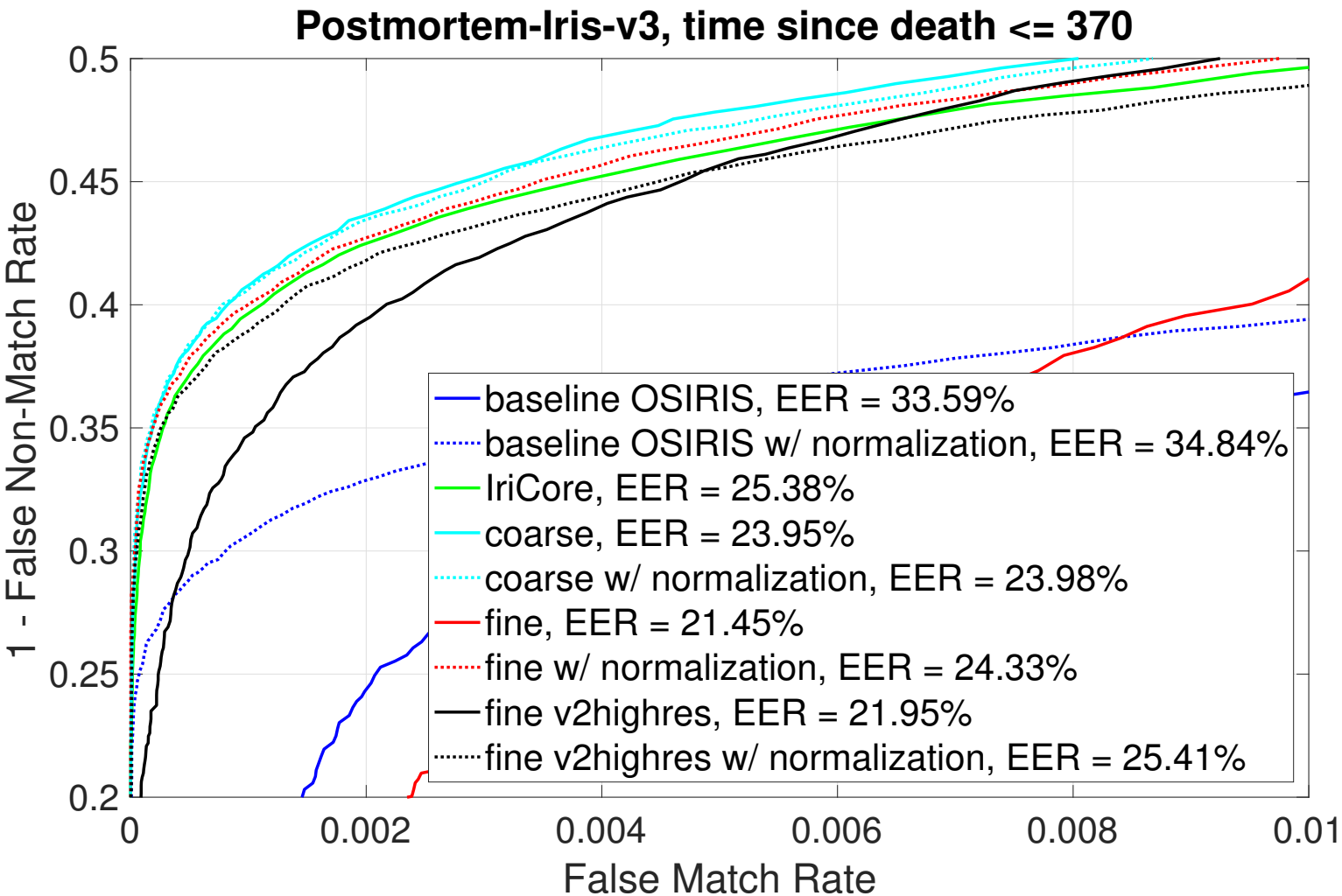
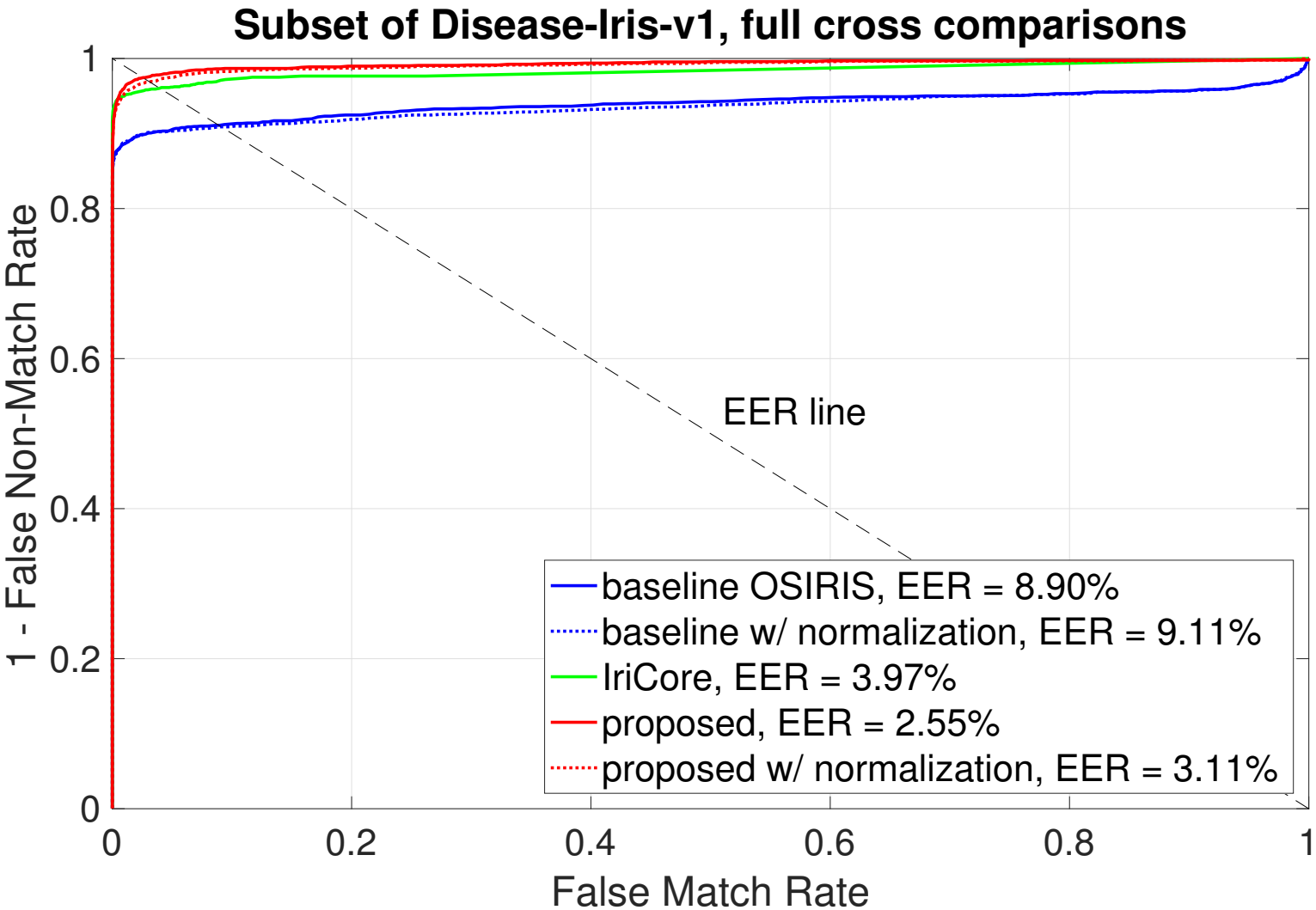


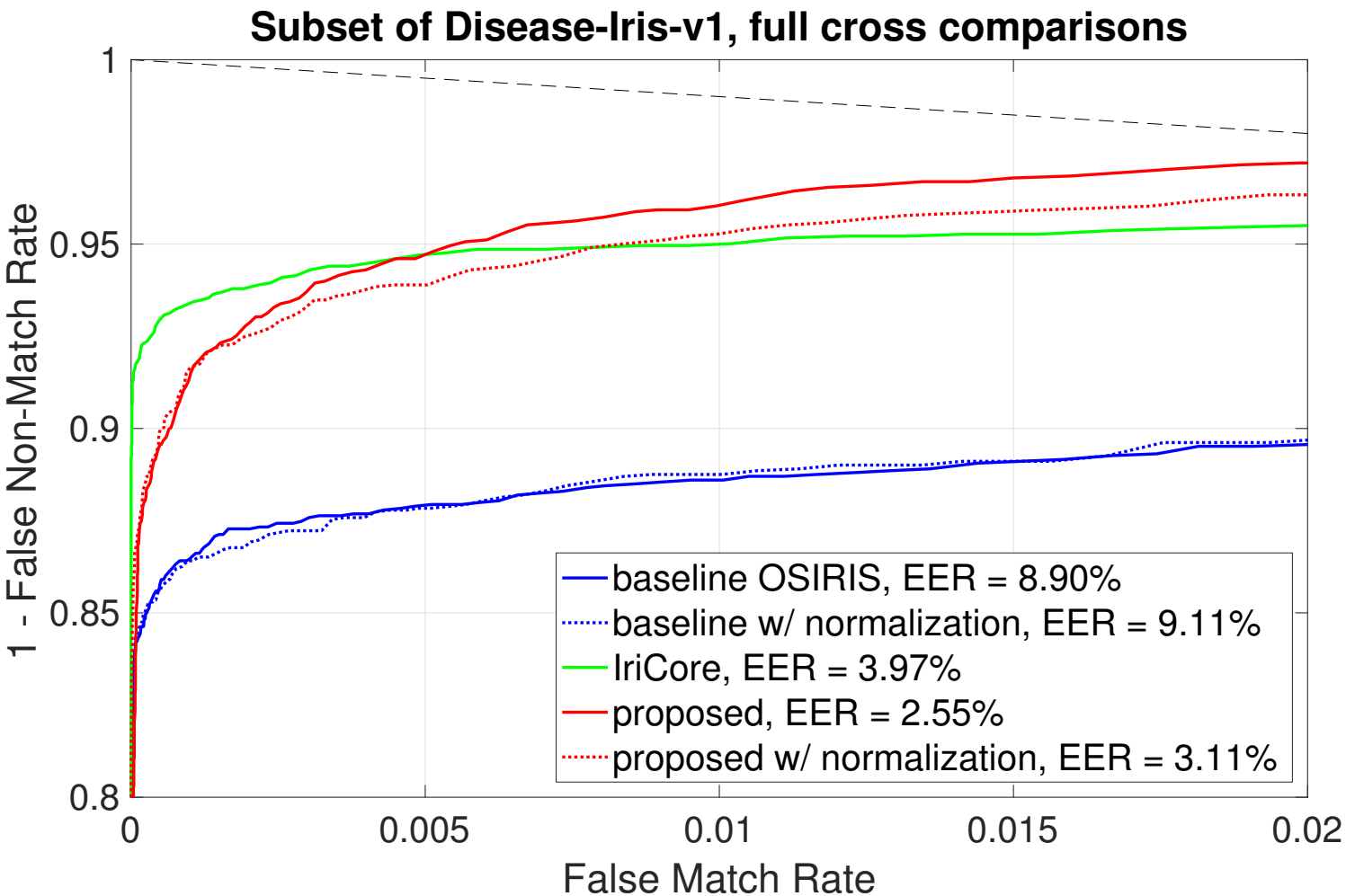
Results

elderly/disease-affected irises



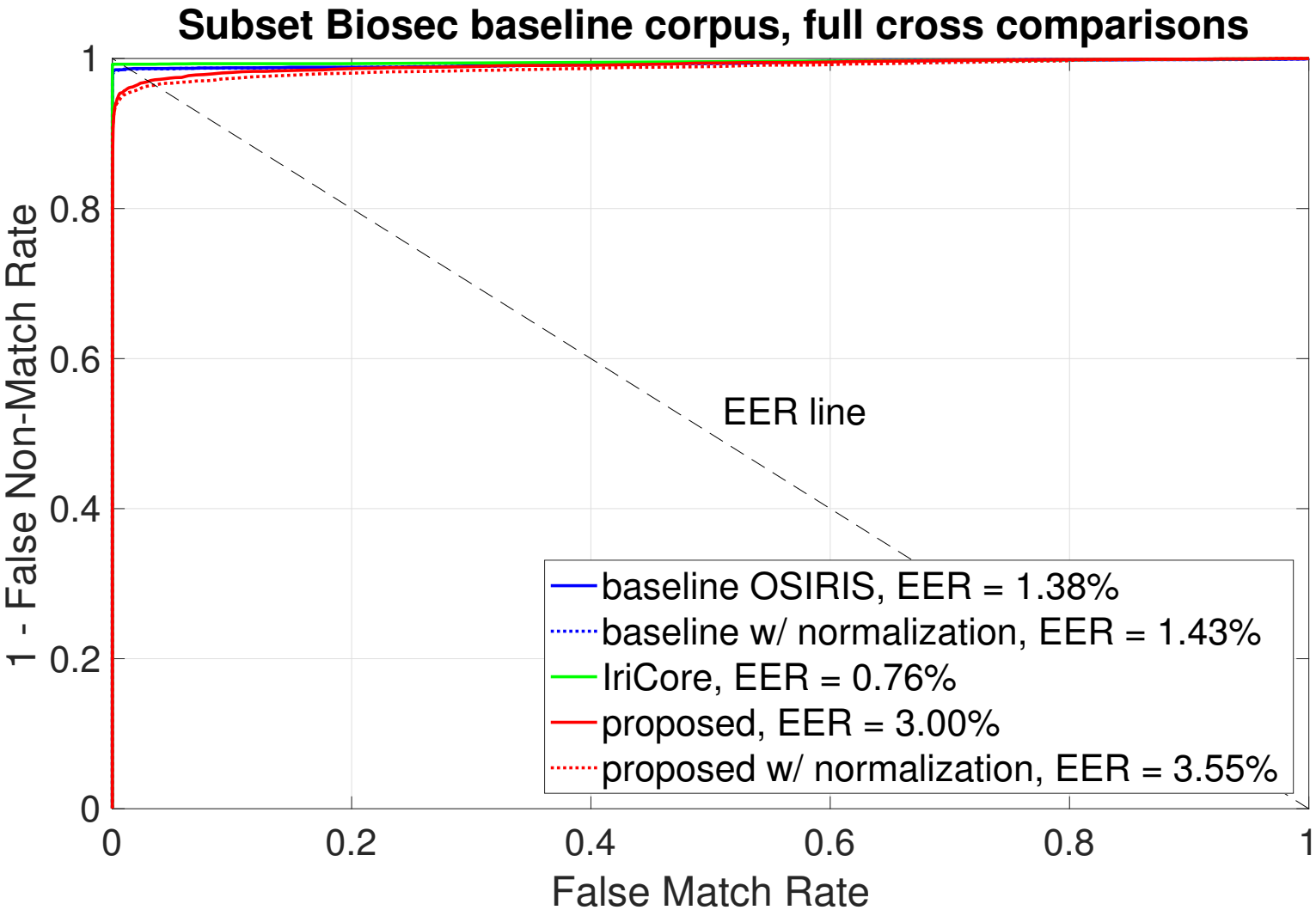
Results

elderly/disease-affected irises (close-up)



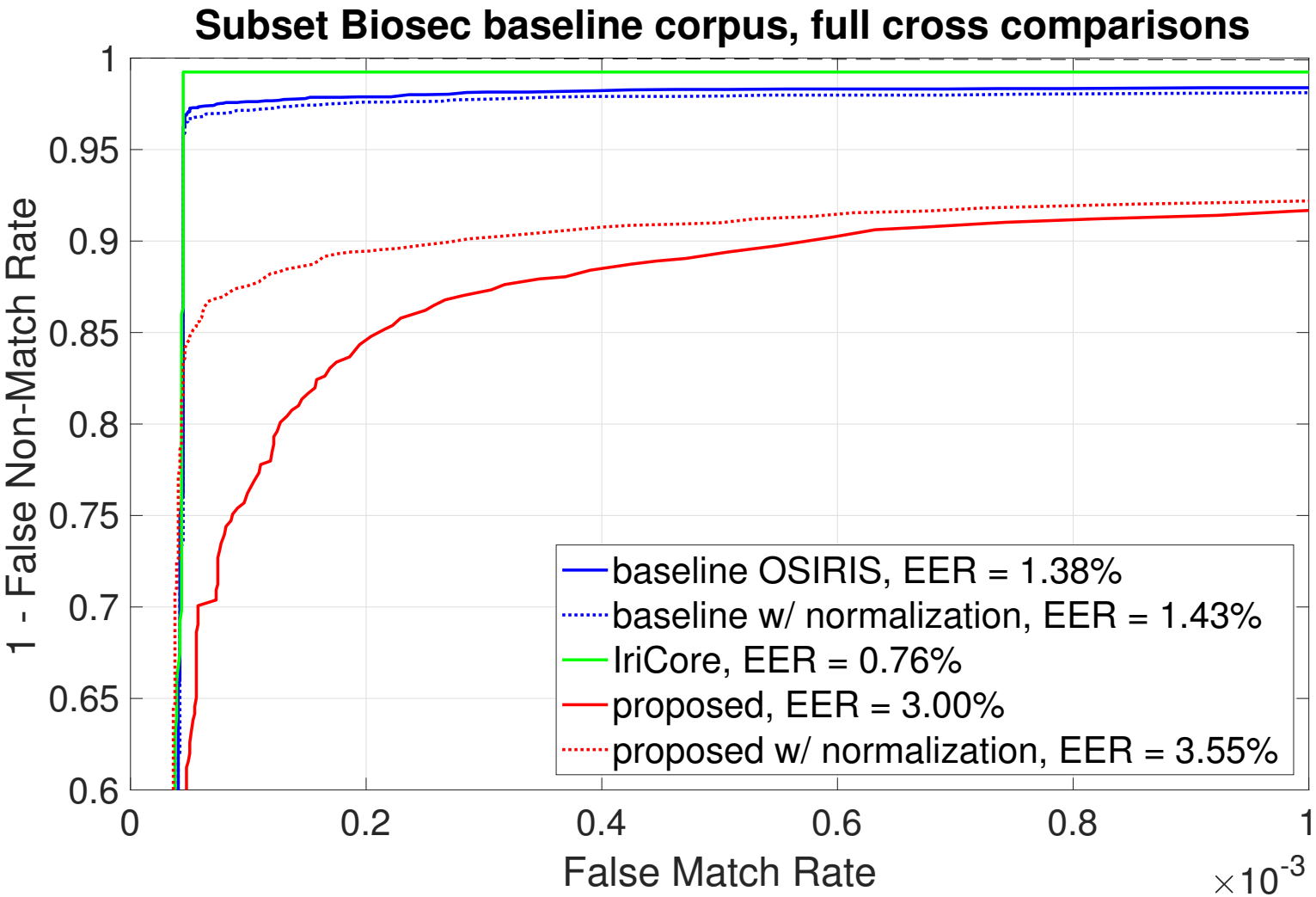
Results

healthy irises



Results

healthy irises (close-up)



Conclusions

Robust post-mortem iris recognition with DCNN-based image segmentation

- our solution achieves close-to-perfect recognition accuracy when samples collected less than 10 hours after death are considered, producing EER=1%
- as time progresses, the accuracy drops, but the proposed solution outperforms stock OSIRIS by at least 12% of EER
- on a challenging dataset of images collected from the elderly with ophthalmic conditions, the advantage is evident with EER=2.55% compared to 8.9% yielded by OSIRIS

Paper intended for submission to:

- Image and Vision Computing Journal, Elsevier (JCR list, 35 points)

Limitations

Robust post-mortem iris recognition with DCNN-based image segmentation

- small database size: only ≈4000 images (train + test)
- for selected longer time post-mortem horizons the IriCore method may be better in low FMR (<0.001) registers
- but it's difficult to generalize on such a small dataset
- **requires further tuning for healthy data**
  - re-training the segmentation model with healthy iris datasets
  - Hough transform part
- remaining TODO: domain (post-mortem) specific iris filtering

Reproducibility

Together with the paper come the following:

- source codes of iris localization and image segmentation method that can serve as a **drop-in replacement for any method employing iris normalization**
- additional three DCNN models for image segmentation
- new, previously unpublished dataset of post-mortem iris images: Warsaw-BioBase-Postmortem-Iris-v3

These are available to interested researchers for non-commercial purposes:

`http://zbum.ia.pw.edu.pl/EN/node/46`

(following paper acceptance)

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