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A Benchmark for Iris Location and a Deep Learning Detector Evaluation

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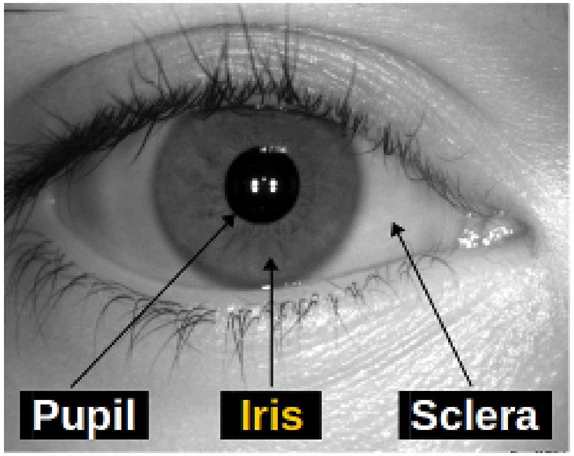
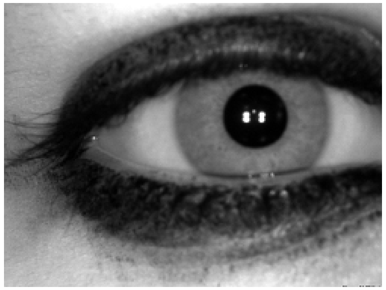
Introduction



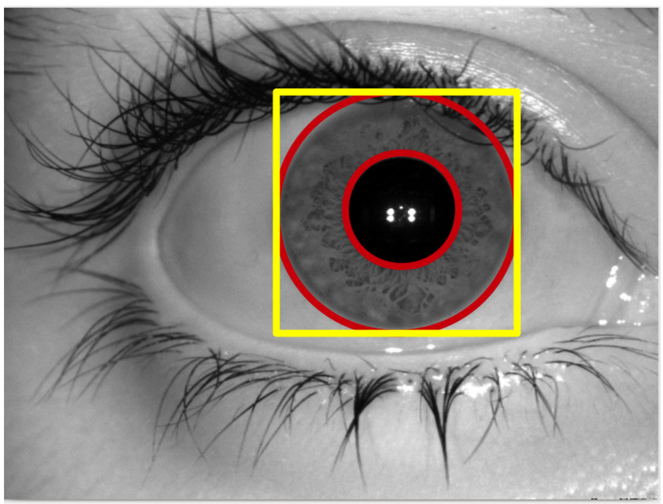
- Several characteristics of the human body can be used for person recognition: face, fingerprints, sclera, retina, voice, iris, among others.
- Biometric systems based on iris
  - High degree of uniqueness;
  - Remains unchanged over time;
  - The identification process is non-invasive.
- **Iris location** is usually the initial step in recognition, authentication and identification systems.
- Periocular region



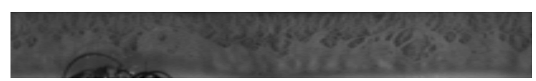



Introduction

- Many works in the literature locate the iris through a circle.
  - In these works, iris normalization is usually required after location.



Iris extraction through circle location.



Iris normalization.

- With the advancement of deep learning approaches, it was noted the importance of using regions around the iris, not just the perfect circle.
  - Thus, normalization is not required.

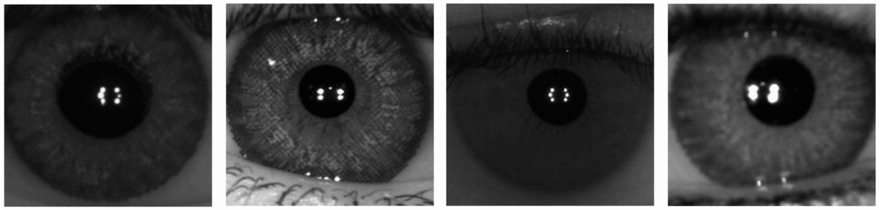
- This work defines the iris location task as the determination of the smallest square bounding box that encompasses the entire iris region.

Objective

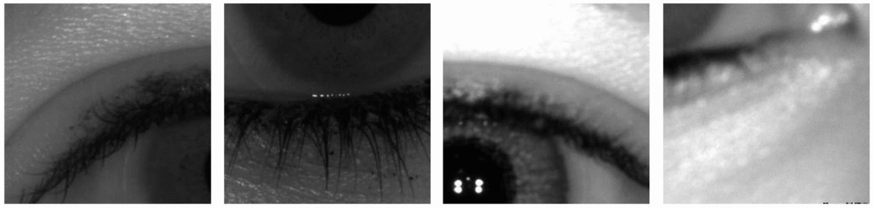
- Evaluate, as baselines, the following approaches:
  - A sliding window detector based on a linear Support Vector Machines (**SVM**) classifier trained with Histogram of Oriented Gradients (**HOG**) features;
  - The real-time **Fast-YOLO** object detector, fine-tuned for iris images.

Baselines

- **HOG & SVM**
  - For training, positive and negative samples are extracted.
    - 1 positive | 20 negative
  - The sliding window approach (at different scales) is applied to the test images.
  - Using the SVM output, the window that presents the highest positive score is considered the iris location.



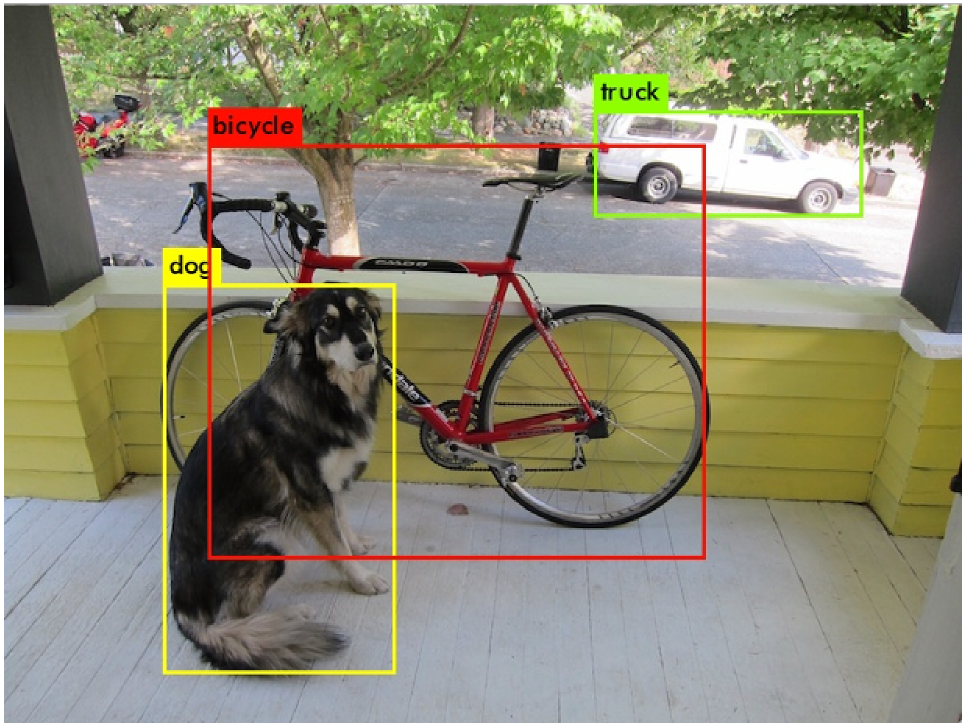
Positive Samples



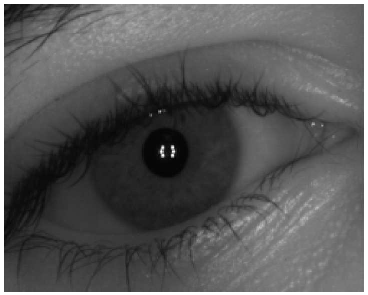
Negative Samples

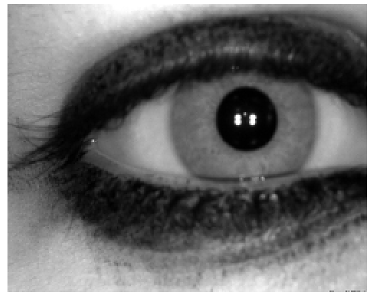
Baselines

- ***You Only Look Once (YOLO)***
  - YOLOv2 [Redmon, 2017] is a state-of-the-art real-time object detector that uses a model with 19 convolutional layers and 5 maxpooling layers.
  - **Fast-YOLO** [Redmon, 2016] is a model focused on a speed/accuracy trade-off that uses fewer convolutional layers and fewer filters in those layers.



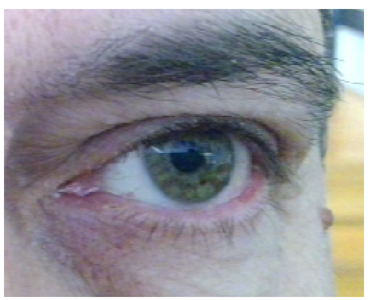
Databases

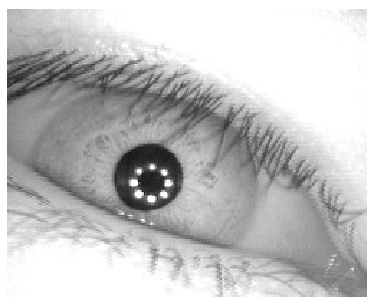

IIIT-D CLI (Vista sensor)

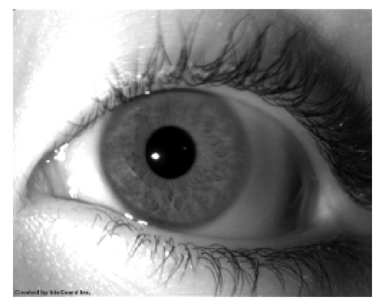

IIIT-D CLI (Cogent sensor)


BERC

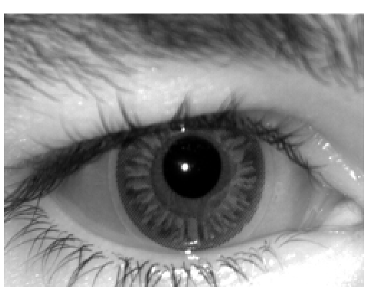

MobBIO (Fake)


MobBIO (Real)


CASIA-IrisV3 Interval


NDCCL (AD100 sensor)

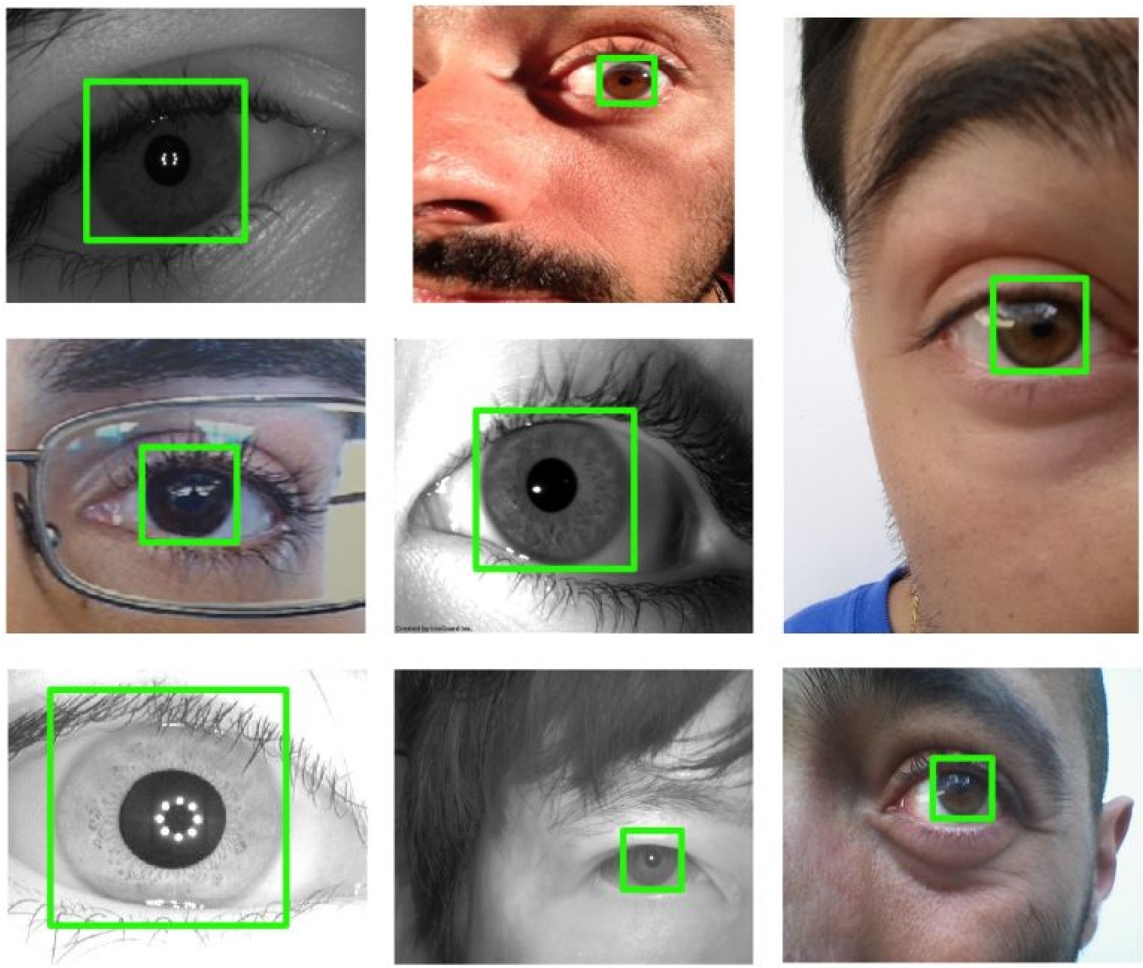

NDCCL (LG4000 sensor)


NDCLD15

The iris location annotations are **publicly available** to the research community.

https://web.inf.ufpr.br/vri/databases/iris-location-annotations

Iris Location - Annotations



- Generally, the iris region is not a square bounding box.

Experiments

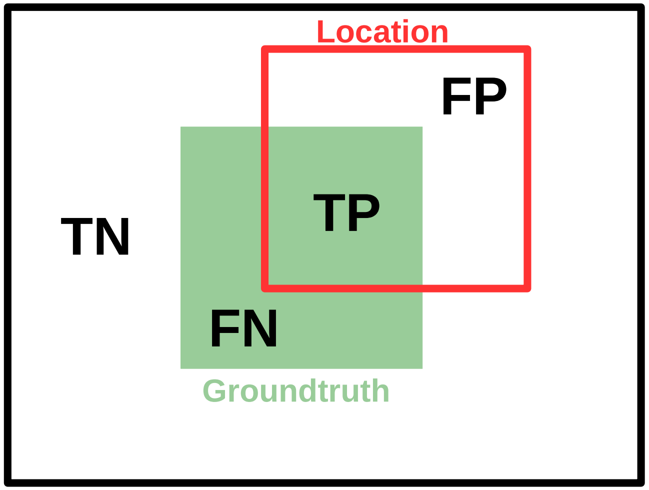
- **Metrics:**

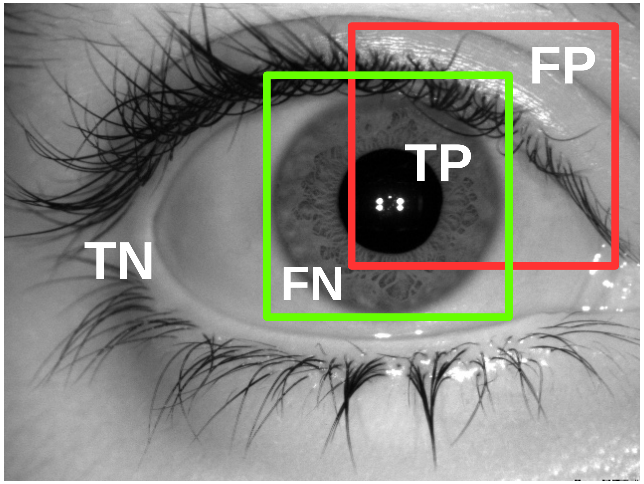
$$Recall = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$IoU = \frac{TP}{FP + TP + FN}$$

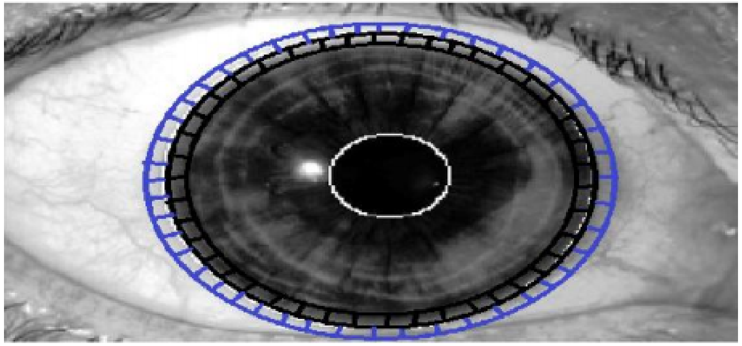
$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$





Experiments

- **The experiments are described in four different scenarios:**
  - *Intra-sensor;*
  - *Inter-sensor;*
  - Combined sensors (same databases);
  - Combined sensors (mixed databases);
- Comparison with the iris location method proposed by [Daugman, 2004].
  - This operator searches for the circular path where there is the maximum change in pixel values, by varying the radius and the center of the circular contour.



Experiments

Intra-sensor Results

Database	Recall			Precision			Accuracy			IoU		
	Daugman	HOG SVM	Fast YOLO	Daugman	HOG SVM	Fast YOLO	Daugman	HOG SVM	Fast YOLO	Daugman	HOG SVM	Fast YOLO
NDCCL												
AD100	84.60	92.39	**98.78**	82.49	94.78	**95.03**	94.28	96.98	**98.49**	80.41	87.52	**93.84**
LG4000	93.41	96.72	**97.81**	92.15	90.80	**97.73**	97.53	97.24	**99.05**	89.67	87.76	**95.06**
IIIT-D CLI												
Vista	85.49	94.51	**97.85**	89.34	92.24	**93.71**	95.38	98.10	**98.28**	80.82	87.23	**91.76**
Cogent	86.24	**96.44**	96.02	92.82	87.99	**95.58**	96.34	96.67	**98.33**	82.61	84.76	**91.84**
MobBIO												
Real	76.32	95.77	**96.81**	74.71	72.26	**94.02**	85.26	95.33	**98.97**	70.79	68.76	**91.02**
Fake	75.81	93.28	**96.06**	73.45	74.33	**95.05**	84.81	95.26	**98.90**	70.12	68.99	**91.27**
BERC	88.19	92.83	**98.10**	85.64	87.95	**93.56**	98.72	98.49	**99.71**	79.10	85.10	**91.15**
CASIA IrisV3 Interval	96.38	96.97	**97.79**	**96.23**	88.48	96.02	**97.38**	92.21	97.10	90.95	86.17	**91.24**
NDCLD15	91.63	96.04	**97.28**	89.76	90.29	**95.71**	96.67	97.14	**98.54**	85.34	86.85	**93.25**

Experiments

Inter-sensor Results

Database	Set		Recall		Precision		Accuracy		IoU	
	Train	Test	HOG SVM	Fast YOLO	HOG SVM	Fast YOLO	HOG SVM	Fast YOLO	HOG SVM	Fast YOLO
NDCCL	AD100	LG4000	**92.95**	79.25	**91.13**	89.18	**96.84**	92.67	**85.78**	68.71
	LG4000	AD100	93.22	**97.99**	93.15	**93.59**	96.78	**97.94**	86.76	**91.63**
IIIT-D CLI	Vista	Cogent	**96.89**	96.13	89.89	**94.21**	96.43	**97.98**	83.94	**90.57**
	Cogent	Vista	93.44	**98.26**	**93.61**	87.97	**97.08**	96.65	**87.55**	80.92

- The results obtained by the Fast-YOLO model were not satisfactory in some cases.
  - We believe that this is due to the fact that the training set does not have many samples and these samples are relatively homogeneous, so the model did not achieved a good generalization.

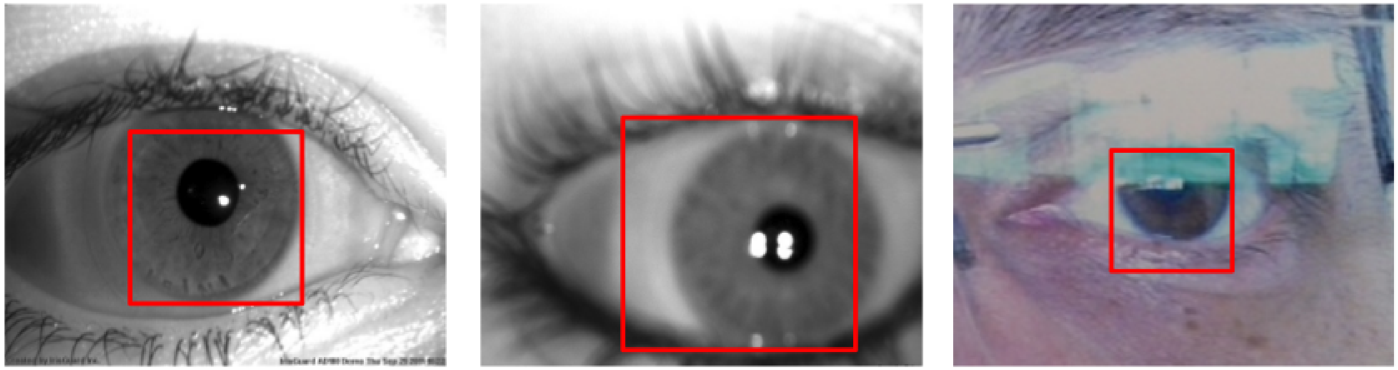
Experiments

Combined Sensors - Results

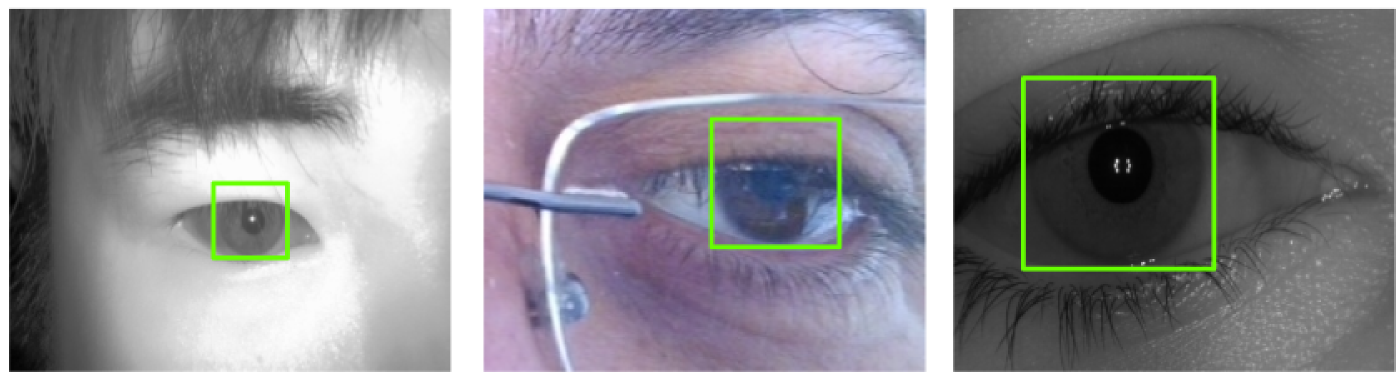
Database	Set: Train	Set: Test	Recall: HOG SVM	Recall: Fast YOLO	Precision: HOG SVM	Precision: Fast YOLO	Accuracy: HOG SVM	Accuracy: Fast YOLO	IoU: HOG SVM	IoU: Fast YOLO
NDCCL	AD100 & LG4000	LG4000	95.37	**99.29**	92.93	**99.68**	97.48	**99.77**	88.63	**98.91**
	AD100 & LG4000	AD100	91.77	**99.37**	94.77	**97.42**	96.85	**99.36**	86.91	**96.85**
IIT-D CLI	Vista & Cogent	Cogent	96.73	**97.26**	87.15	**96.48**	96.50	**98.49**	84.17	**92.50**
	Vista & Cogent	Vista	94.20	**98.34**	92.74	**93.79**	97.01	**98.55**	87.41	**91.78**

- With a larger number of images acquired from different sensors in the training set, Fast-YOLO was able to better generalize, increasing the correct iris location in most cases.

Experiments



(a)



(b)

- Samples of iris location obtained in the experiments: (a) poor results achieved due to a homogeneous training set; (b) good results achieved with images of different sensors on the training set.

Experiments

Results combining all databases (%)

Method	Set		Recall	Precision	Accuracy	IoU
	Train	Test				
Fast-YOLO	All	All	**97.13**	**95.20**	**98.32**	**92.54**
Daugman	-	All	86.45	86.28	94.04	81.09

- The Fast-YOLO model obtained better results in all metrics used.

Conclusions

- The Fast-YOLO object detector presented promising results in all databases used.
  - The iris location runs in real time (0.02 seconds per image, on average)
- Is important to have a sufficiently large number of images for training.
  - The number and variety of images in the training set directly affects the generalization capability of the learned model.
- We manually annotated 4 of the 6 databases used in this work, and those annotations are publicly available to the research community.
- Future work:
  - Perform experiments with more databases.
  - Analyze the impact that iris location exerts on iris recognition, spoofing and other applications.
  - Study how a shorter and shallow network than Fast-YOLO can be designed for our single-class object detection problem, the iris location.

Thank you!

www.inf.ufpr.br/rblsantos/