ETTAC 2020

1st Workshop on Eye Tracking Techniques, Applications and Challenges

https://vision.unipv.it/ettac2020/

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In conjunction with

ICPR 2020

Introduction

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- Speaker: Gonzalo Garde Lecumberri
- Ph. D. Student in Public University of Navarre (UPNA), Spain
- Member of the Gaze Interaction for Everyone (GI4E) research group in the same university

Synthetic gaze data augmentation for improved user calibration

Gonzalo Garde, Andoni Larumber-Bergera, Sonia Porta, Rafael Cabeza, Arantxa Villanueva

Objectives

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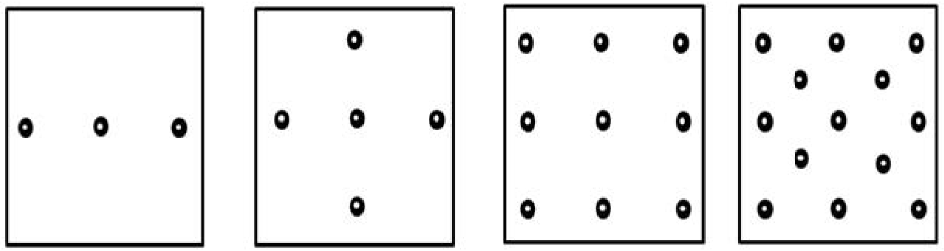
- To question the impact of the balance between generalization and personalization in Deep Learning-based Gaze Estimation solutions

- To study the effect of pretraining the model over different domains before training our system for our final application.

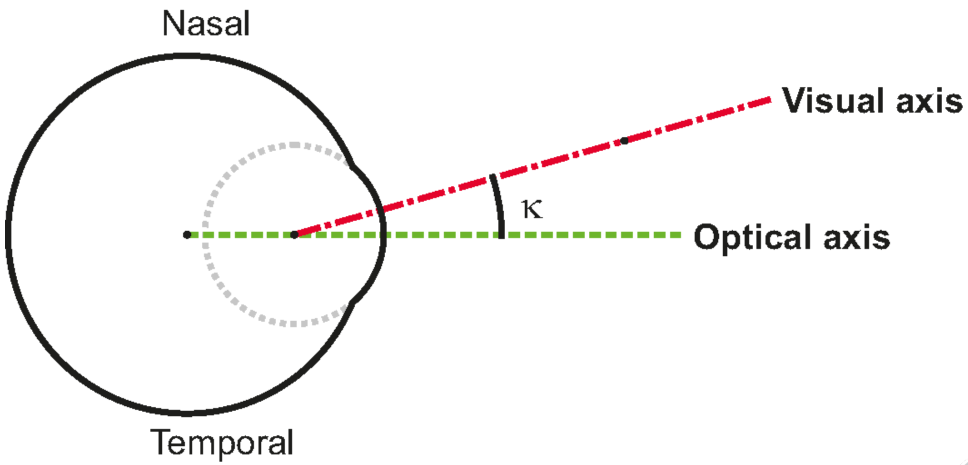
Research introduction: calibration

In Gaze Estimation, personalization is achieved through calibration



Examples of grid of calibration based on points

To calibrate: adjust system using individual's intrinsic aspects



Simplified model of the eye

Research introduction: high resolution – low resolution systems

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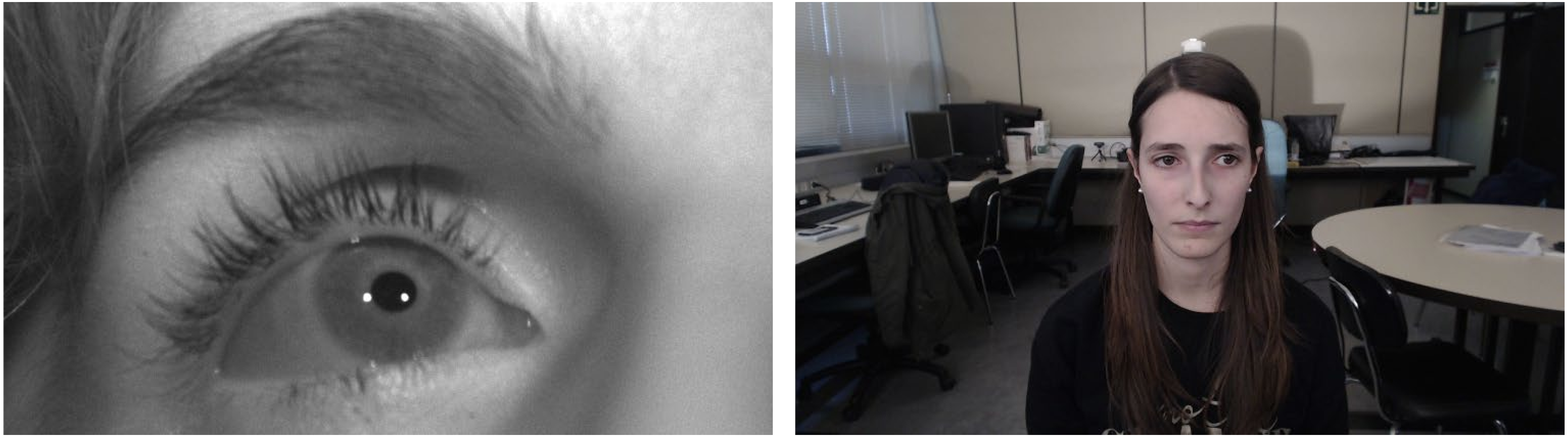


High resolution vs low resolution

In both type of systems, calibration has probed to improve the obtained accuracy

Research introduction: size limitations

Requisite to implement a Deep Learning solution: large enough databases

If learning in a supervised manner…

Requisite to implement a Deep Learning solution: large enough databases correctly labelled

Two posible solutions:

- Using synthetic databases or enviroments
- Pretraining a model in a different topic and using it as starting point (“transfer-learning”)

Research introduction: transfer-learning

Basis: if a network learns to extract features from images to solve a task, part of these features can be handy to solve others image-related problems

The closer the original domain to the new one, the better the learning transference

Pretrained models in frameworks:

TensorFlow PyTorch

Research design: databases

3 databases were needed, 2 for the pretraining of the model and 1 as target.

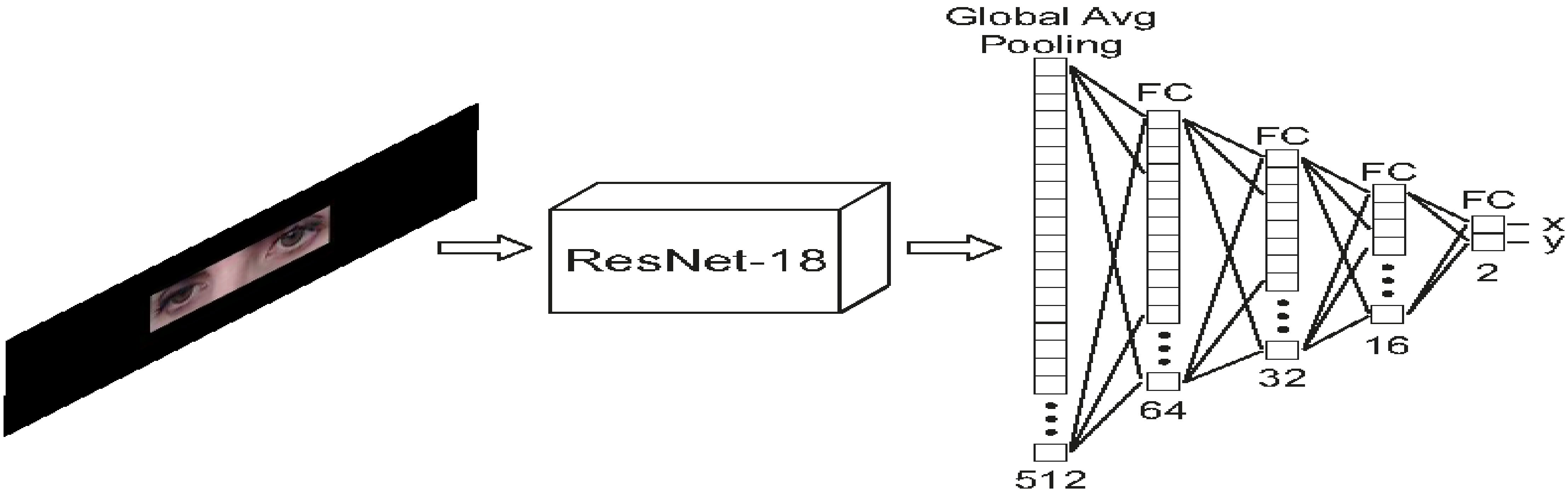
IMAGENET	U2Eyes	I2Head
General-purpose database	Close domain database	Target database

They were not used in this project directly. Our starting models were pre-trained over them

Research design: images preprocessing

Image preprocessing

Research design: network architecture



Network architecture

Research design: training

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The training process could be divided in two parts:

Starting point → 12 trainings

Select among two models*:

- Model pretrained with U2Eyes
- Model with Resnet-18 weights from Imagenet

This part allow us to study the effect of transfer learning in different domains

*https://github.com/GonzaloGardeL/Synthetic-gaze-data-augmentation-for-improved-user-calibration

Research design: training

The training process could be divided in two parts:

Starting point → 12 trainings

The model is trained over images from I2Head. In these 12 variations, we change the nature of the training dataset from only calibration to calibration + generalization

With this block, we study the balance between generalization and personalization

Research design: training

Model	Train # Users/Images	Calibration # Users/Images	Total Train # Images	Test # Users/Images
ImageNet	K/K*130	1/34	K*130+34	1/130
U2Eyes	K/K*130	1/34	K*130+34	1/130

K varies from 0 (only calibration images in the training dataset) to 11 (calibration images + 11 additional users)

- Trained over 240 epochs
- Adam optimizer
- Euclidean distance of the real look-at-point and the estimated look-at-point

A learning rate Schedule based in Cyclic learning rate was used, although other could be used

Research results

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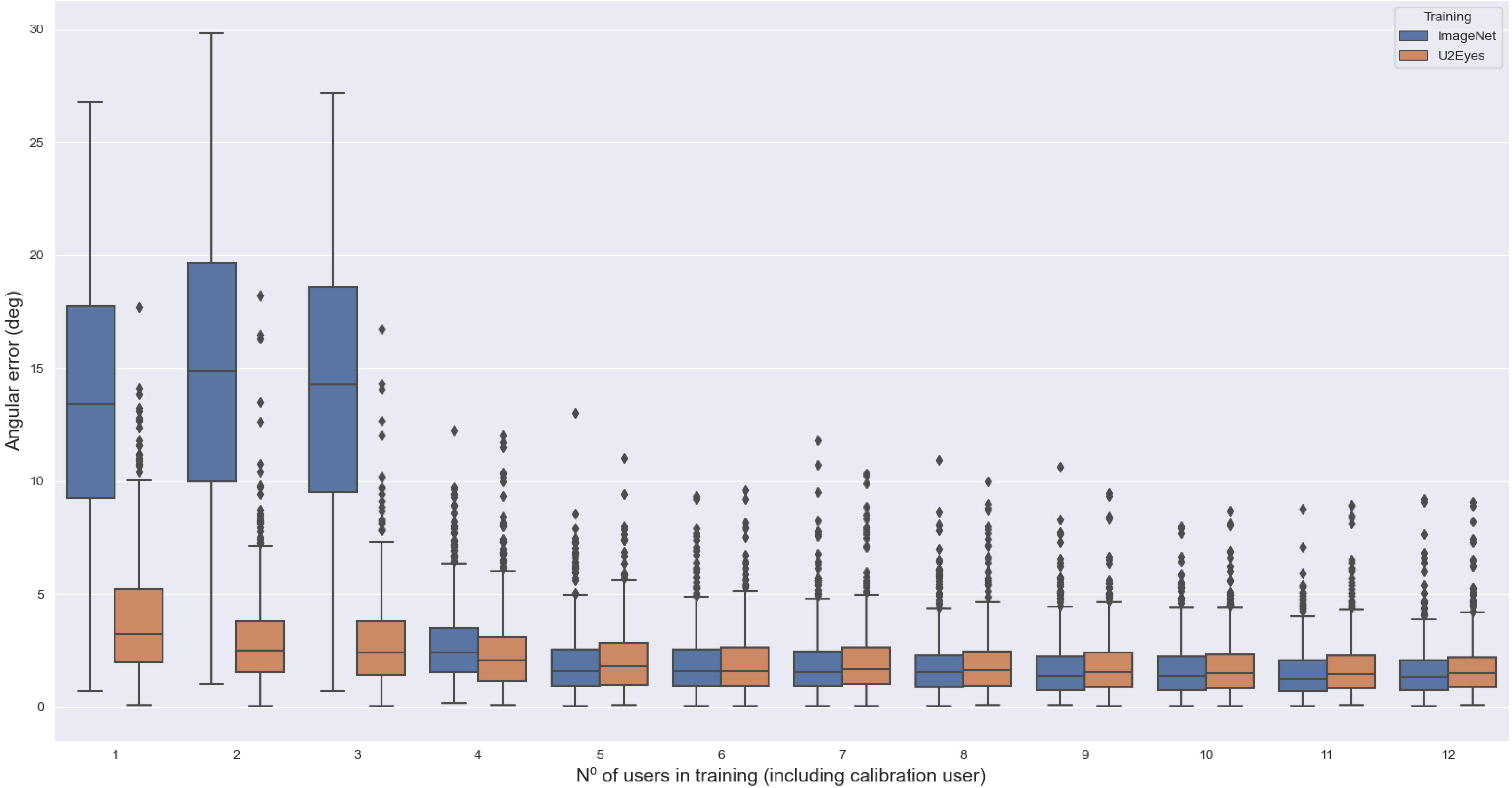

Research results

Users in training	Mean (°)		Median (°)	
	Imagenet	U2Eyes	Imagenet	U2Eyes
1	13.615	**3.891**	13.401	**3.243**
2	**14.812**	2.967	**14.880**	2.522
3	14.069	2.861	14.255	2.404
4	2.867	2.488	2.567	2.149
5	2.004	2.149	1.631	1.867
6	2.028	1.965	1.675	1.667
7	1.987	2.039	1.617	1.746
8	1.877	1.968	1.639	1.724
9	1.758	1.860	1.471	1.611
10	1.681	1.818	1.412	1.588
11	1.615	1.777	**1.334**	**1.485**
12	**1.559**	**1.714**	1.344	1.486

Research results: discusion

From the obtained results, we highlight two cases to study:

- Correlation number of training images – accuracy
- Comparison of the results obtained for each of the pretraining methods

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As the number of users decreases, the accuracy tend to worse

For 12 users, accuracy close to high-resolution systems is obtained (**1.5º**)

Research results: discusion

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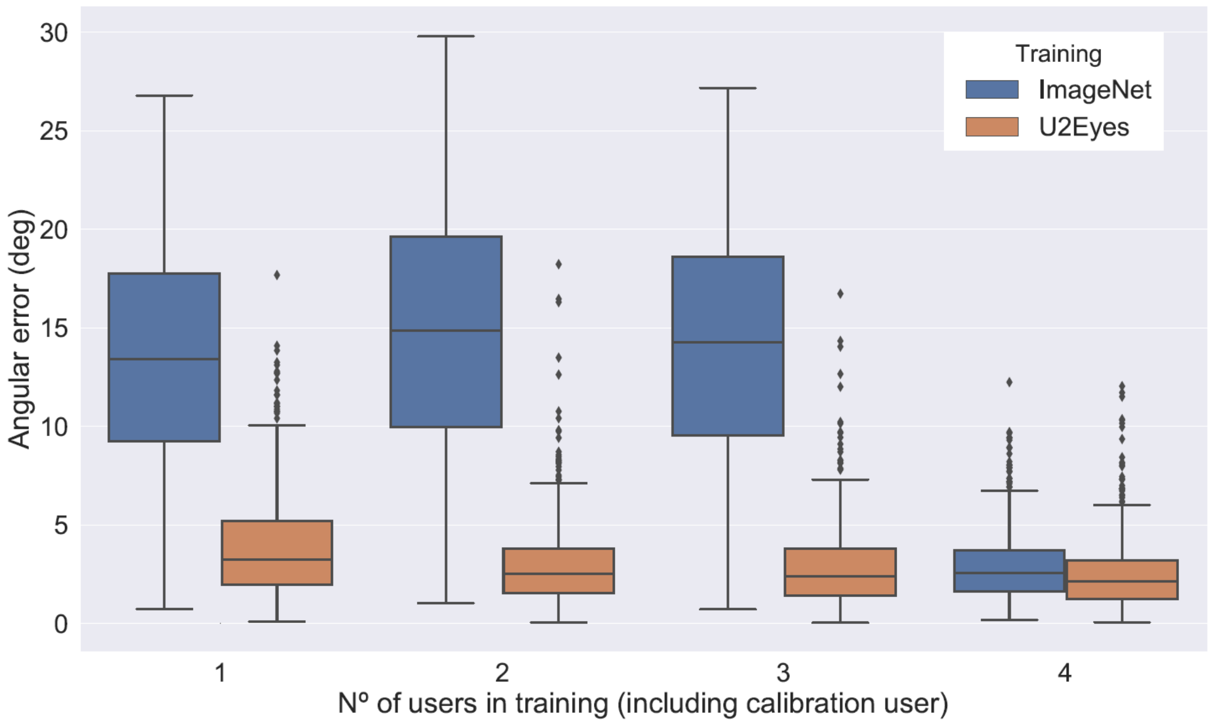

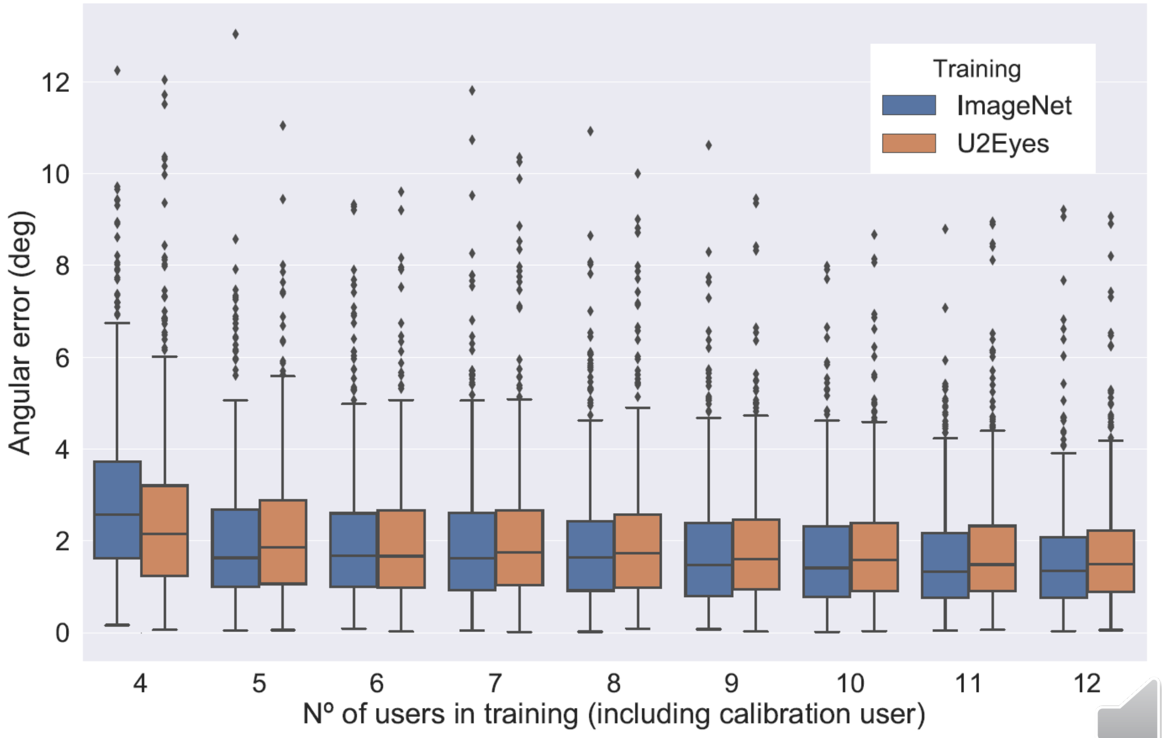

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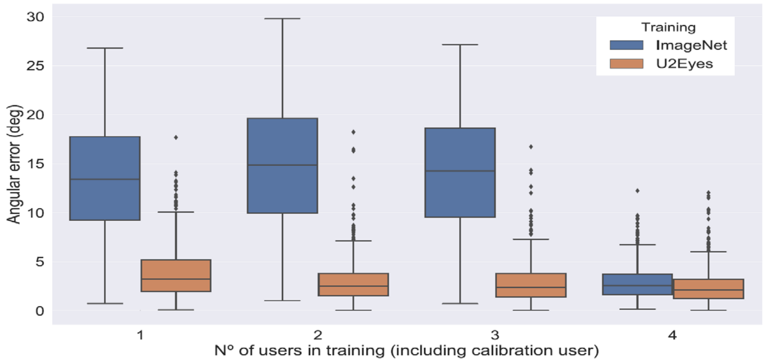

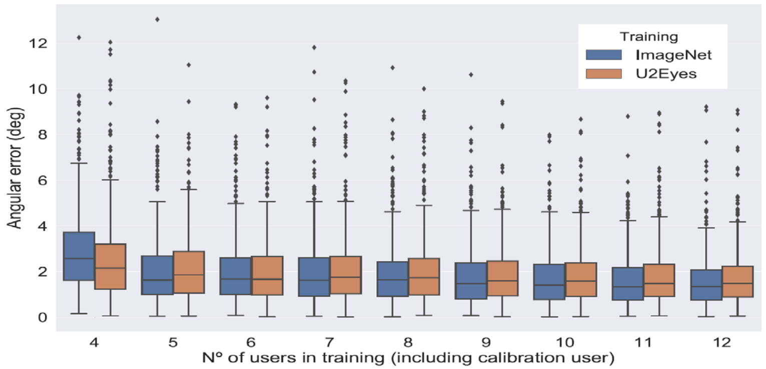

Hypothesis:

- If training dataset is long enough for the Imagenet model to learn, it benefits from real-world variability
- If not, the U2Eyes model is more robust because, as it was trained in a similar domain, is more capable of continuing learning

Conclusions

From the obtained results, we conclude that:

- Results close to high-resolution systems can be obtained (1.5º) by using calibration in low-resolution systems based on Deep Learning
- The importance of providing domain images during the training process has been confirmed, and also the benefits of pre-training the network in a closer domain instead of in a more general dataset, to compensate the lack of useful gaze data images that characterize gaze estimation problems

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Thank you!

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