



Comparing classical and deep approaches for face recognition in a smartgym application

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Organization

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Motivation

1. Football Club Barcelona's smartgym project aims to develop a system to aid gymnasium training.
2. System should **identify and track down athletes** within the facility, allowing self configuration of the exercise machines according to the user and computing training times of each one of them.
3. The **face recognition** method should perform with precision in real-time on reduced sets of subjects and samples per individual.



Objectives

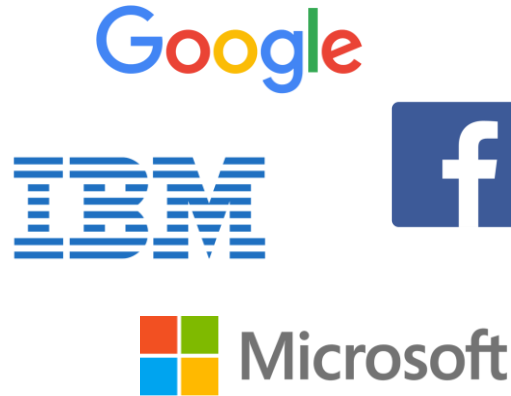
1. Compare **three different** approaches to the **face recognition** task, 2 classical and one deep learning based.
2. Evaluate **precision performance** over different **samples per subject** size.
3. Compute face recognition **times**.
4. Analyze viability for **experimental field implementation** and further tests.



State of the Art

Training data is crucial for the final algorithms **performance**. Many current methods rely on really **big databases**, most of them being still **proprietary**.

Public databases provide a platform for the study of possible solutions for the project.



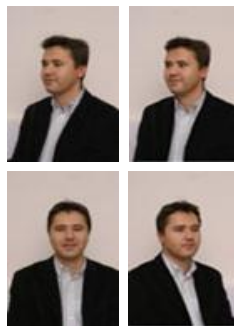
State of the Art

Face recognition Databases examples



[1] FERET:

1. **14126** images.
2. **1199** subjects.
3. **~12** samples per subject.
4. **180°** face rotation.
5. **First** big face database.



[2] Scface:

1. **4160** images.
2. **130** subjects.
3. **32** samples per subject.
4. **180°** face rotation.
5. Samples with **surveillance cameras**



[3] MIT-CBCL:

1. **3240** images.
2. **10** subjects.
3. **324** samples per subject.
4. **0° to 34°** face rotation.
5. **3D synthetic masks.**

[1] - P. J. Phillips, S. Z. Der, P. J. Rauss, and O. Z. Der, FERET (face recognition technology) recognition algorithm development and test results. Army Research Laboratory Adelphi, MD, 1996.

[2] - M. Grgic, K. Delac, and S. Grgic, "Scface – surveillance cameras face database," Multimedia Tools and Applications, vol. 51, no. 3, pp. 863–879, 2011.

[3] - B. Heisele, B. Weyrauch, V. Blanz, and J. Huang, "Component-based face recognition with 3d morphable models," 2012 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, vol. 05, p. 85, 2004.

State of the Art

Face recognition method examples

| Name | Method | Images (millions) | Accuracy | Code |
|-----------------------|----------------|-------------------|----------|------------|
| FaceNet [1] | CNN | 200 | 99.63% | Unofficial |
| DeepID3 [2] | CNN | 0.29 | 99.53% | No |
| VGG Face EL [3] | CNN | 5 | 99.13% | Yes |
| DeepFace [4] | CNN | 4.4 | 97.35% | Unofficial |
| TL Joint Bayesian [5] | Joint Bayesian | 0.099 | 96.33% | No |
| High-dim LBP [6] | LBP | 0.099 | 95.17% | Unofficial |

Top Face recognition methods tested on Labeled Faces in the Wild.

- [1] - F. Schroff, D. Kalenichenko, and J. Philbin, "Facenet: A unified embedding for face recognition and clustering." in CVPR. IEEE Computer Society, 2015.
- [2] - Y. Sun, D. Liang, X. Wang, and X. Tang, "Deepid3: Face recognition with very deep neural networks." CoRR, vol. abs/1502.00873, 2015.
- [3] - O. M. Parkhi, A. Vedaldi, and A. Zisserman, "Deep face recognition." in BMVC, X. Xie, M. W. Jones, and G. K. L. Tam, Eds. BMVA Press, 2015.
- [4] - Y. Taigman, M. Yang, M. Ranzato, and L. Wolf, "DeepFace: Closing the Gap to Human-Level Performance in Face Verification," in 2014 IEEE Conference on Computer Vision and Pattern Recognition. IEEE, Jun. 2014.
- [5] - X. Cao, D. P. Wipf, F. Wen, G. Duan, and J. Sun, "A practical transfer learning algorithm for face verification." in ICCV. IEEE Computer Society, 2013.
- [6] - D. Chen, X. Cao, L. Wang, F. Wen, and J. Sun, "Bayesian face revisited: A joint formulation." in ECCV (3), ser. Lecture Notes in Computer Science, A. W. Fitzgibbon, S. Lazebnik, P. Perona, Y. Sato, and C. Schmid, Eds., vol. 7574. Springer, 2012.

Methods

The three methods tested are:

- 1. Eigenfaces [1]
 - 2. Fisherfaces [2]
 - 3. VGG Face net [3]
- } Representative of **classical approaches**.
- } Only CNN method with **official code** made **public**.

[1] - M. Turk and A. Pentland, "Eigenfaces for recognition," J. Cognitive Neuroscience, vol. 3, no. 1, pp. 71–86, Jan. 1991.

[2] - P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, "Eigenfaces vs. fisherfaces: Recognition using class specific linear projection." pp. 711–720, 1997.

[3] - O. M. Parkhi, A. Vedaldi, and A. Zisserman, "Deep face recognition." in BMVC, X. Xie, M. W. Jones, and G. K. L. Tam, Eds. BMVA Press, 2015, pp. 41.1–41.12.

Eigenfaces

Eigenfaces seeks to **maximize data scatter**, and find the principal vectors to describe the image space.

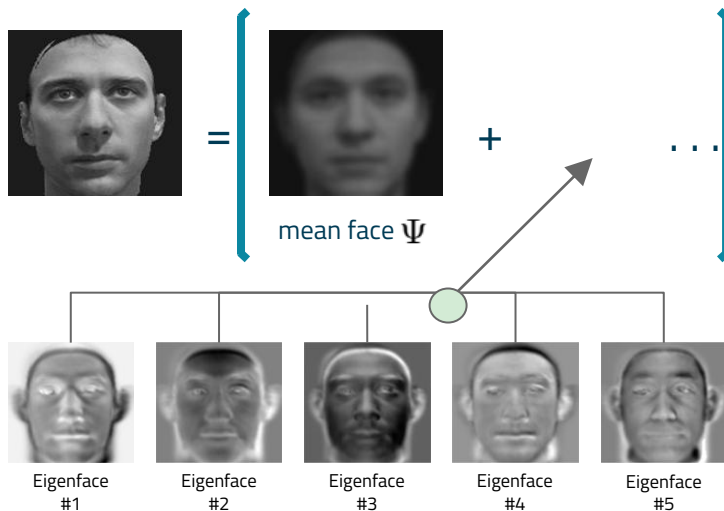
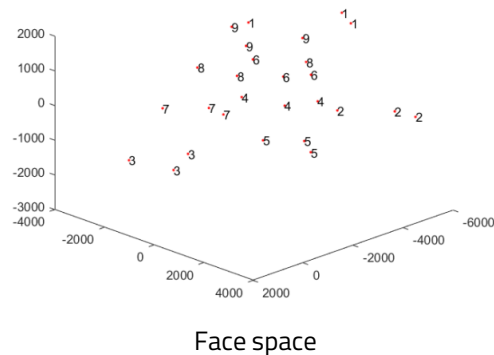
A new image x is **projected** into the face space by:

$$\omega_k = \mathbf{u}_k^T (x - \Psi) \quad k = 1, \dots, M'$$

With \mathbf{u}_k an eigenface.

This gives the **descriptor** by the weight vector

$$\Omega^T = [\omega_1, \omega_2, \dots, \omega_{M'}]$$

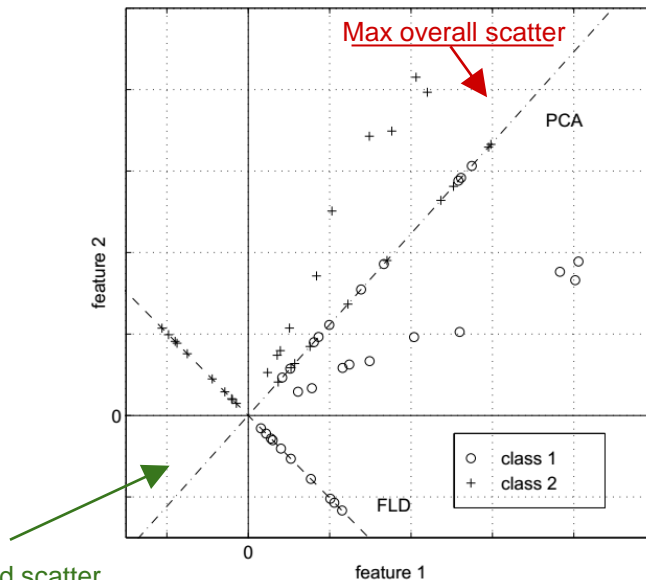


Fisherfaces



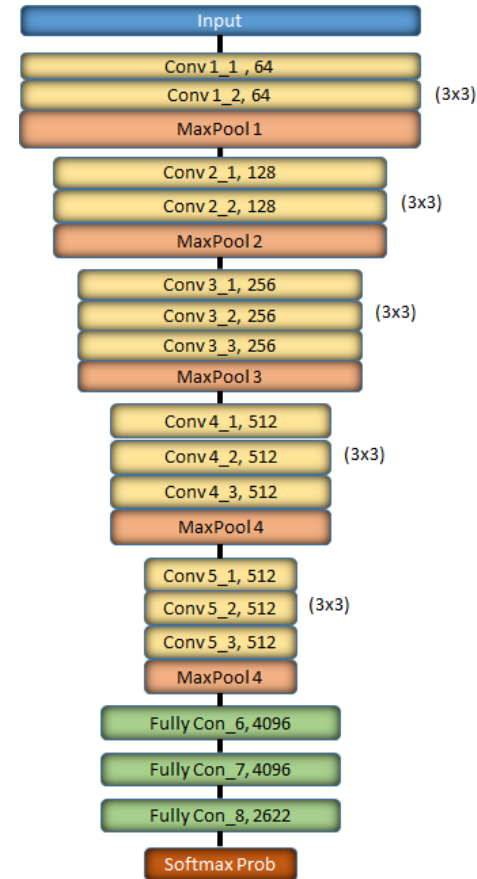
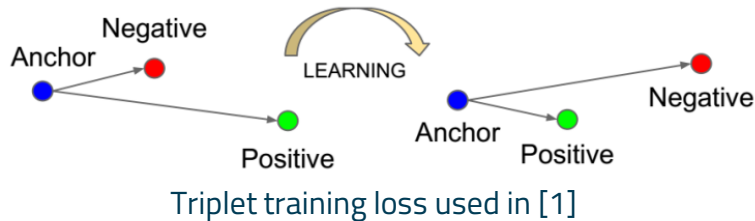
Fisherfaces adds the condition of **maximizing** the ratio of the determinant of the **between-class scatter** matrix of projected samples, to the determinant of the **within-class scatter** matrix of the projected samples.

$$\begin{aligned}\Omega_{opt} &= \arg \max_{\Omega} \frac{|\Omega^T S_B \Omega|}{|\Omega^T S_W \Omega|} \\ &= [\omega_1, \omega_2, \dots, \omega_{M'}]\end{aligned}$$



VGG Face net

1. Based on the CNN from 2014 Simonyan and Zisserman's proposal.
2. VGG Face was trained specifically to identify 2622 subjects from a custom built database on celebrities' face pictures [1].
3. With triplet loss training reaches 0.9913 accuracy on LFW dataset.



VGG Face architecture

[1] - O. M. Parkhi, A. Vedaldi, and A. Zisserman, "Deep face recognition." in BMVC, X. Xie, M. W. Jones, and G. K. L. Tam, Eds. BMVA Press, 2015, pp. 41.1–41.12.

Experiments

Hardware platform:

- Intel **Core i7 6500U** CPU processor with **2.6 GHz** clock, **12 GB DDR3L 1600 MHz** SDRAM and one **NVIDIA GeForce GT 940M 2GB** DDR3.

Program language:

- **Eigenfaces** and **Fisherfaces** programmed on **Matlab R2016b** for Windows.
- **VGG Face** programmed on **Pycaffe** for Linux.

Dataset preparations:

All samples were processed with **frontalization**, cropping the **face detection** after.



Original 20°



Frontalized



Cropped detection

MIT-CBCL database used.

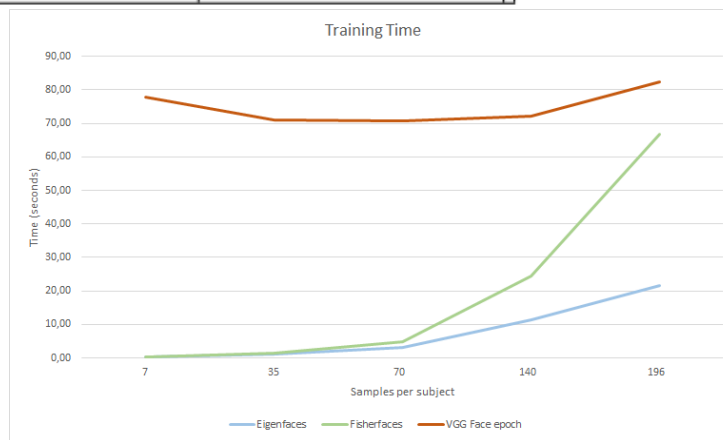
Results

Training Time

| Samples per subject | Eigenfaces(s) | Fisherfaces(s) | VGG Face (min) |
|---------------------|---------------|----------------|-----------------|
| 7 | 0.16 | 0.37 | 129.86 (77.92s) |
| 35 | 1.09 | 1.46 | 177.28 (70.91s) |
| 70 | 3.10 | 4.71 | 176,75 (70.7s) |
| 140 | 11.26 | 24.40 | 180,24 (72,09s) |
| 196 | 21.58 | 66.92 | 205,93 (82,37s) |

Prediction Time

| Eigenfaces | Fisherfaces | VGG Face |
|------------|-------------|----------|
| 1.0765 s | 1.0517 s | 7.1067 s |



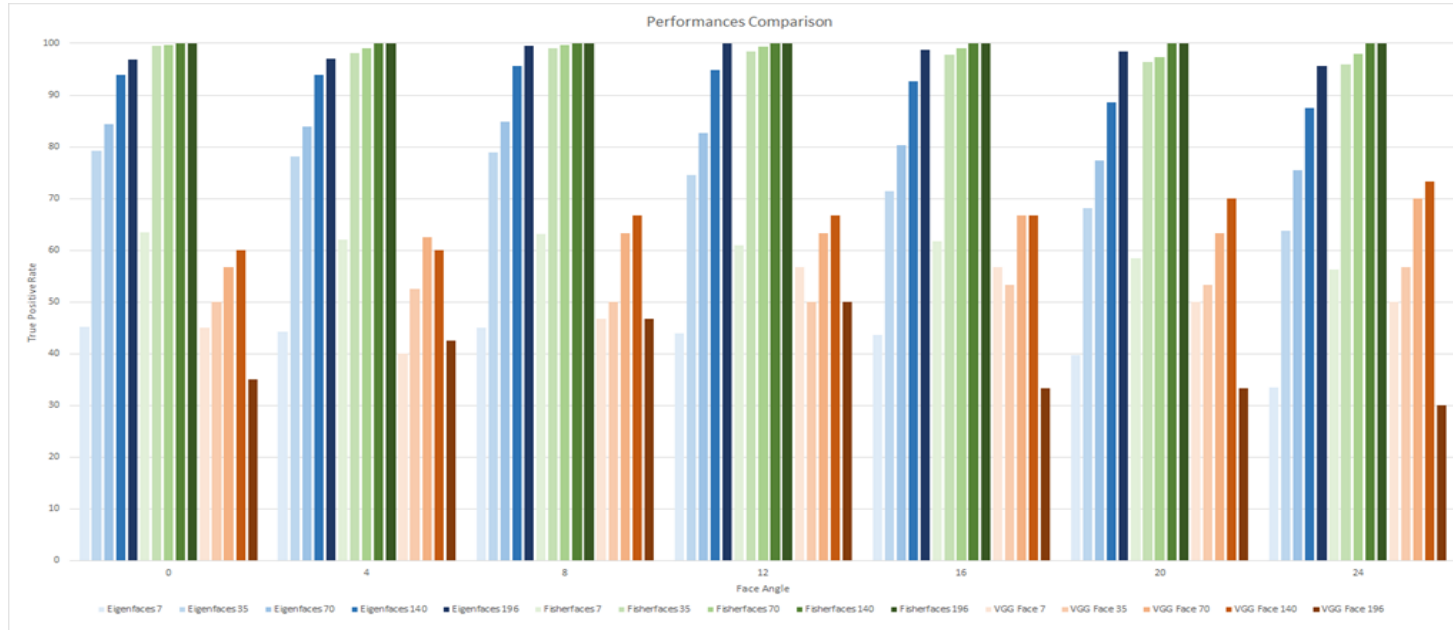
Results

Overall Performance

| Samples per subject | Eigenfaces % | Fisherfaces % | VGG Face % |
|---------------------|--------------|---------------|-------------|
| 7 | 42.14 | 60.85 | 48.4 |
| 35 | 73.43 | 97.9 | 52 |
| 70 | 81.28 | 98.87 | 62.8 |
| 140 | 92.42 | 100 | 65.2 |
| 196 | 98.04 | 100 | 38.4 |

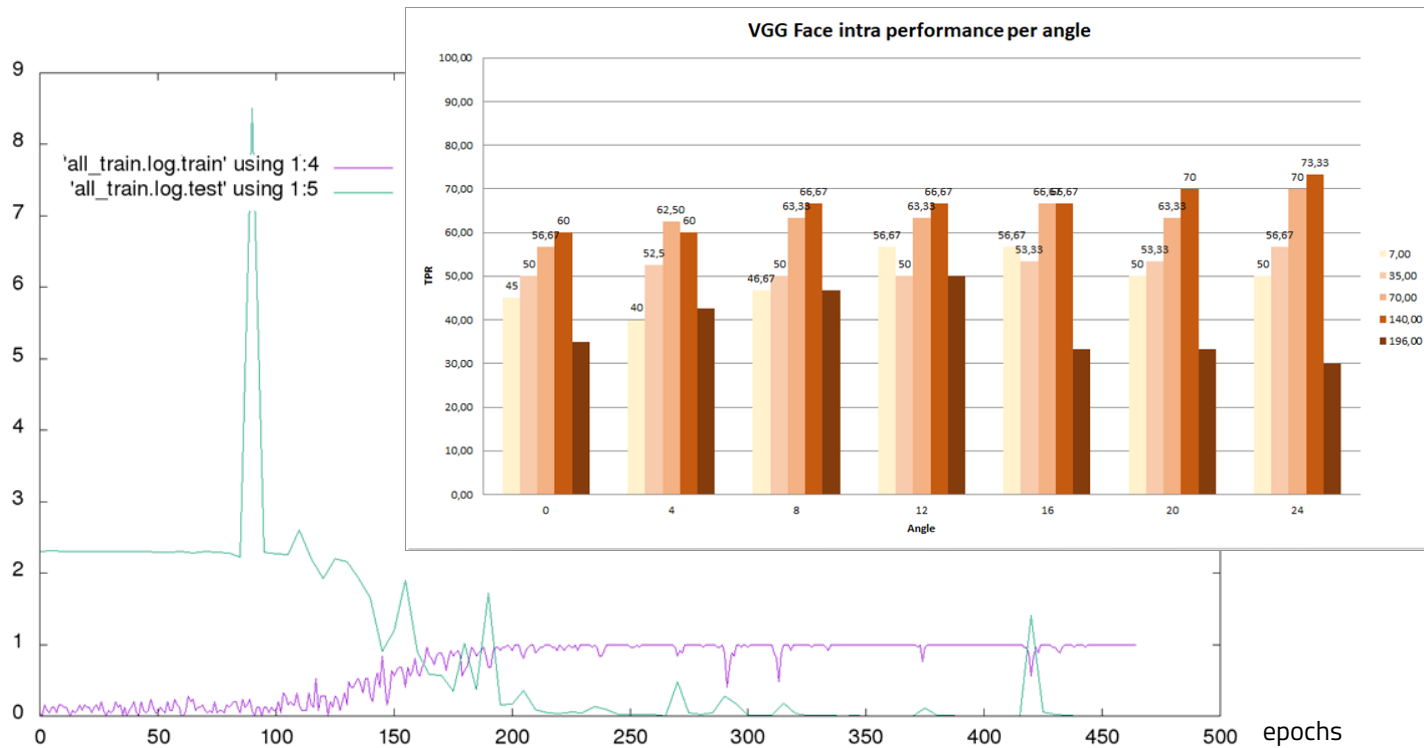
Face recognition with **train and test sets splits** over a database of **frontalized faces** using a **10-folds scheme**.

Results



Performance comparison for each face rotation angle between the 3 models, when varying samples per subject. Eigenfaces in **blues**, Fisherfaces in **greens**, VGG Face in **browns**.

VGG overfitting observations

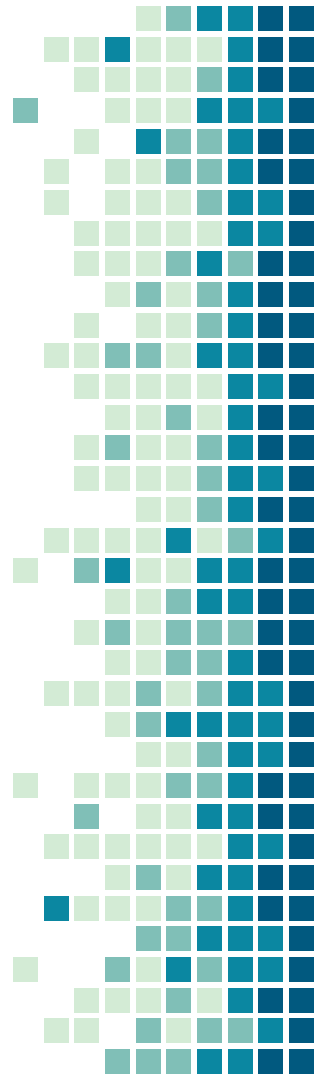


Conclusions and future work

- Reached **near real-time** recognition with **over 95%** accuracy (**Eigenfaces** and **Fisherfaces**) for non optimized code, on **MIT-CBCL database**.
- **Viable field tests** with chosen methods.
- MIT-CBCL **dataset** is too **small** for **VGG Face** and facilitates **overfitting** without intense **supervision**.

Future work includes:

- Construction of **FCB's athletes face database**.
- VGG Face **triplet loss training** to boost **performance**.
- **Tests** on data with **more subjects**.
- **Tests** on **simultaneous recognitions** to define final **hardware** requirements.



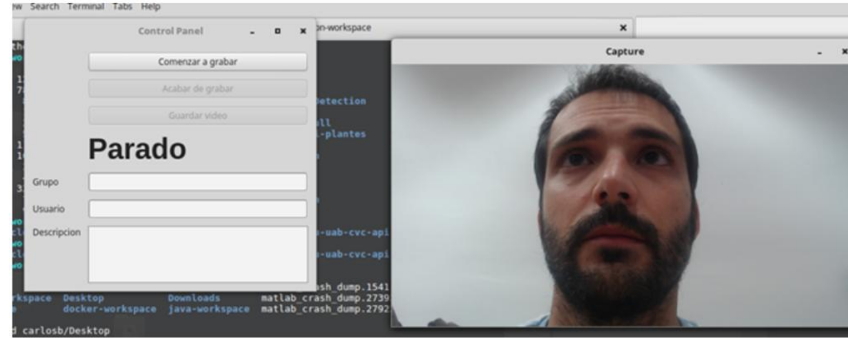
Appendix

Experimental setup for face recognition in FCB's gym facilities based on Linux and Raspberry Pi platform was developed.

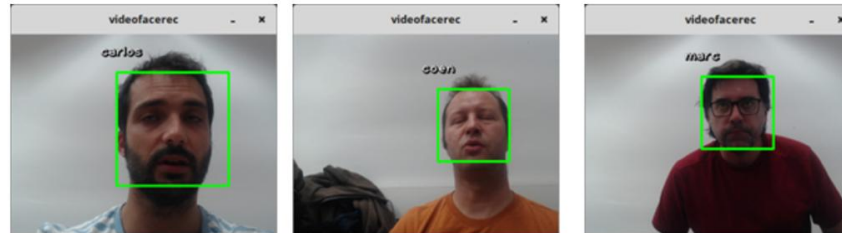
It includes the cameras, server and dedicated application to build FCB's database.



Raspberry Pi unit



Application to build FCB's gym database.



Tests for face recognition with the setup in laboratory.

Thank you!

Aknowledgements:

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Questions?