

FACIAL LANDMARKS DETECTION USING A **CASCADE OF RECOMBINATOR NETWORKS**

Univ. Politécnica de Madrid



Pedro Diego López, Roberto Valle and Luis Baumela



<u>http://www.dia.fi.upm.es/~pcr/research.html</u> **PCR**

November 21, 2018



I. PROBLEM DEFINITION

Facial landmarks detection analysis problems.



Facial landmarks detection is a crucial step for many face

- Head-pose estimation: yaw, pitch, roll
- Face recognition/verification: Ryan Gosling
- Facial expression recognition: happy, surprise, ...
- Attributes estimation: gender, age, ...
- Face alignment/morphing/replacement

2. STATE-OF-THE-ART

sensitive to the starting point of the regression process.



• ERT-based models are easy to parallelize and implicitly impose shape consistency in their estimations (ERT [4], cGPRT [6]). Very

2. STATE-OF-THE-ART



the final shape.

 Current state-of-the-art methods are based on CNN methods. DAN [5] and SHN [11] are among the top performers. Both use a VGG-based and a Stacked Hourglass network respectively to regress



2. STATE-OF-THE-ART

- because of the difficulty in imposing a valid face shape.







• Advantages. CNN approaches are robust to face deformations and pose changes due to the large receptive fields of deep nets.

Disadvantages. Loss of feature maps resolution and lack accuracy









3. CONTRIBUTIONS



Maximum of probability maps determine the landmarks positions.

3. CONTRIBUTIONS

 CRN is composed of S stages where each stage represents a network that combines features across multiple branches B.





3. CONTRIBUTIONS

- We present a loss function that is able to handle missing landmarks. $\mathcal{L} = \sum_{i=1}^{N} \left(-\frac{1}{||\mathbf{w}_{i}^{g}||_{1}} \sum_{l=1}^{L} \left(\mathbf{w}_{i}^{g}(l) \cdot \mathbf{m}_{i}^{g}(l) \cdot \log(\mathbf{m}_{i}(l)) \right) \right)$
- Aggressive data augmentation with large face rotations, translations and scalings, labeling landmarks falling outside of the bounding box as missing.













4. EXPERIMENTS

• 300W public

| | Common | | Challenging | | I | |
|-------------|--------|---------|-------------|---------|--------|------|
| Method | pupils | corners | pupils | corners | pupils | |
| | NME | NME | NME | NME | NME | NM |
| RCN [3] | 4.70 | _ | 9.00 | _ | 5.54 | _ |
| RCN+DKM [3] | 4.67 | _ | 8.44 | _ | 5.41 | _ |
| DAN [5] | 4.42 | 3.19 | 7.57 | 5.24 | 5.03 | 3.59 |
| TSR [7] | 4.36 | - | 7.56 | - | 4.99 | - |
| RAR [10] | 4.12 | - | 8.35 | - | 4.94 | - |
| SHN [11] | 4.12 | - | 7.00 | 4.90 | - | - |
| CRN (S=1) | 4.26 | 3.07 | 8.69 | 6.01 | 5.09 | 3.62 |
| CRN (S=2) | 4.12 | 2.97 | 7.90 | 5.47 | 4.83 | 3.44 |

Table 1: Error of face alignment methods on the 300W public test set.



4. EXPERIMENTS

• 300W private

| | Indoor | | | Outdoor | | | |
|-----------|---------|---------|--------|---------|---------|--------|-----|
| Method | corners | | | C | | | |
| | NME | AUC_8 | FR_8 | NME | AUC_8 | FR_8 | NM |
| DAN $[5]$ | - | - | - | _ | - | - | 4.3 |
| SHN [11] | 4.10 | - | - | 4.00 | - | - | 4.0 |
| CRN (S=1) | 4.42 | 45.91 | 1.66 | 4.45 | 45.25 | 2.66 | 4.4 |
| CRN (S=2) | 4.28 | 47.36 | 2.66 | 4.25 | 47.32 | 2.00 | 4.2 |

Table 2: Error of face alignment methods on the 300W private test set.



4. EXPERIMENTS

COFW and AFLW

| Method | NME | $\begin{array}{c} { m pupils} \\ { m AUC_8} \end{array}$ | FR_8 | Method | $\begin{array}{c} \text{height} \\ NME \end{array}$ |
|---|-----------------------|--|---------------|---|---|
| RAR [10] Wu <i>et al.</i> [9] SHN [11] | $6.03 \\ 5.93 \\ 5.6$ | - - - | - - - | Bulat <i>et al.</i> [2] CCL [13] TSR [7] | $ \begin{array}{c c} 2.85 \\ 2.72 \\ 2.17 \end{array} $ |
| $\begin{array}{c} \mathbf{CRN} (S=1) \\ \mathbf{CRN} (S=2) \end{array}$ | 5.75 5.49 | $30.91 \\ 33.13$ | 11.04 7.88 | $\begin{array}{c} \mathbf{CRN} (S=1) \\ \mathbf{CRN} (S=2) \end{array}$ | 2.29 2.21 |
| (~ -) | | | | | |

Table 3: COFW results.

Table 4: AFLW results.



5. RESULTS









































6. CONCLUSIONS

- in 300W, COFW and AFLW in-the-wild data sets.
- Is the facial landmarks detection problem solved? No.
- and head-pose simultaneously.

• Our improvements to the RCN baseline together with the cascade approach and the data augmentation achieve state-of-the-art results

• Future work. Multitask learning for estimate landmark visibilities



7. REFERENCES

- 1. Amador, E., Valle, R., Buenaposada, J.M., Baumela, L.: Benchmarking head pose estimation in-the-wild. In: Proc. Iberoamerican Congress on Pattern Recognition (CIARP) (2017)
- 2. Bulat, A., Tzimiropoulos, G.: Binarized convolutional landmark localizers for human pose estimation and face alignment with limited resources. In: Proc. Interna-10. tional Conference on Computer Vision (ICCV) (2017)
- 3. Honari, S., Yosinski, J., Vincent, P., Pal, C.J.: Recombinator networks: Learning coarse-to-fine feature aggregation. In: Proc. IEEE Conference on Computer Vision 11. and Pattern Recognition (CVPR) (2016)
- 4. Kazemi, V., Sullivan, J.: One millisecond face alignment with an ensemble of regression trees. In: Proc. IEEE Conference on Computer Vision and Pattern Recognition 12. (CVPR) (2014)
- 5. Kowalski, M., Naruniec, J., Trzcinski, T.: Deep alignment network: A convolutional neural network for robust face alignment. In: Proc. IEEE Conference on Computer 13. Vision and Pattern Recognition Workshops (CVPRW) (2017)
- 6. Lee, D., Park, H., Yoo, C.D.: Face alignment using cascade gaussian process regression trees. In: Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2015)
- 7. Lv, J., Shao, X., Xing, J., Cheng, C., Zhou, X.: A deep regression architecture with two-stage re-initialization for high performance facial landmark detection. In: Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2017)

8. Sun, Y., Wang, X., Tang, X.: Hybrid deep learning for face verification. IEEE Trans. Pattern Analysis and Machine Intelligence (TPAMI) 38, 1997–2009 (2016) 9. Wu, Y., Ji, Q.: Robust facial landmark detection under significant head poses and

occlusion. In: Proc. International Conference on Computer Vision (ICCV) (2015) Xiao, S., Feng, J., Xing, J., Lai, H., Yan, S., Kassim, A.A.: Robust facial land-

mark detection via recurrent attentive-refinement networks. In: Proc. European Conference on Computer Vision (ECCV) (2016)

Yang, J., Liu, Q., Zhang, K.: Stacked hourglass network for robust facial landmark localisation. In: Proc. IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW) (2017)

Zafeiriou, S., Trigeorgis, G., Chrysos, G., Deng, J., Shen, J.: The menpo facial landmark localisation challenge: A step towards the solution. In: Proc. IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW) (2017)

Zhu, S., Li, C., Change, C., Tang, X.: Unconstrained face alignment via cascaded compositional learning. In: Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2016)



8. QUESTIONS

