Coarse-to-Fine Auto-Encoder Networks (CFAN) for Real-Time Face Alignment

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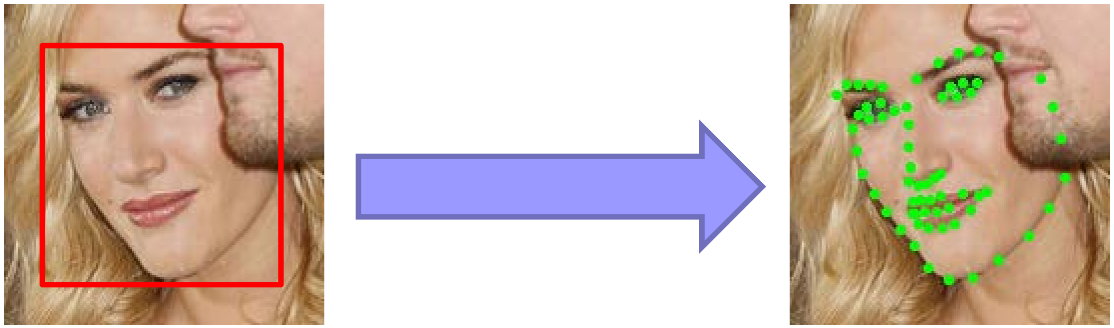
Outline

- Problem
- Related Work
- Motivation
- Method
  - Global SAN
  - Local SAN
  - Coarse-to-fine strategy
- Experiments
- Conclusion

Problem

- Face Alignment：
  - Predict facial landmarks from the face region



- Application
  - Face recognition
  - Expression recognition
  - Face animation …

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Challenges

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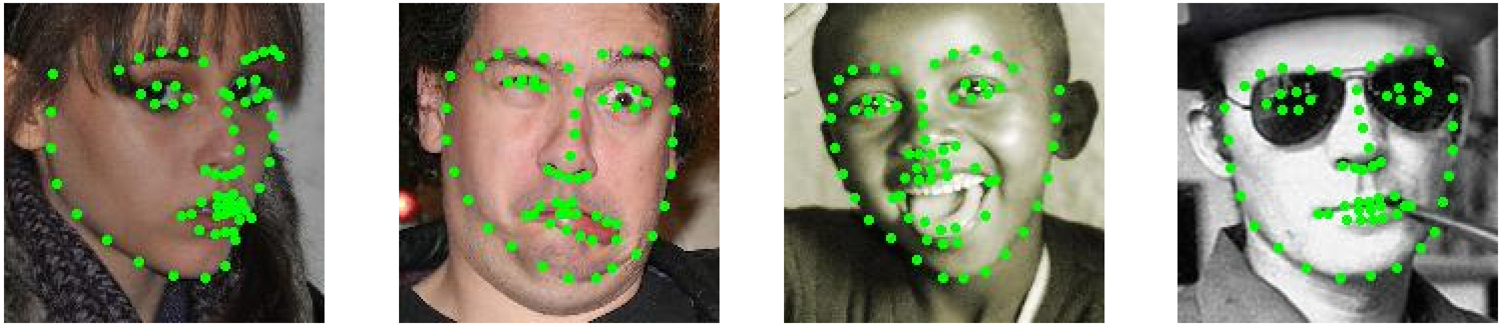
- Appearance -> Shape: a complex mapping
- Large appearance & shape variations
  - Head pose
  - Expressions
  - Illumination
  - Partial occlusion



Related Work

- ASM & AAM [Cootes'95; Gu'08; Cootes'01; Matthews'04]
  - Sensitive to initial shapes
  - Sensitive to noise
  - Hard to cover complex variations
- DCNN [Sun'13; Toshev'14]
  - Fragile to partial occlusions
- Shape regression model
  - CPR,ESR,RCPR [Dollar'10; Cao'12; Burgos-Artizzu'13]
  - DRMF [Asthana'13]
  - SDM [Xiong'13]

Motivation

Cascade shape regression models for face alignment

$$\Delta \boldsymbol{S_j} = \boldsymbol{H_j}(\emptyset(\boldsymbol{I}, \boldsymbol{S_{j-1}}))$$

- **Global regression for better initialization $\boldsymbol{S_0}$**

Motivation

Cascade shape regression models for face alignment

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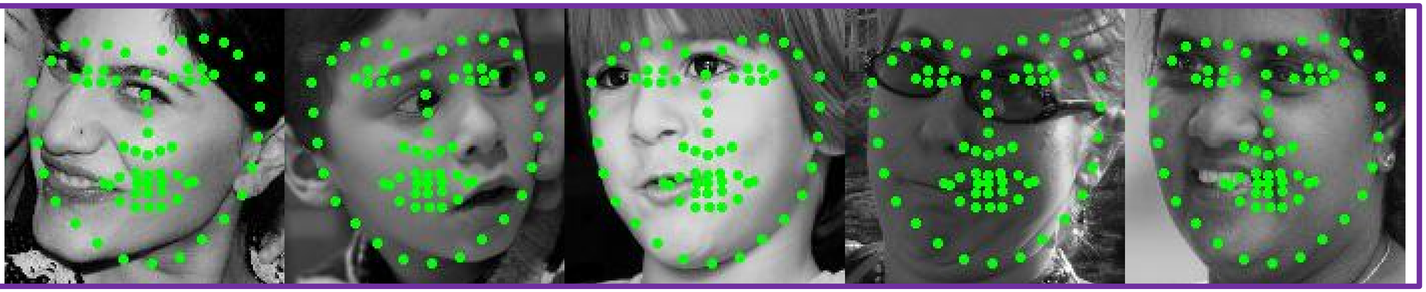
Mean Shape



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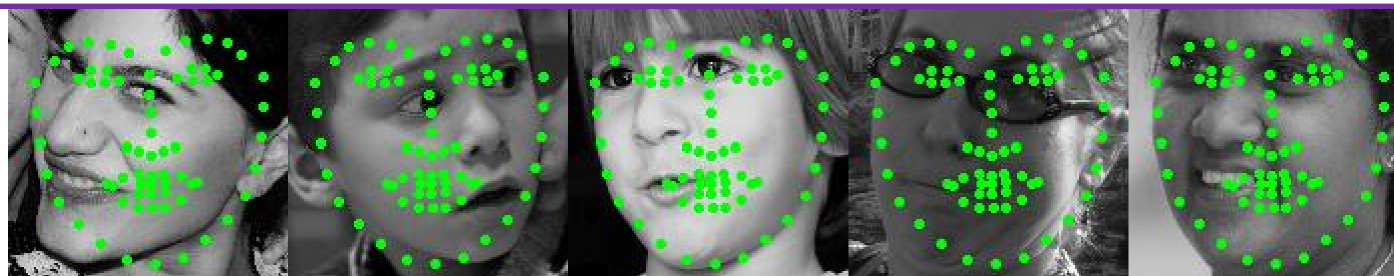
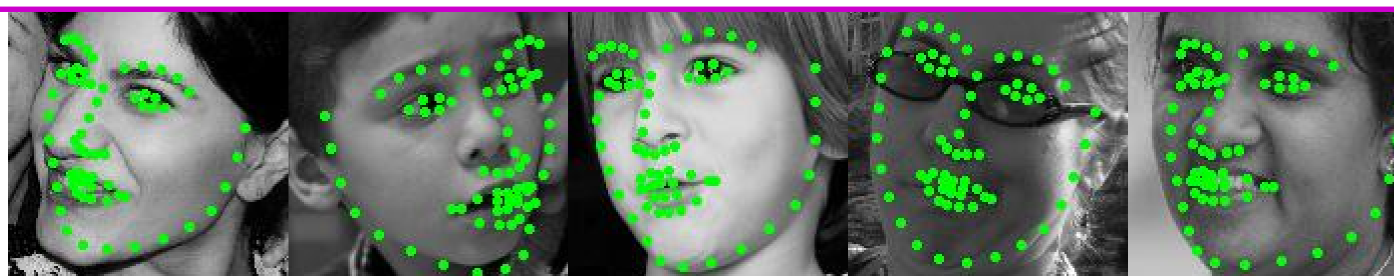


Global Regression

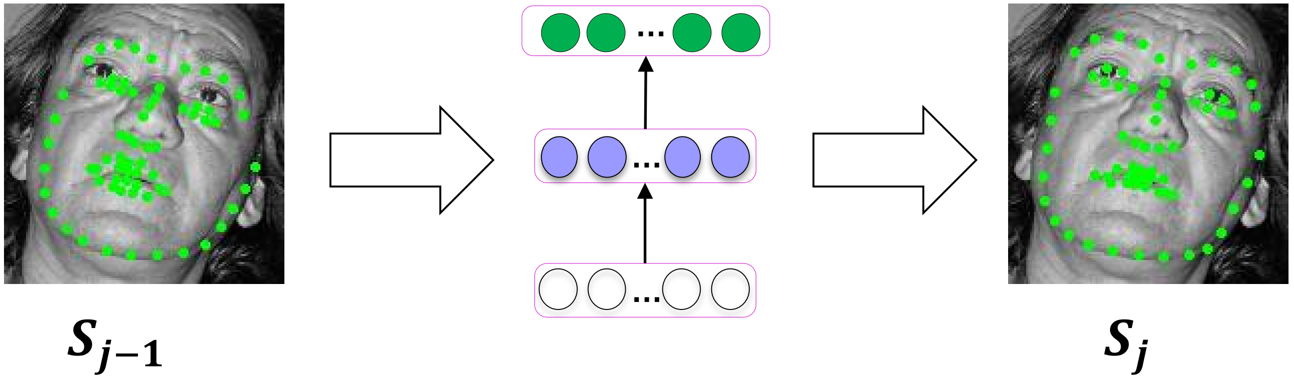


Motivation

Cascade shape regression models for face alignment

$$\Delta S_j = H_j(\emptyset(I, S_{j-1}))$$

- **Global regression** **for better initialization S_0**
- **Deep networks for** **nonlinear regression function H_j**



Motivation

Cascade shape regression models for face alignment

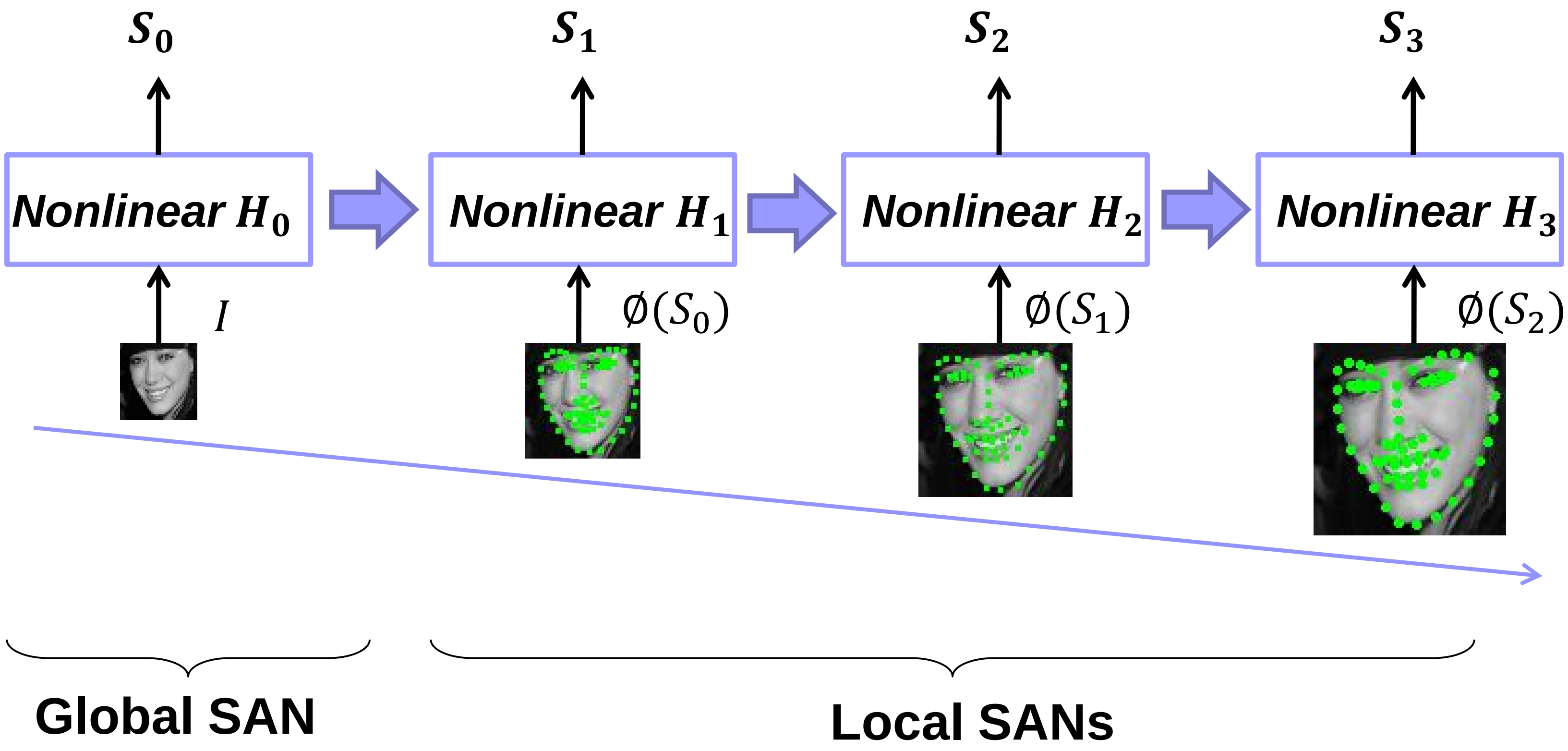
$$\Delta S_j = H_j(\emptyset(I, S_{j-1}))$$

- Global regression for better initialization S_0
- Deep networks for nonlinear regression function H_j
- Cascade H_j in a coarse-to-fine architecture

Coarse-to-fine Cascade

Our Method(1/7)

- Schema of Coarse-to-Fine AE Networks



SAN: Stacked Auto-encoder Network

Our Method(2/7)

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- Pipeline

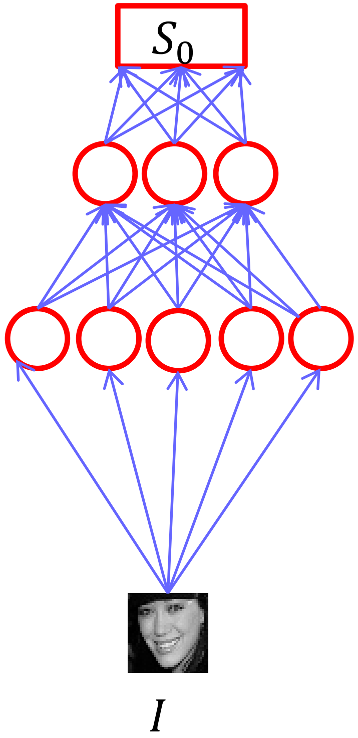
Our Method(2/7)

- Pipeline

I

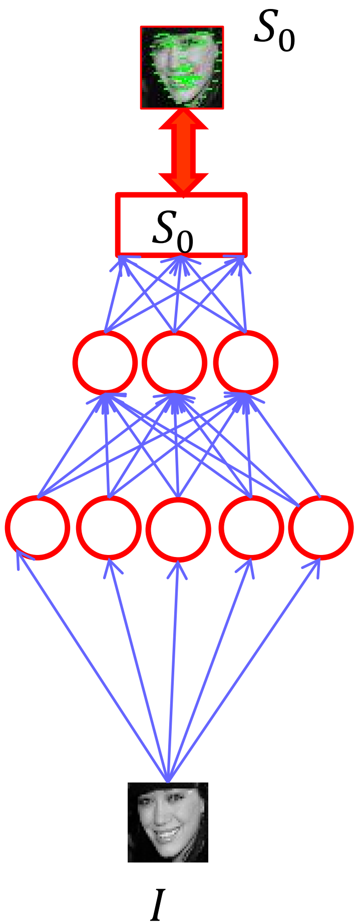
Our Method(2/7)

- Pipeline



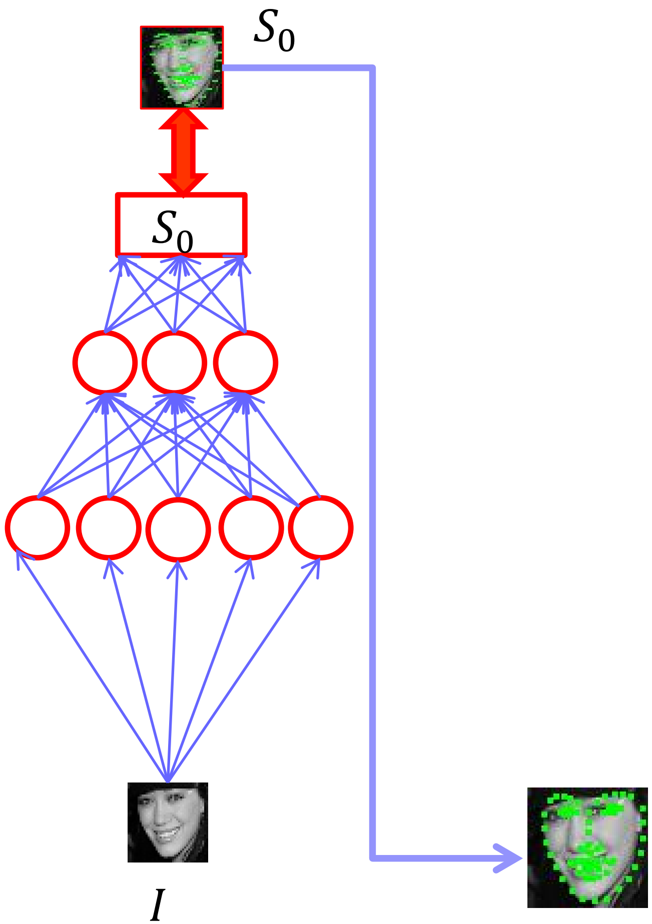
Our Method(2/7)

- Pipeline



Our Method(2/7)

- Pipeline



Our Method(2/7)

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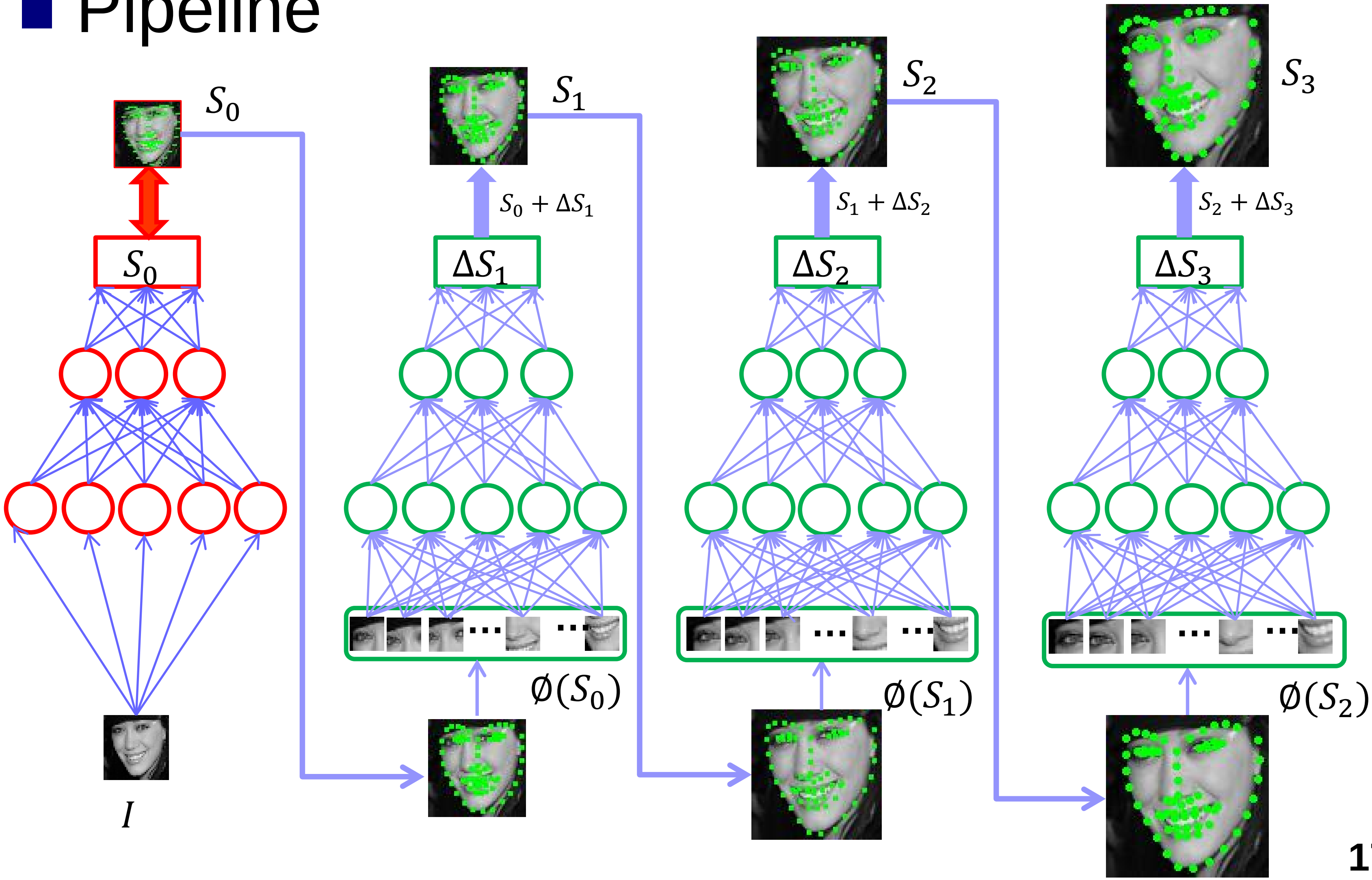
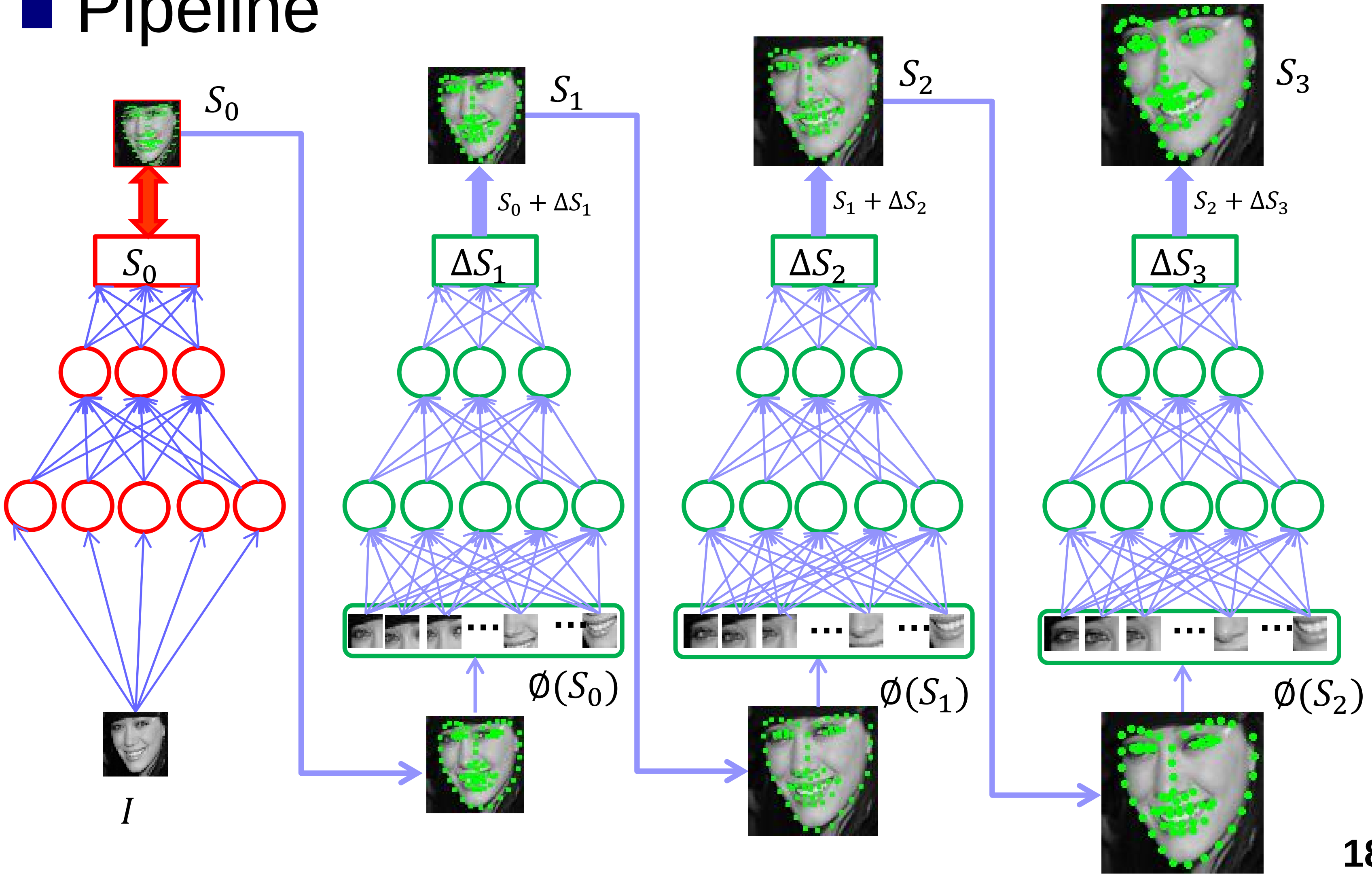
- Pipeline



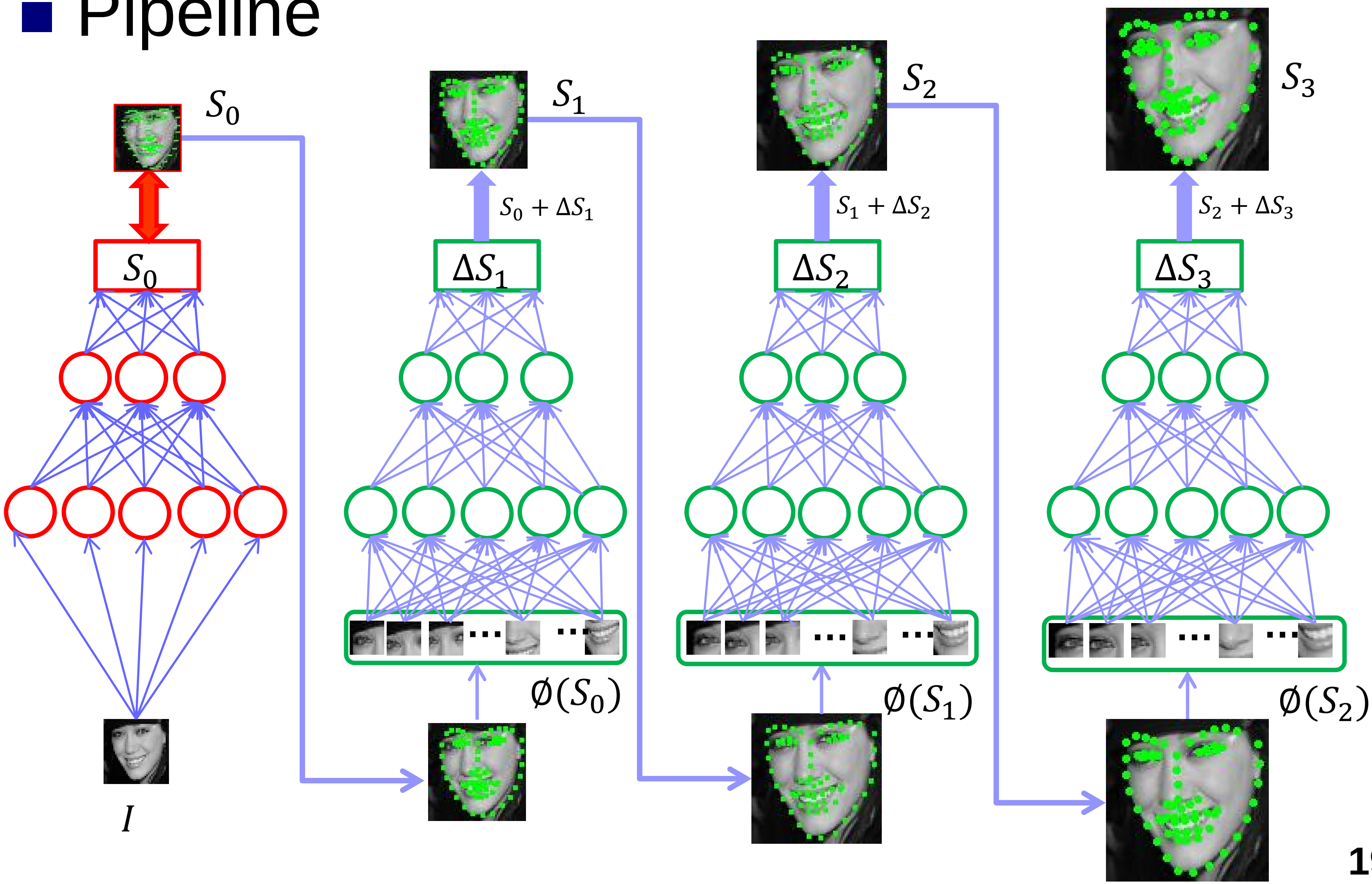
Our Method(3/7)

- Pipeline



Our Method(3/7)

- Pipeline

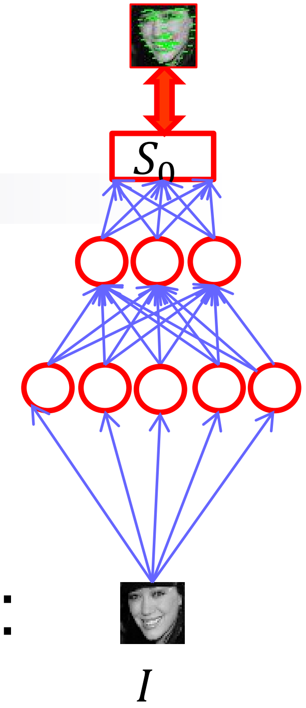


Our Method(4/7)

- Global SAN:
  - Mapping H_0 from image I to shape S.

$$H_0 : S \leftarrow I$$

  - Model H_0 as a Stacked Auto-encoder:

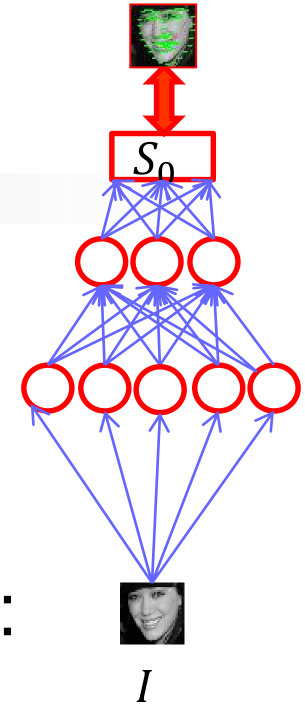


$$H_0^* = \arg\min_{H_0} \|S - f_k(f_{k-1}(\ldots f_1(I)))\|_2^2 + \alpha \sum_{i=1}^{k} \|W_i\|_F^2$$

$$f_i(a_{i-1}) = \sigma(W_i a_{i-1} + b_i) \triangleq a_i, i = 1, \ldots, k-1$$

$$f_k(a_{k-1}) = W_k a_{k-1} + b_k \triangleq S_0$$

Our Method(4/7)



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Regression — Regularization

$$f_i(a_{i-1}) = \sigma(W_i a_{i-1} + b_i) \triangleq a_i, i = 1, \dots, k-1$$

$$f_k(a_{k-1}) = W_k a_{k-1} + b_k \triangleq S_0$$

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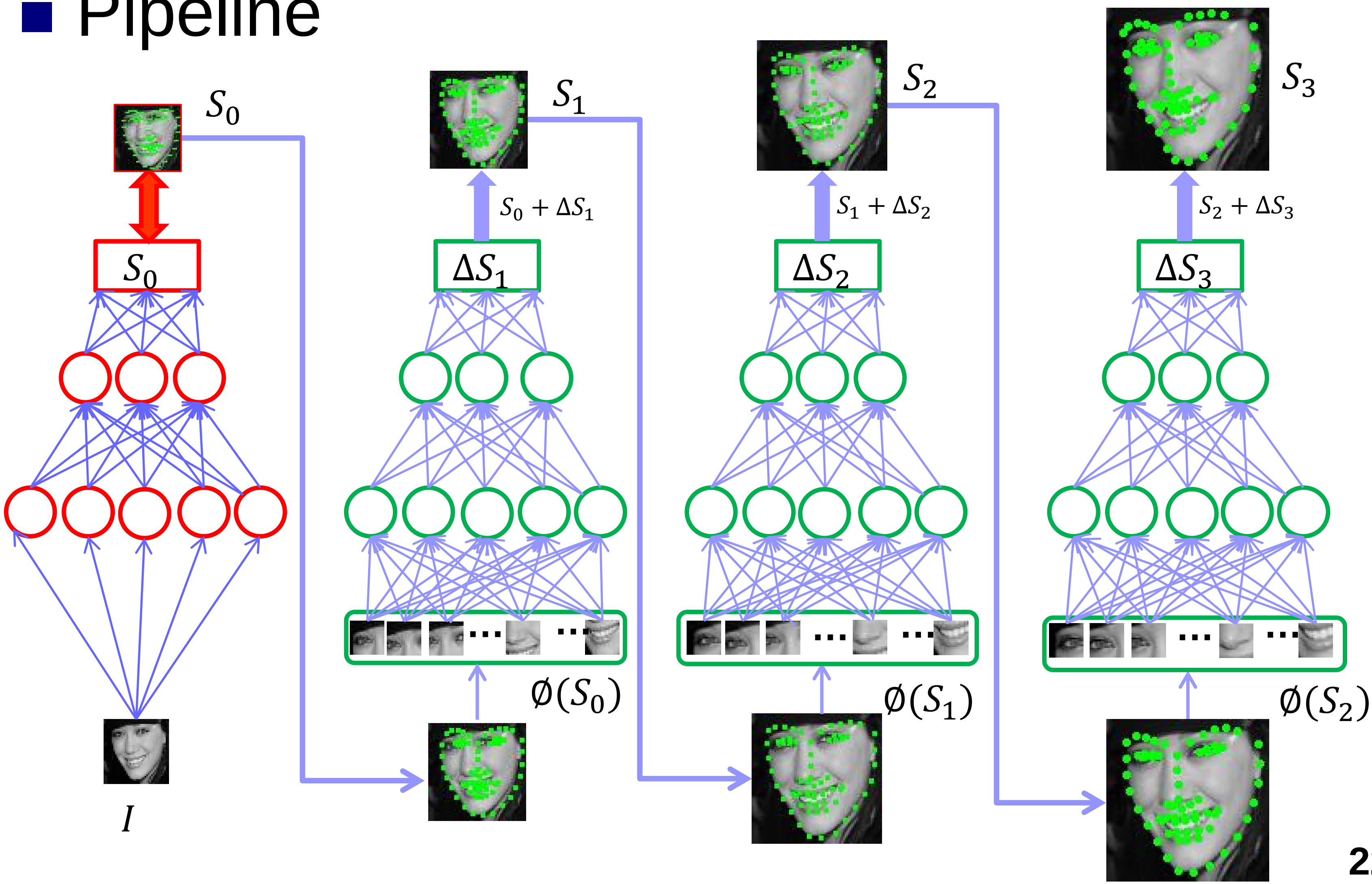
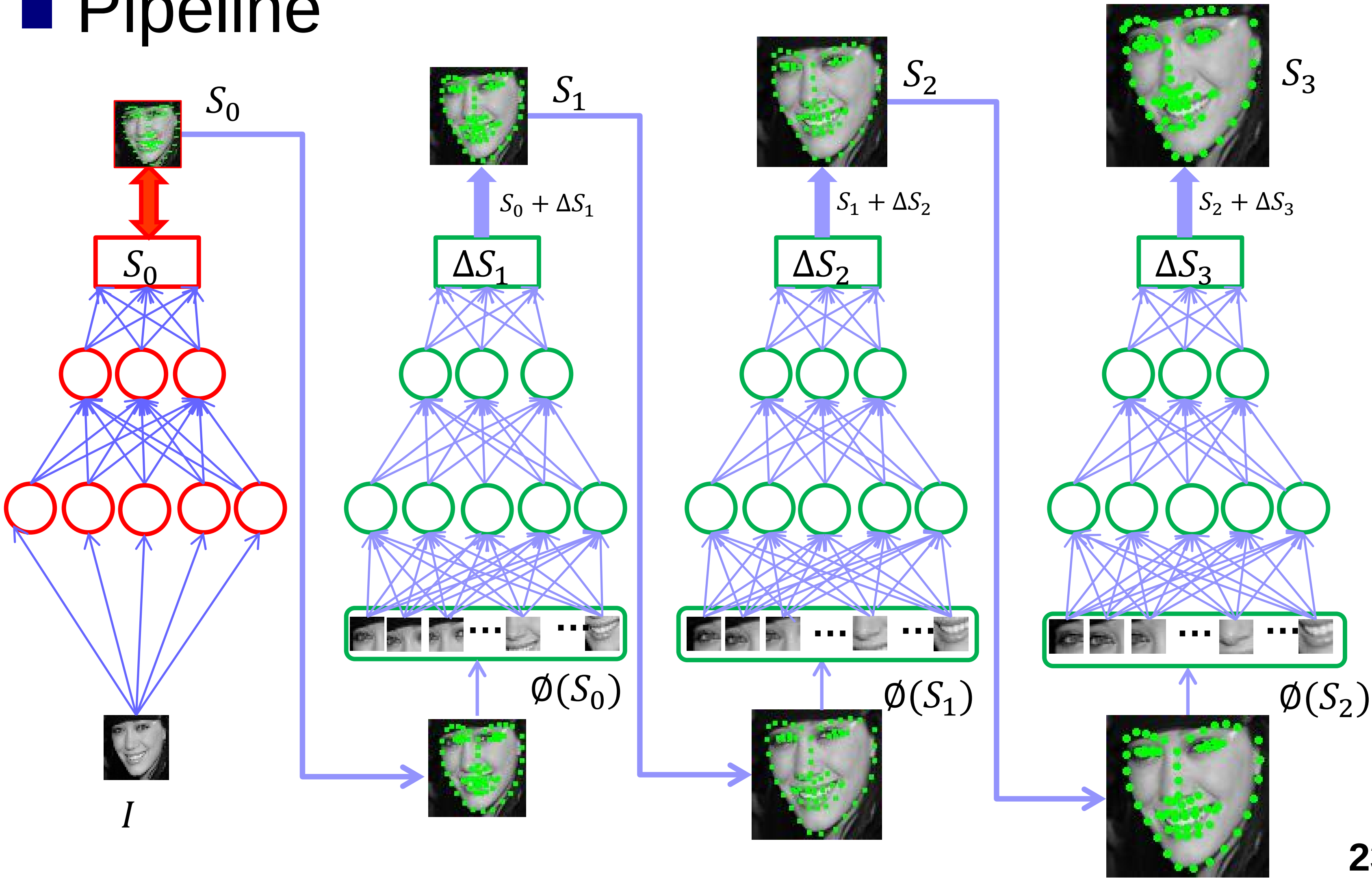
Our Method(5/7)

- Pipeline



Our Method(5/7)

- Pipeline



Our Method(6/7)

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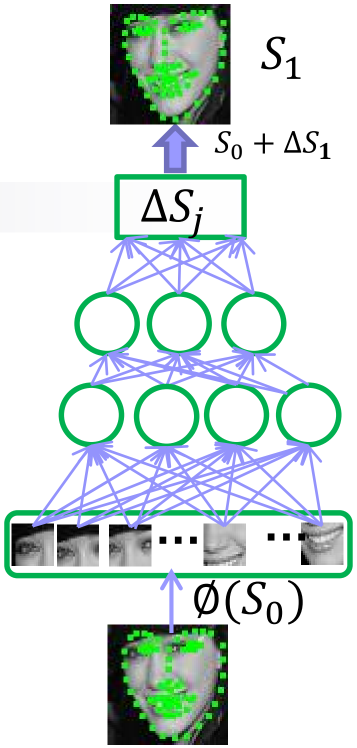
- Local SAN:
  - Initialize shape S_0 from global SAN.
  - Refine the shape with local feature
    - predict shape deviation with AE



$$H_1^* = \arg\min_{H_1} \left\| \Delta S_1 - h_k^1 \left(\dots h_1^1(\emptyset(S_0)) \right) \right\|_2^2 + \alpha \sum_{i=1}^{k} \left\| W_i^1 \right\|_F^2$$

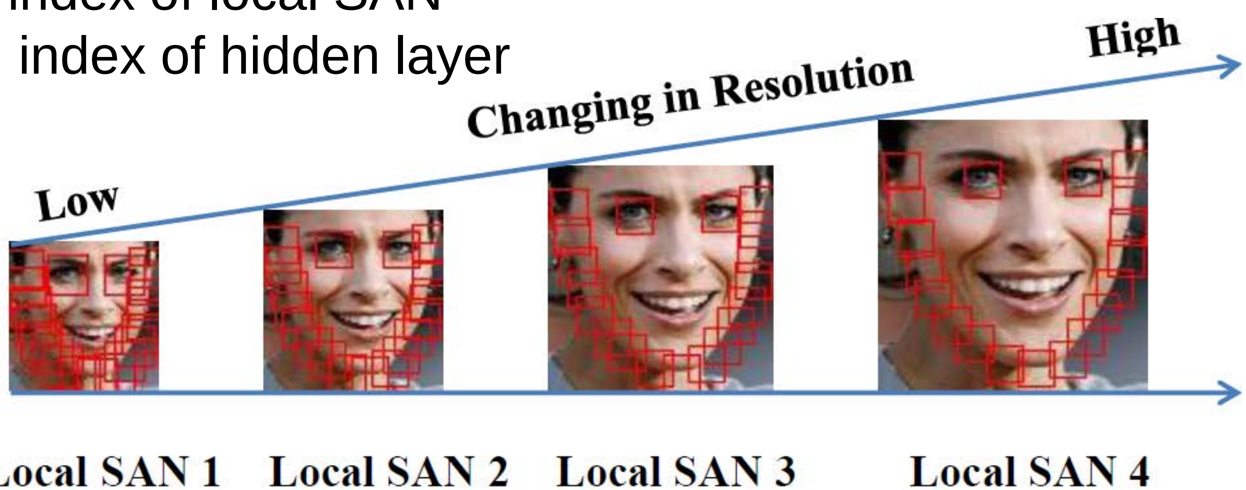
$$\Delta S_1 = S - S_0$$

Our Method(7/7)

- Coarse-to-fine Cascade:

$$H_j^* = \arg\min_{H_j} \left\| \Delta S_j - h_k^j \left(\dots h_1^j \left(\phi \left(S_{j-1} \right) \right) \right) \right\|_2^2 + \alpha \sum_{i=1}^{k} \| W_i^j \|_F^2$$

j: index of local SAN
k: index of hidden layer



S_0 S_1 S_2 S_3

Large Search Region/Step ⟶ **Tiny Search Region/Step**

Experiments(1/8)

- Datasets
  - **XM2VTS** [Messer'99]
    - 2360 face images collected over 4 sessions under the controlled settings
  - **LFPW** [Belhumeur'11]
    - 1132 training images and 300 test images collected from wild condition
  - **HELEN** [Le'12]
    - 2330 high-resolution face images collected from the wild, 2000 images for training and 330 images for test
  - **AFW** [Zhu'12]
    - 205 images with 468 faces collected from the wild

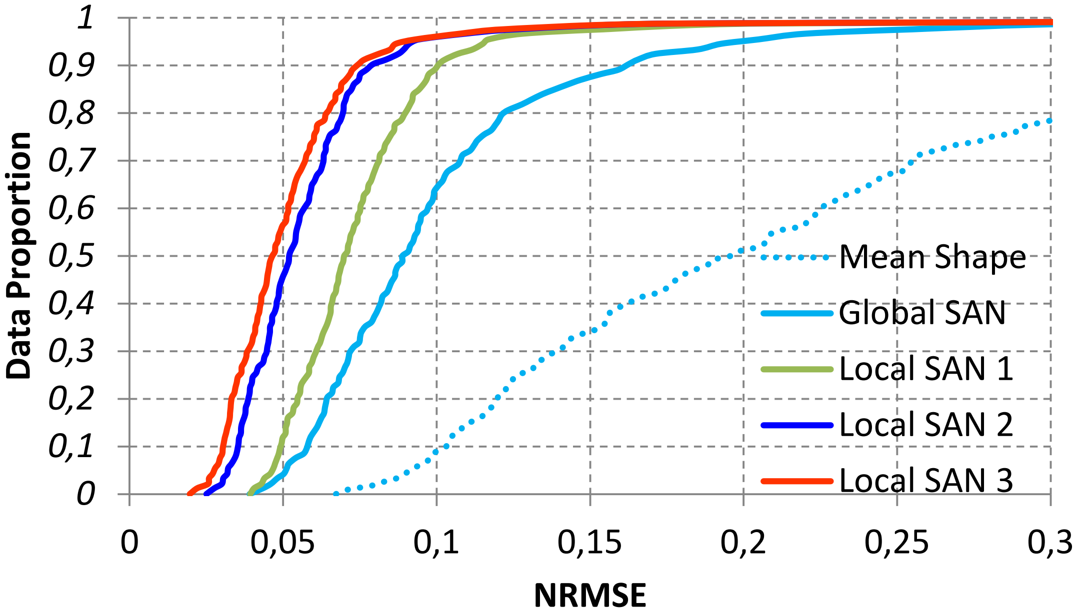
Experiments(2/8)

- Evaluation of Successive SANs

Performance gain of each SAN
(Conduct on LFPW)

Experiments(2/8)

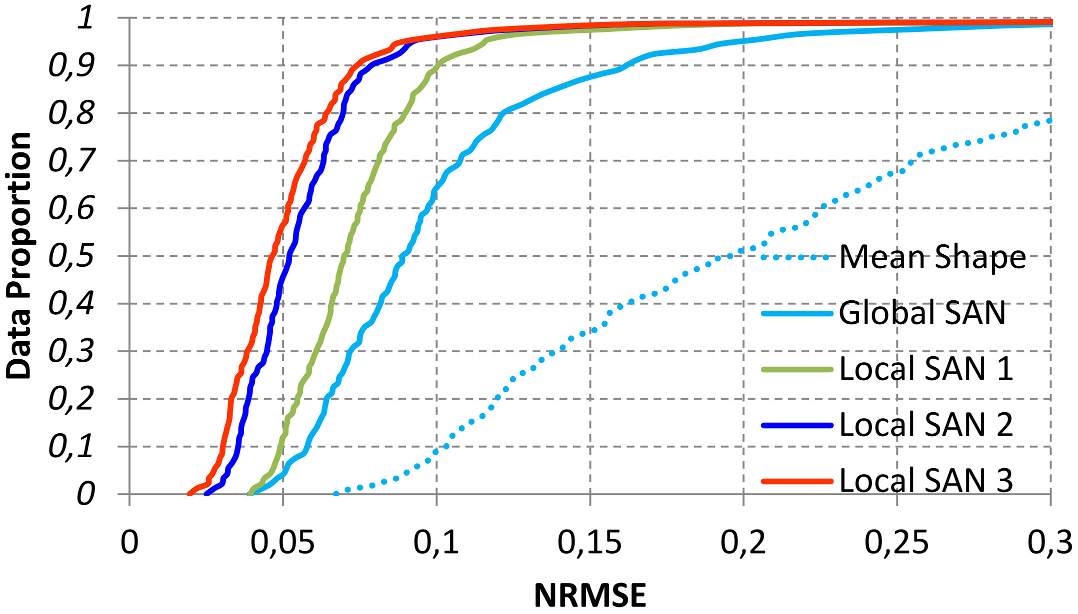
- Evaluation of Successive SANs



Performance gain of each SAN (Conduct on LFPW)

Experiments(2/8)

- Evaluation of Successive SANs



Performance gain of each SAN (Conduct on LFPW)

Experiments(2/8)

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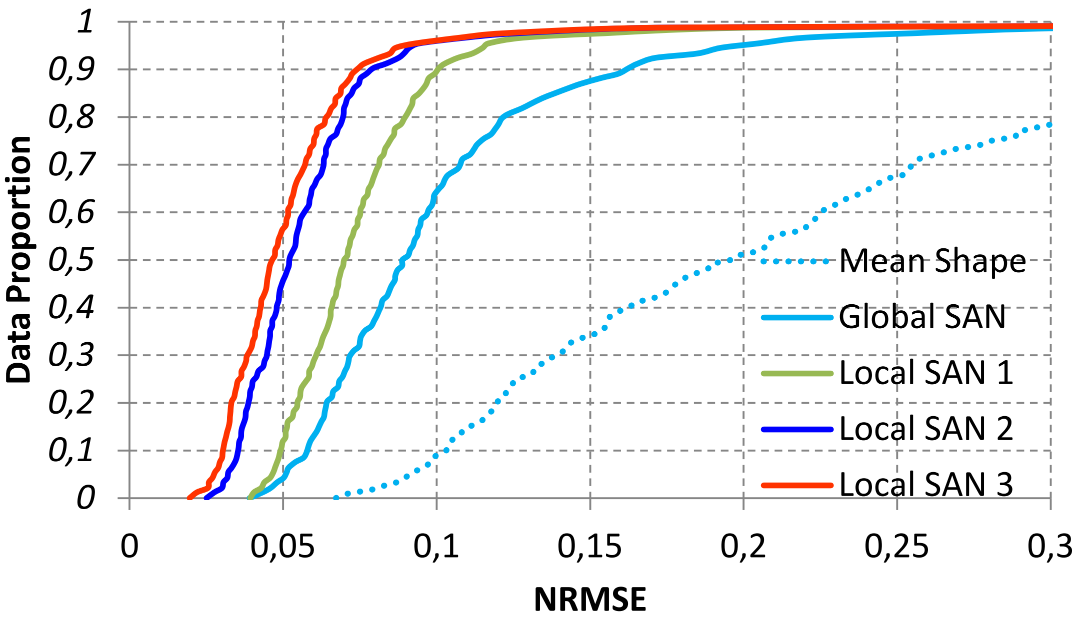

Performance gain of each SAN (Conduct on LFPW)

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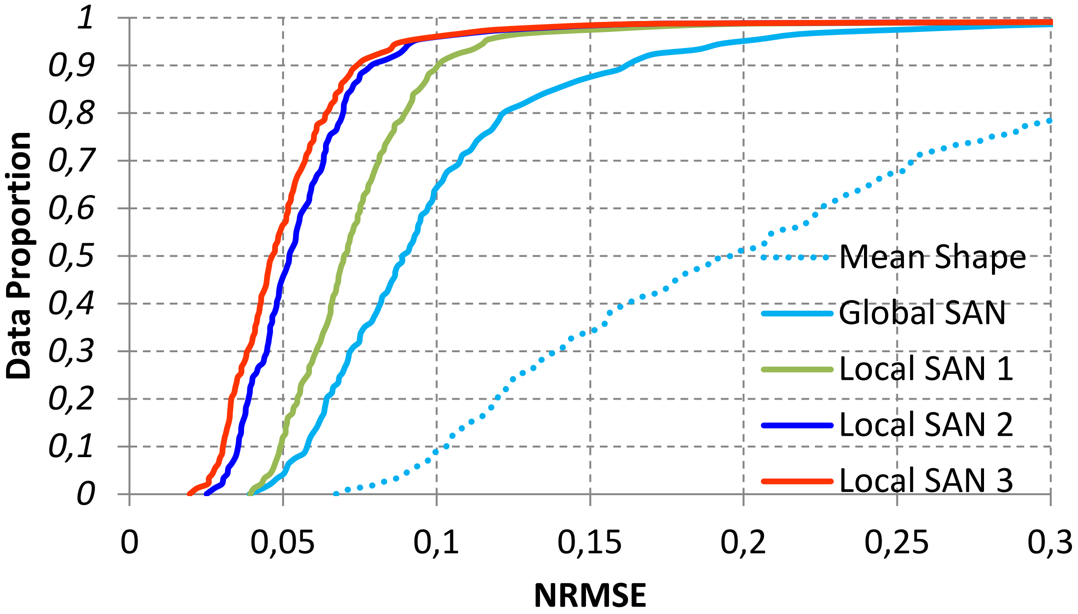

Performance gain of each SAN (Conduct on LFPW)

Experiments(2/8)

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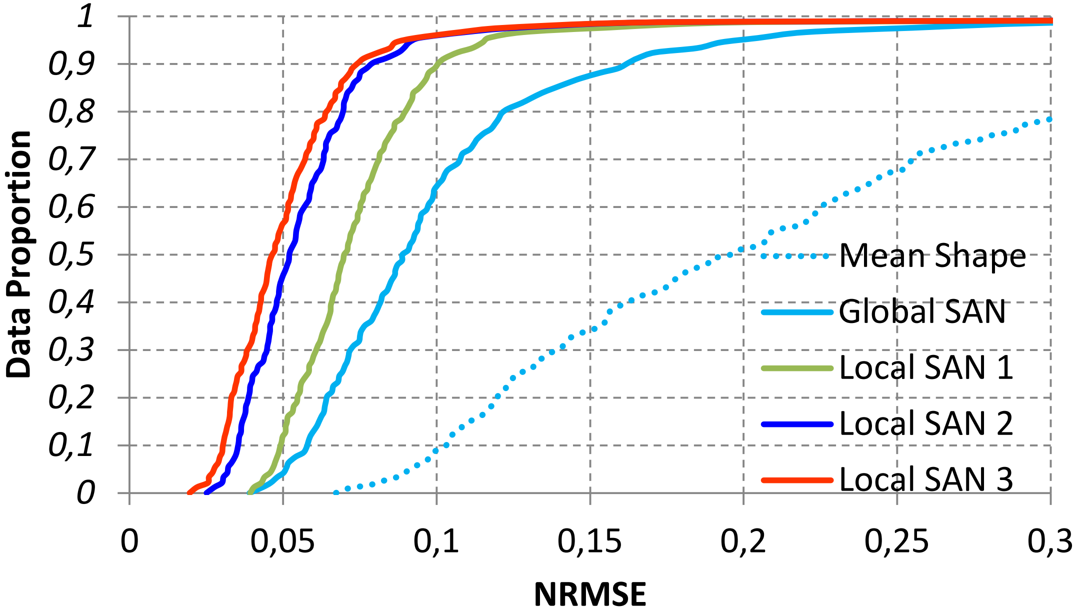

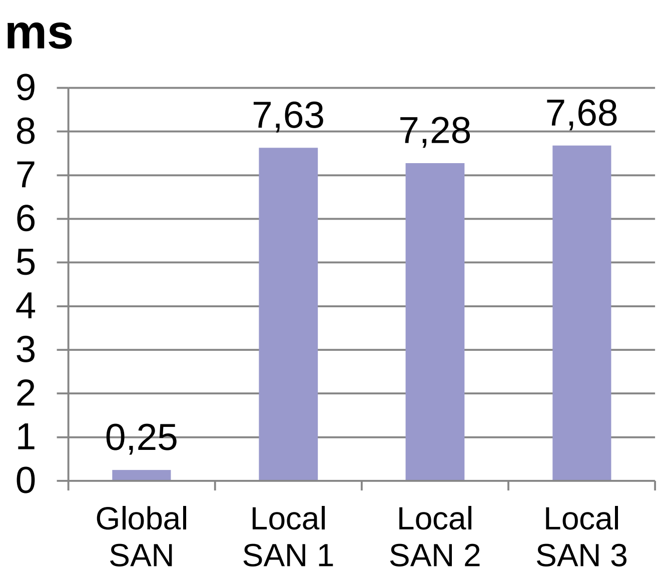

Performance gain of each SAN (Conduct on LFPW)

Run Time (ms)

Experiments(3/8)

- Comparative Methods
  - Local Models with Regression Fitting
    - SDM [Xiong'13]
    - DRMF [Asthana'13]
  - Tree-structured Models
    - Zhu et al. [Zhu'12]
    - Yu et al. [Yu'13]
  - Deep Model
    - DCNN [Sun'13]

Experimental Result(4/8)

- Performance comparisons on HELEN

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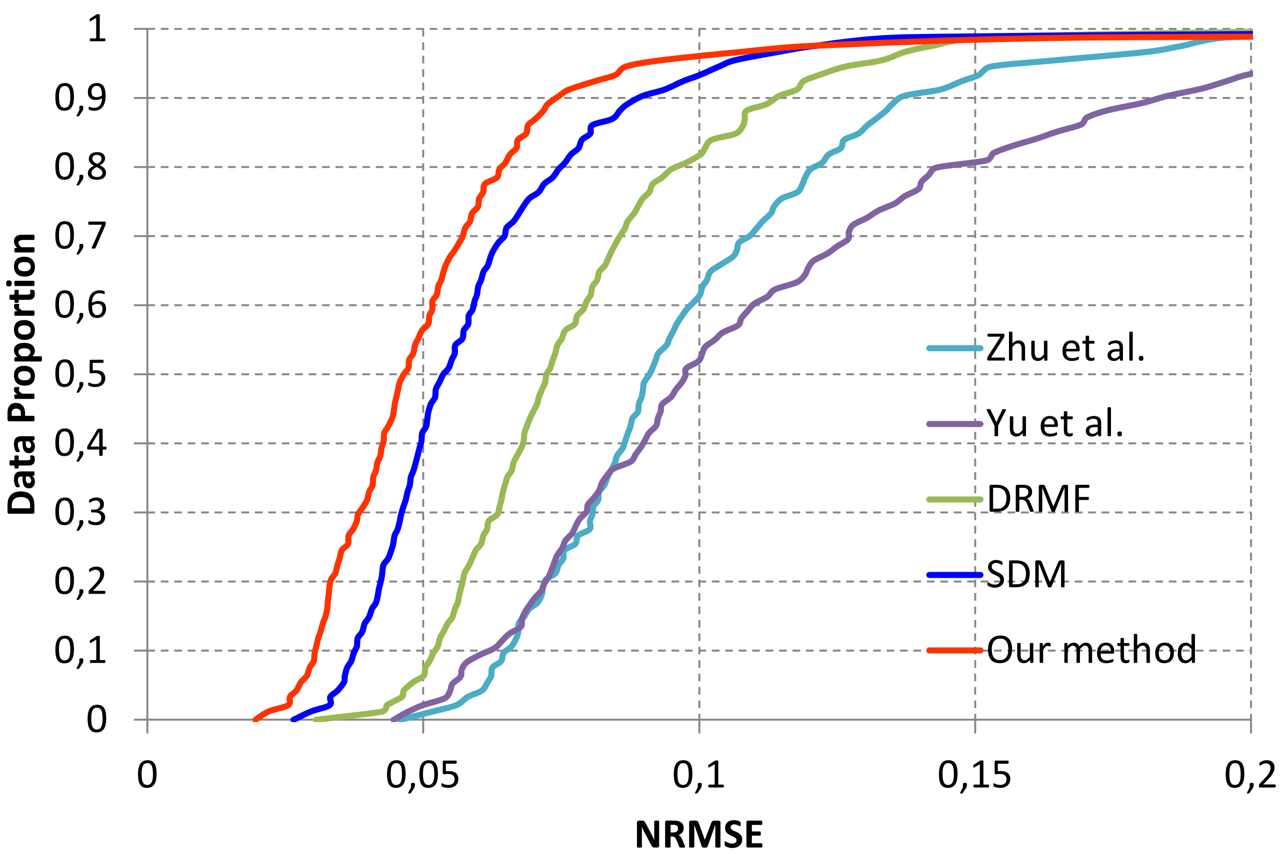
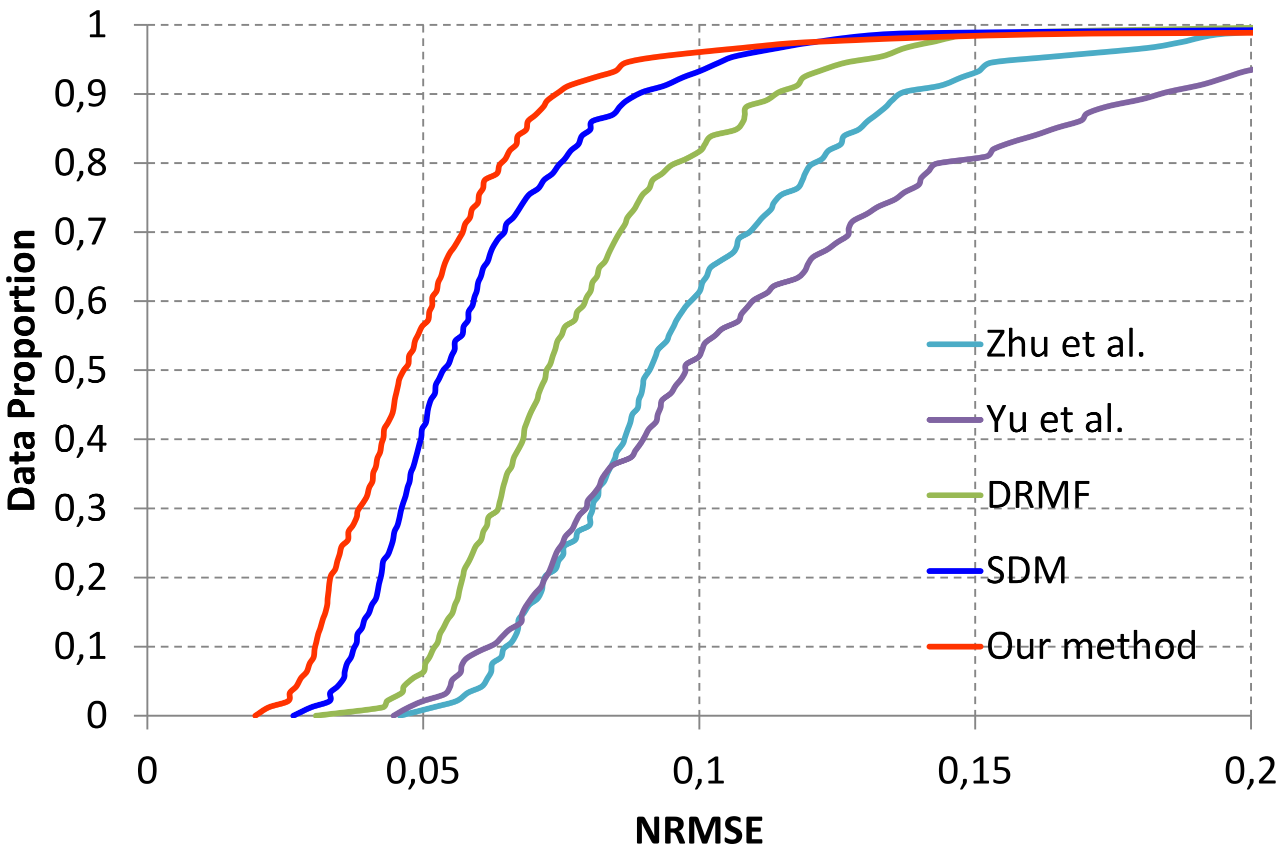
Experimental Result(4/8)

- Performance comparisons on HELEN



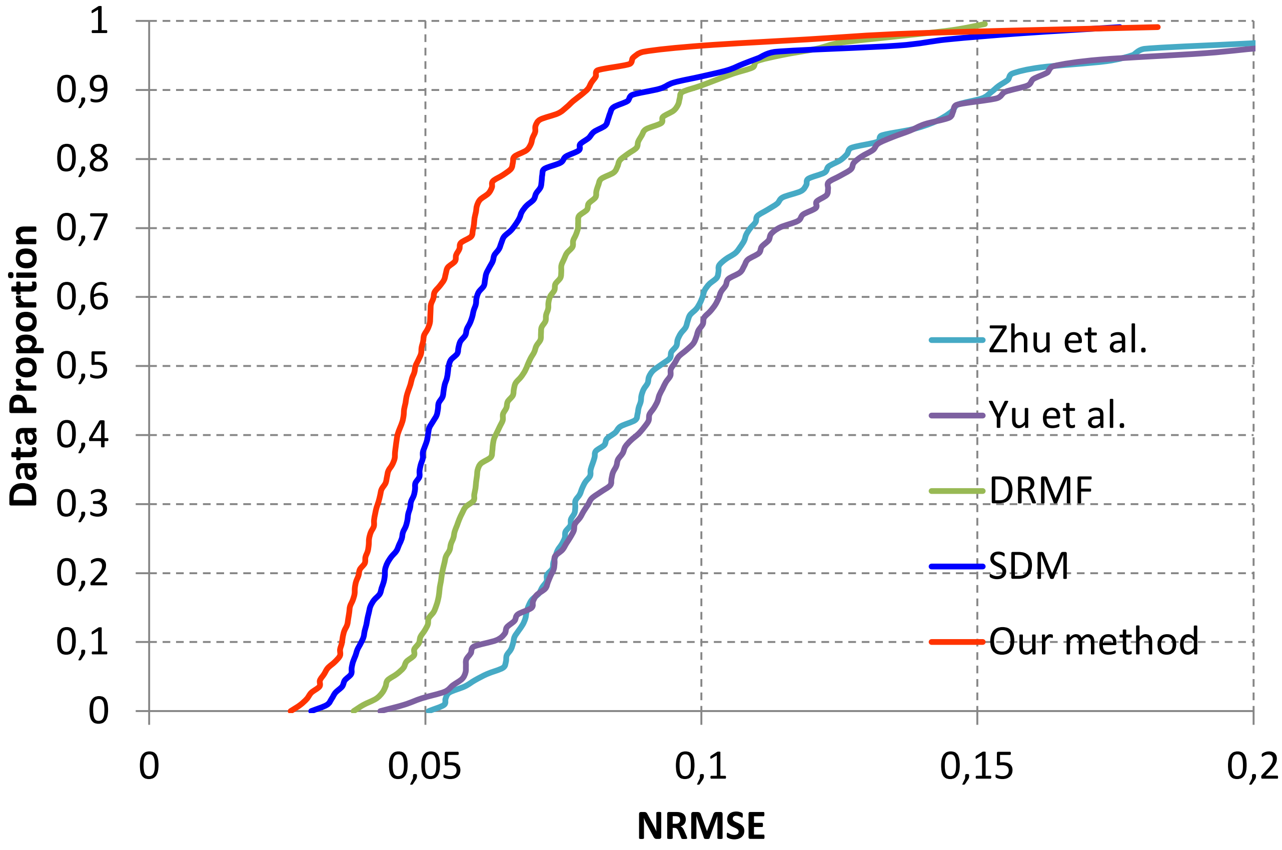
Experimental Result(4/8)

- Performance comparisons on HELEN



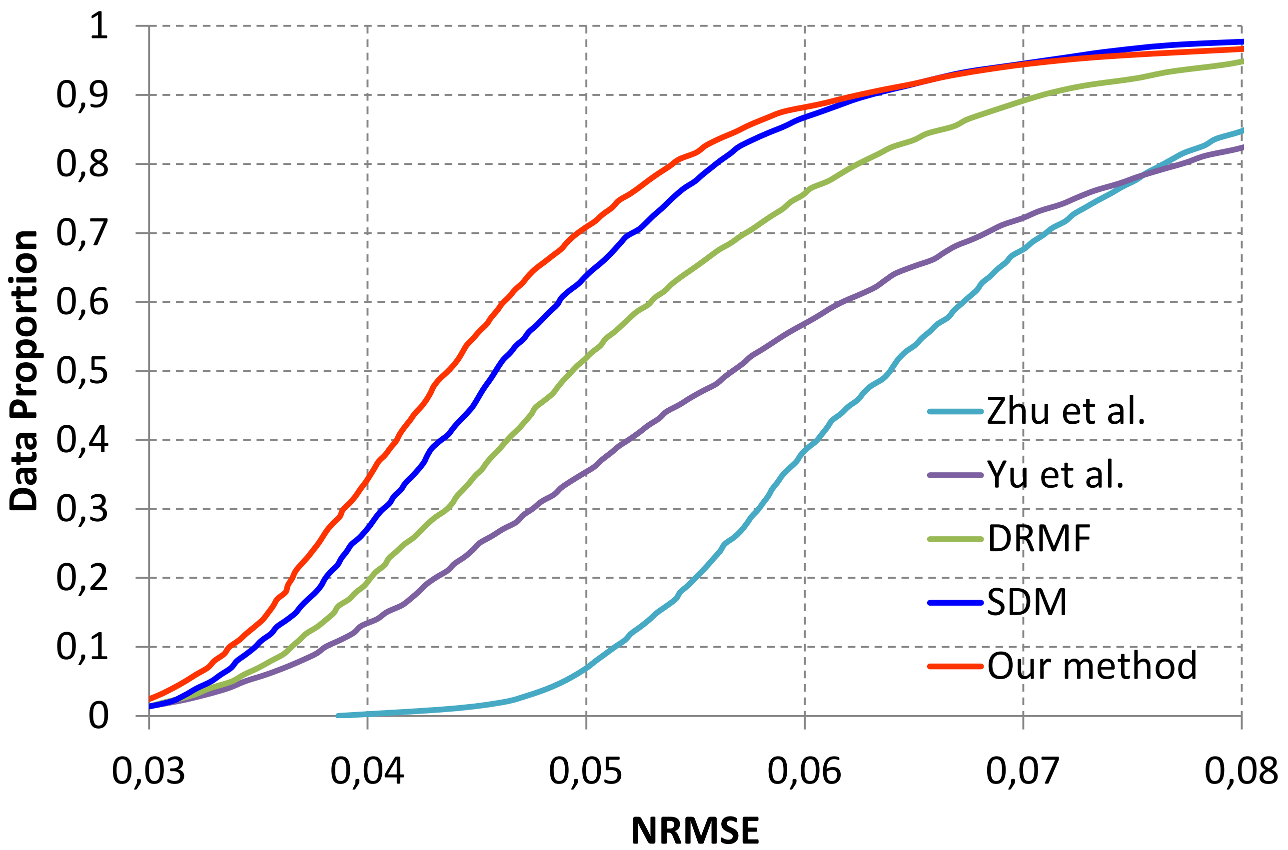
Experimental Result(5/8)

- Performance comparisons on LFPW



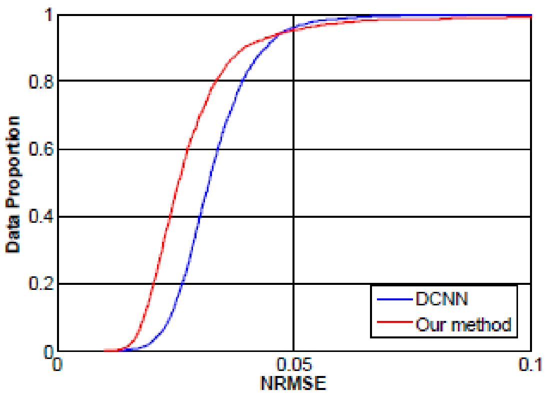
Experimental Result(6/8)

- Performance comparisons on XM2VTS

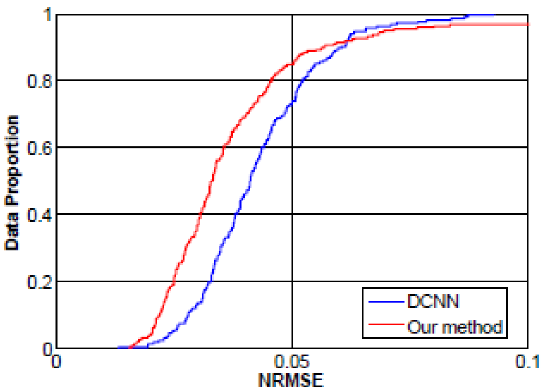


Experimental Result(7/8)

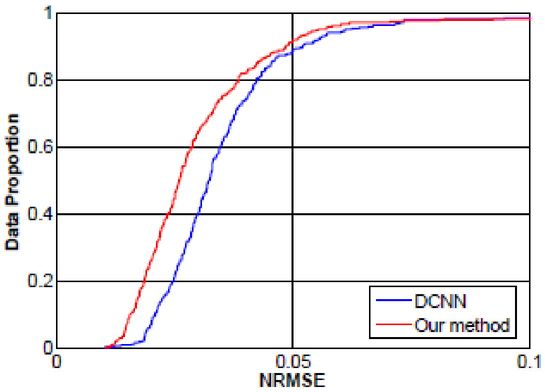
- Comparisons with DCNN



XM2VTS



LFPW



HELEN

Note: The performance is evaluated in terms of five common landmarks

Experimental Result(8/8)

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Experimental Result(8/8)

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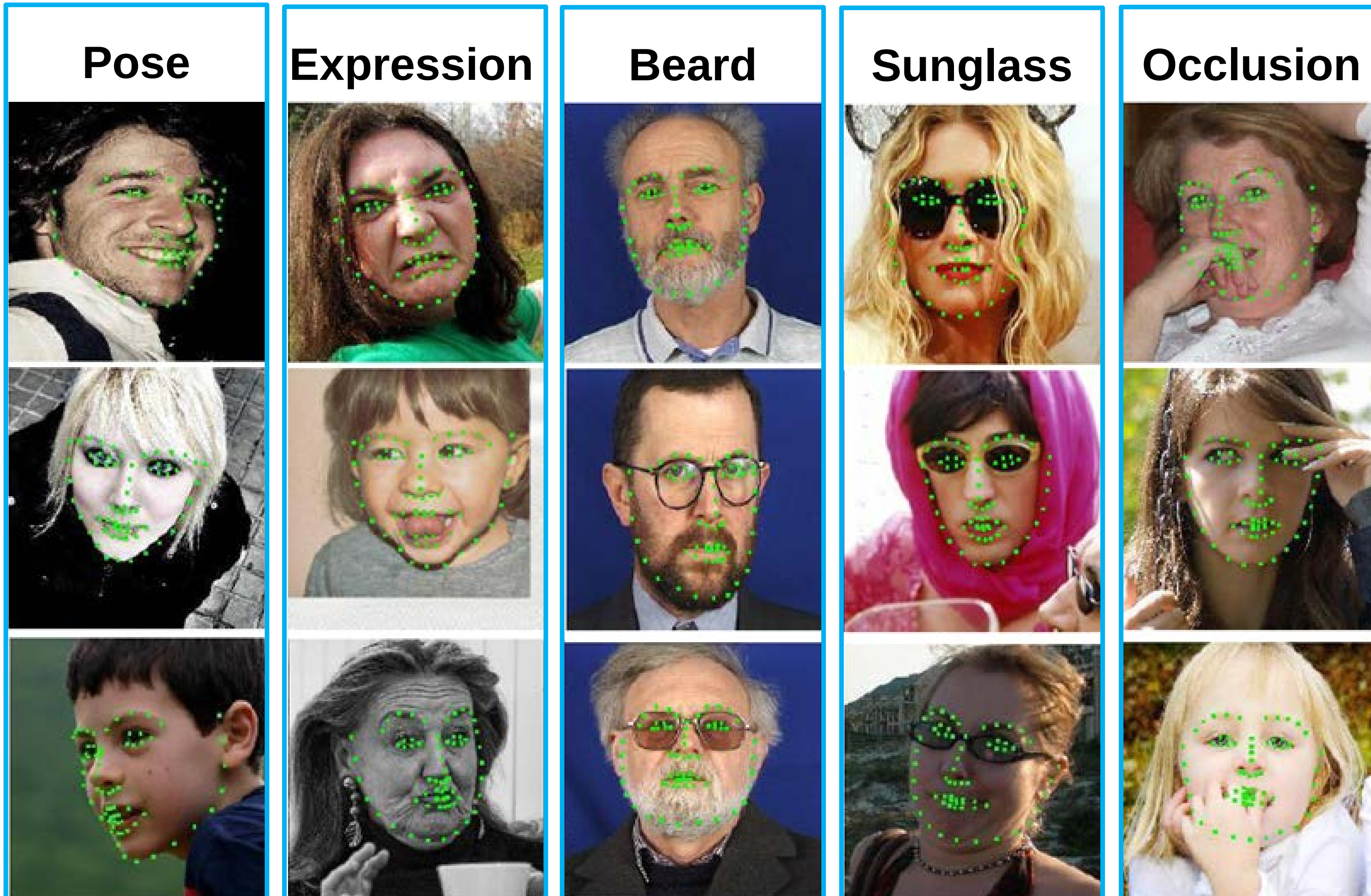

Conclusions

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- Global SAN achieves more accurate initialization
- SAE well characterizes the non-linearity from appearance to face shape
- Coarse-to-fine strategy is effective
  - Alleviate the local minimum problem
- Impressive improvement and real-time performance

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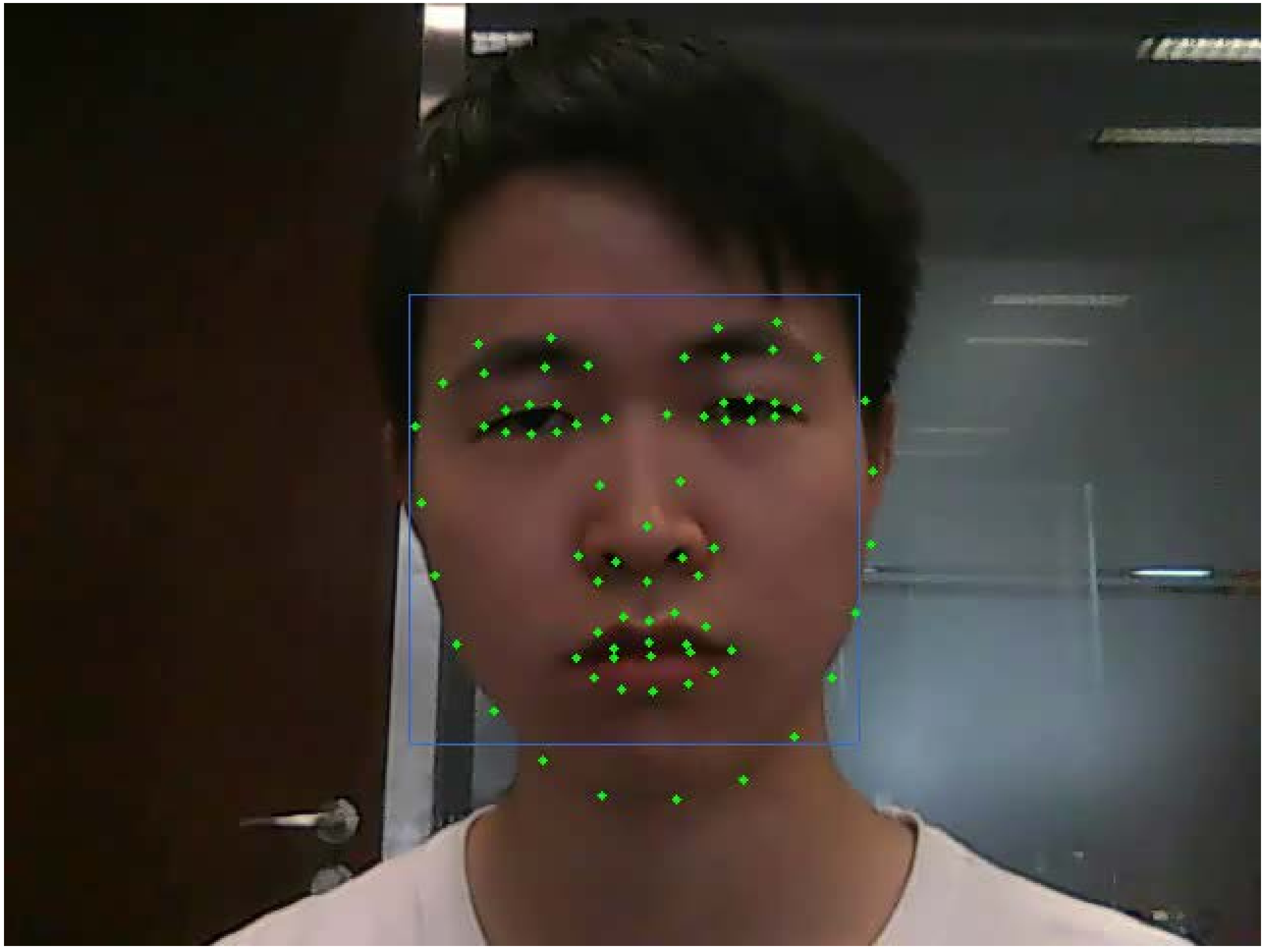
Model is available online!

http://vipl.ict.ac.cn/resources

Poster ID: P-2A-50

Demo



References

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- Cootes, T.F., Edwards, G.J., Taylor, C.J.: Active appearance models. IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI) 23(6), 681–685 (2001)
- Matthews, I., Baker, S.: Active appearance models revisited. International Journal of Computer Vision (IJCV) 60(2), 135–164 (2004)
- Zhao, X., Shan, S., Chai, X., Chen, X.: Locality-constrained active appearance model. In: Asian Conference on Computer Vision (ACCV), pp. 636–647 (2012)
- Cootes, T.F., Taylor, C.J., Cooper, D.H., Graham, J.: Active shape modelstheir training and application. Computer Vision and Image Understanding (CVIU) 61(1), 38–59 (1995)
- Gu, L., Kanade, T.: A generative shape regularization model for robust face alignment. In: Forsyth, D., Torr, P., Zisserman, A. (eds.) ECCV 2008, Part I. LNCS, vol. 5302, pp. 413–426. Springer, Heidelberg (2008)
- Milborrow, S., Nicolls, F.: Locating facial features with an extended active shape model. In: Forsyth, D., Torr, P., Zisserman, A. (eds.) ECCV 2008
- Cristinacce, D., Cootes, T.F.: Feature detection and tracking with constrained local models. In: British Machine Vision Conference (BMVC), vol. 17, pp. 929–938 (2006)
- Saragih, J.M., Lucey, S., Cohn, J.F.: Face alignment through subspace constrained mean-shifts. In: IEEE International Conference on Computer Vision (ICCV), pp. 1034–1041 (2009)
- Cao, X., Wei, Y., Wen, F., Sun, J.: Face alignment by explicit shape regression. In: IEEE Conference on Computer Vision and Pattern Recognition, CVPR, pp. 2887–2894 (2012)
- Asthana, A., Zafeiriou, S., Cheng, S., Pantic, M.: Robust discriminative response map fitting with constrained local models. In: IEEE Conference on Computer Vision and Pattern Recognition, CVPR (2013)
- Xiong, X., De la Torre, F.: Supervised descent method and its applications to face alignment. In: IEEE Conference on Computer Vision and Pattern Recognition, CVPR (2013)
- Sun, Y., Wang, X., Tang, X.: Deep convolutional network cascade for facial point detection. In: IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 3476–3483 (2013)
- Toshev, A., Szegedy, C.: Deeppose: Human pose estimation via deep neural networks. In: IEEE Conference on Computer Vision and Pattern Recognition, CVPR (2014)

References

- Wu, Y., Wang, Z., Ji, Q.: Facial feature tracking under varying facial expressions and face poses based on restricted boltzmann machines. In: IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 3452–3459 (2013)
- Messer, K., Matas, J., Kittler, J., Luettin, J., Maitre, G.: Xm2vtsdb: The extended m2vts database. In: International Conference on Audio and Video-based Biometric Person Authentication, AVBPA(1999)
- Belhumeur, P.N., Jacobs, D.W., Kriegman, D.J., Kumar, N.: Localizing parts of faces using a consensus of exemplars. In: IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 545–552 (2011)
- Le, V., Brandt, J., Lin, Z., Bourdev, L., Huang, T.S.: Interactive facial feature localization. In: Fitzgibbon, A., Lazebnik, S., Perona, P., Sato, Y., Schmid, C. (eds.) ECCV (2012)
- Zhu, X., Ramanan, D.: Face detection, pose estimation, and landmark localization in the wild. In: IEEE Conference on Computer Vision and Pattern Recognition(CVPR). pp. 2879{2886 (2012)
- Yu, X., Huang, J., Zhang, S., Yan, W., Metaxas, D.N.: Pose-free facial landmark ftting via optimized part mixtures and cascaded deformable shape model. In: IEEE International Conference on Computer Vision (ICCV) (2013)
- Dollar, P., Welinder, P., Perona, P.: Cascaded pose regression. In: IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1078–1085 (2010)
- Burgos-Artizzu, X.P., Perona, P., Doll′ar, P.: Robust face landmark estimation under occlusion. In: IEEE International Conference on Computer Vision, ICCV (2013)