Simultaneous Cascaded Regression

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Introduction

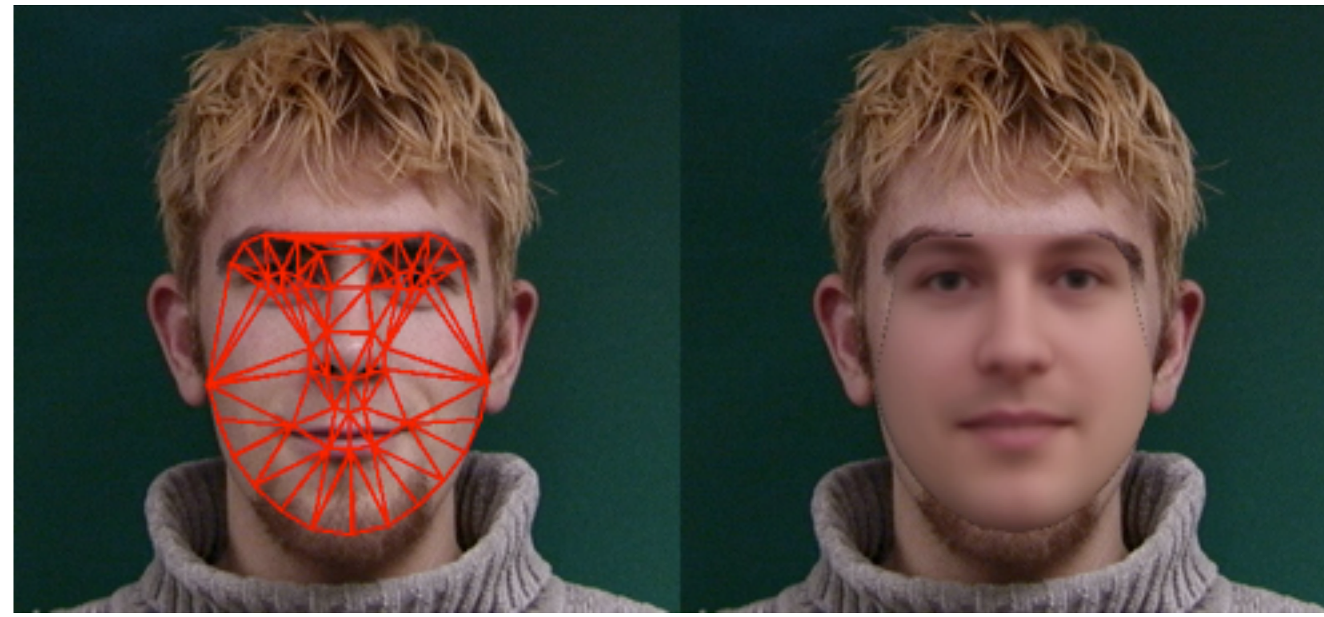
- Facial landmark localization with deformable models (nonrigid face alignment)
- Lucas & Kanade Image Alignment Framework
  - Simultaneous Forwards Additive / Inverse Compositional Algorithm
- Cascaded Regression Framework
- Simultaneous Algorithm: Cascaded Regression Extension
  - Regression w/ both shape and appearance structure

Outline

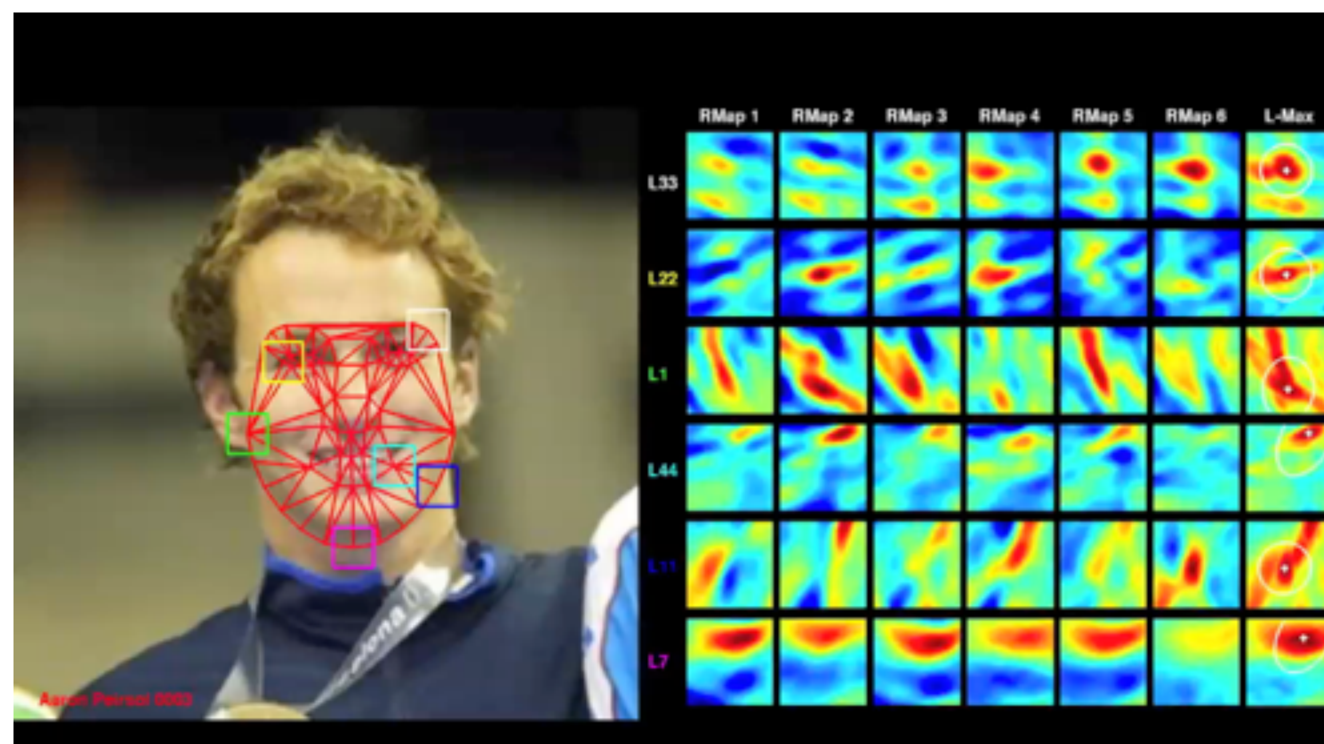
- Related Work
- Base Components
    - Warp Function
    - Parametric Models of Shape and Appearance
- Lucas & Kanade Image Alignment Framework
    - Simultaneous Forwards Additive (SFA)
    - Simultaneous Inverse Compositional (SIC)
- Simultaneous Cascaded Regression (SCR)
- Evaluation Results (LFPW, HELEN, LFW, 300W datasets)

Related Work

- Active Shape Model (ASM)
- Deformable Part Model (DPM)
- Active Appearance Model (AAM)
  - Project-Out Inverse Compositional (PO-IC)
  - Simultaneous Inverse Compositional (SIC)
- Constrained Local Model (CLM)
  - Convex Quadratic Fitting (CQF)
  - Subspace Constrained Mean-Shifts (SCMS)
  - Bayesian CLM (BCLM)
- Cascaded Regression (CR)
  - Supervised Descent Method (SDM)
  - Project-Out Cascade Regression (PO-CR)

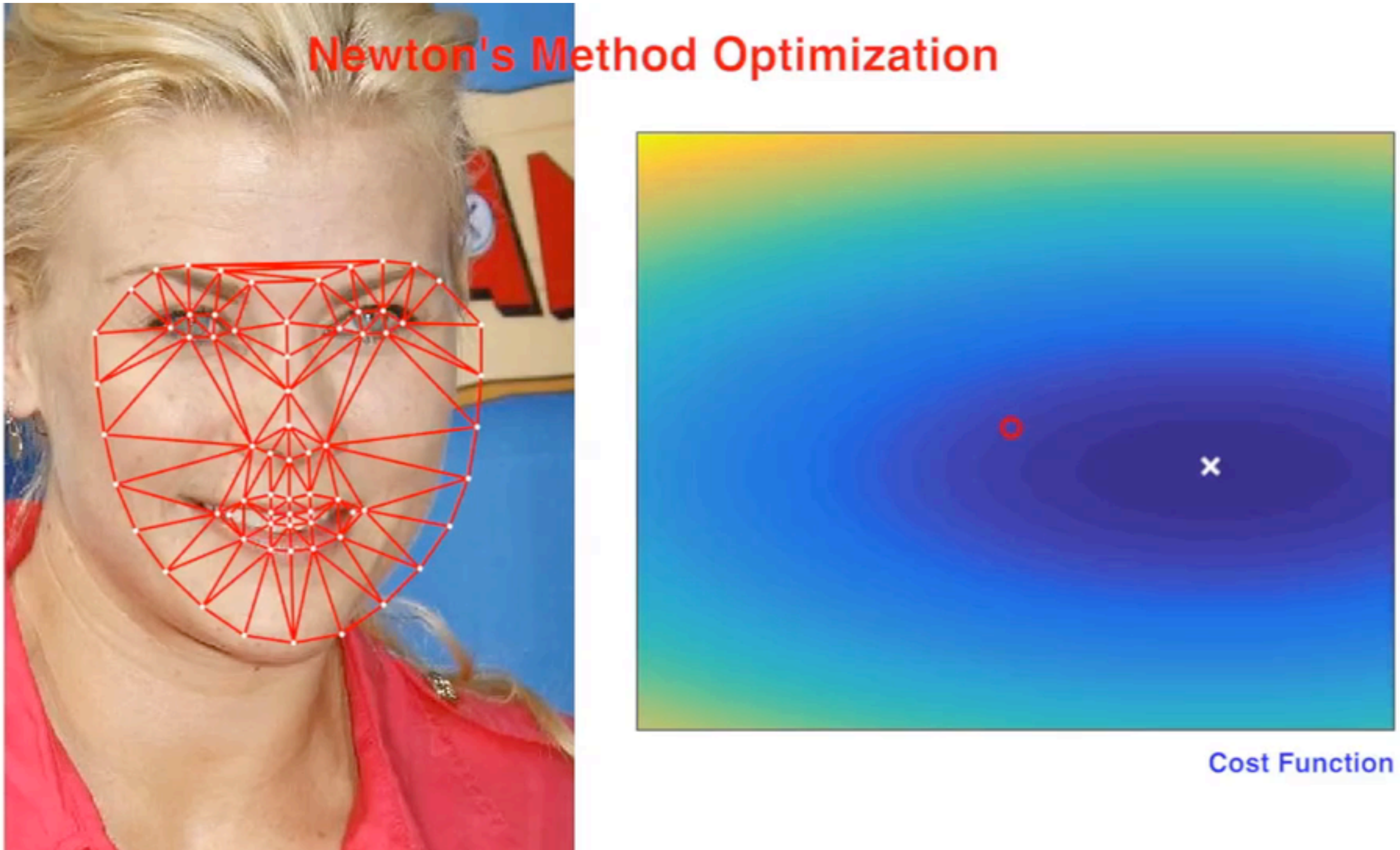


Active Appearance Model (AAM)

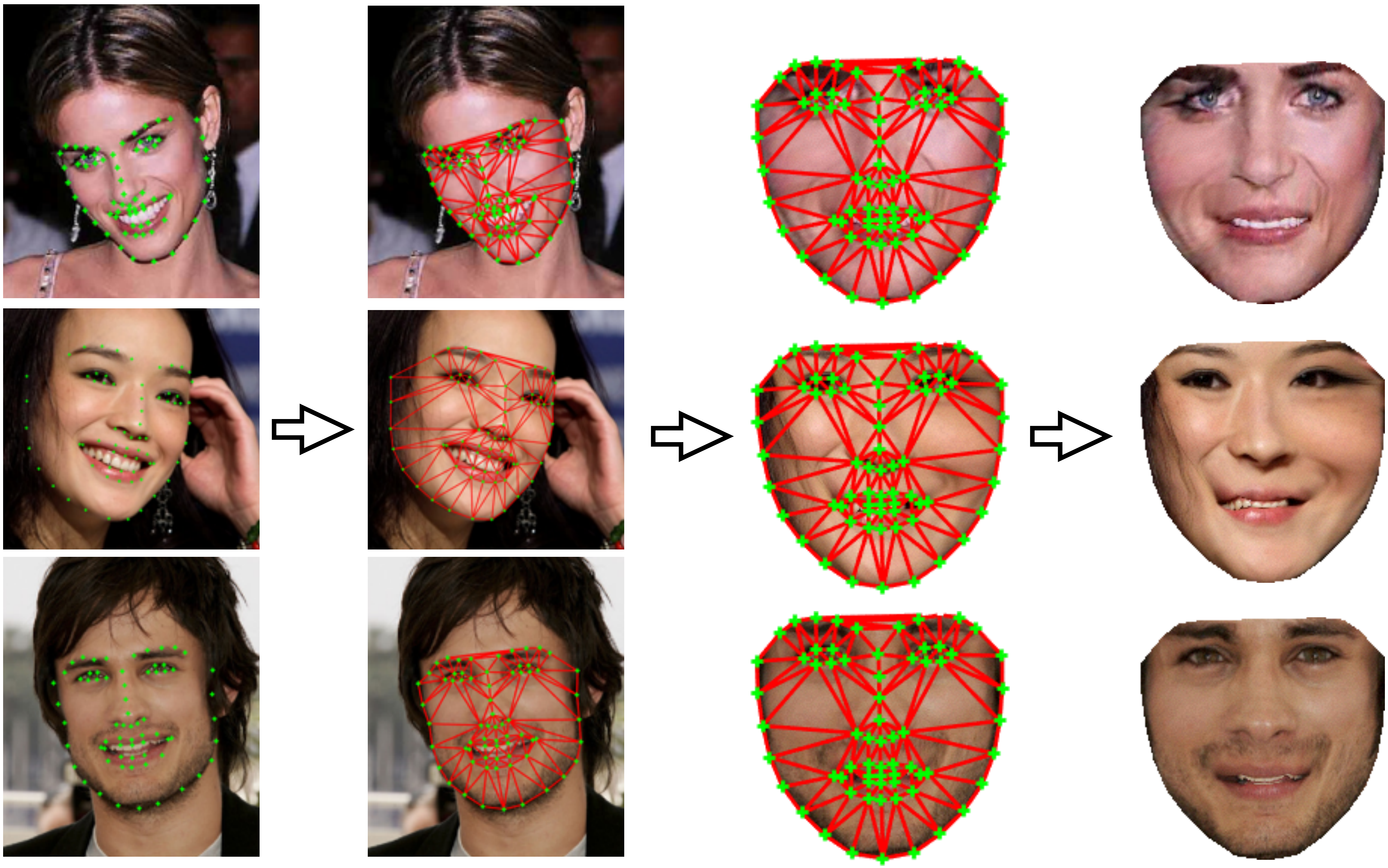


Bayesian Constrained Local Model (BCLM)

Newton Methods vs Cascaded Regression

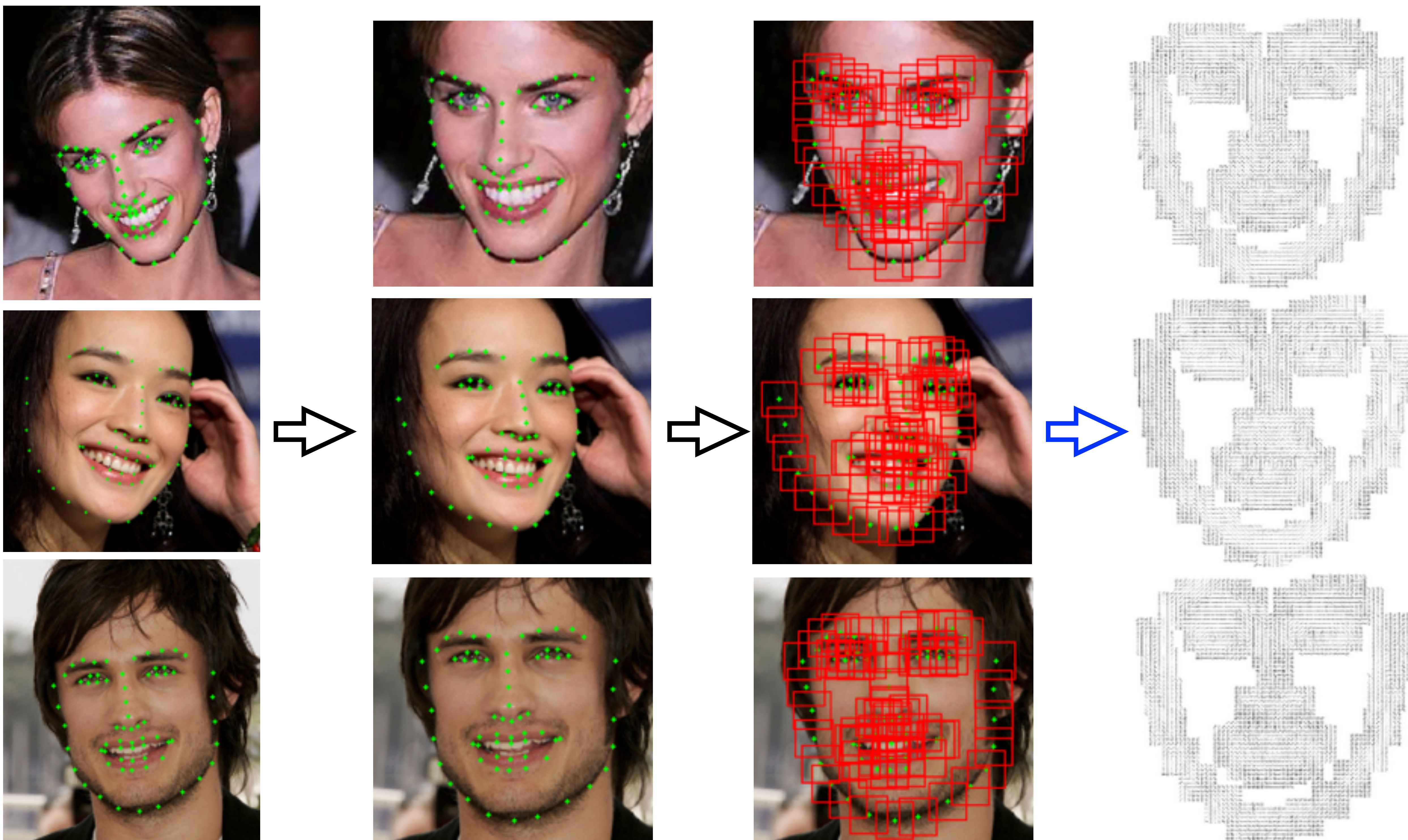


Piecewise Affine Warp (@AAMs) [Not Used Here]



Landmarks | Delaunay Triangulation | Base Mesh | Warped Example

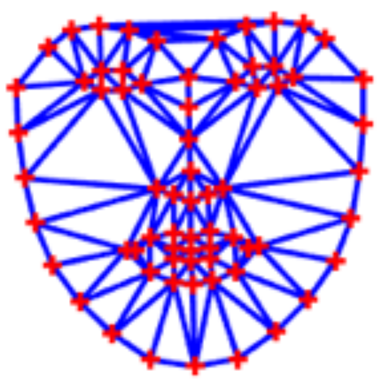
Patch based Local Warp



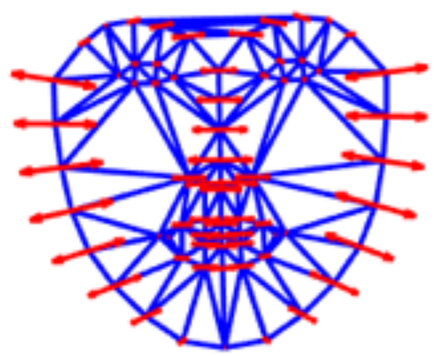
Parametric Shape and Appearance Models

$$\mathbf{s} = (x_1, \ldots, x_v, y_1, \ldots, y_v)^T \in \mathbb{R}^{2v}$$

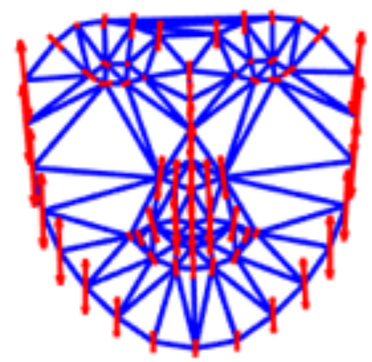
Shape Model



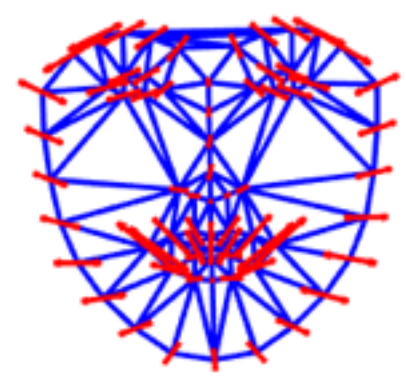
$\mathbf{s}_0$



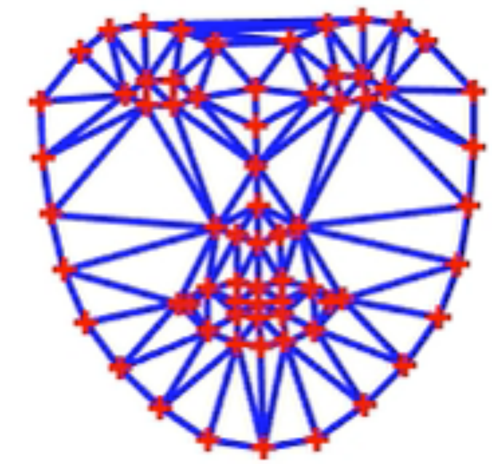
ϕ_1



ϕ_2



ϕ_3



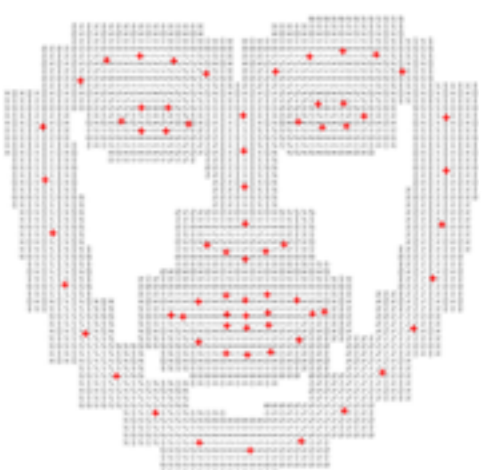
$$\mathcal{W}(\mathbf{s};\mathbf{p}) = \mathbf{s}_0 + \sum_{i=1}^{n+4} \phi_i p_i$$

Appearance Model

$-\mathbf{A}_1(\mathbf{x})$

$-\mathbf{A}_2(\mathbf{x})$

$-\mathbf{A}_3(\mathbf{x})$



$\mathbf{A}_0(\mathbf{x})$

$+\mathbf{A}_1(\mathbf{x})$

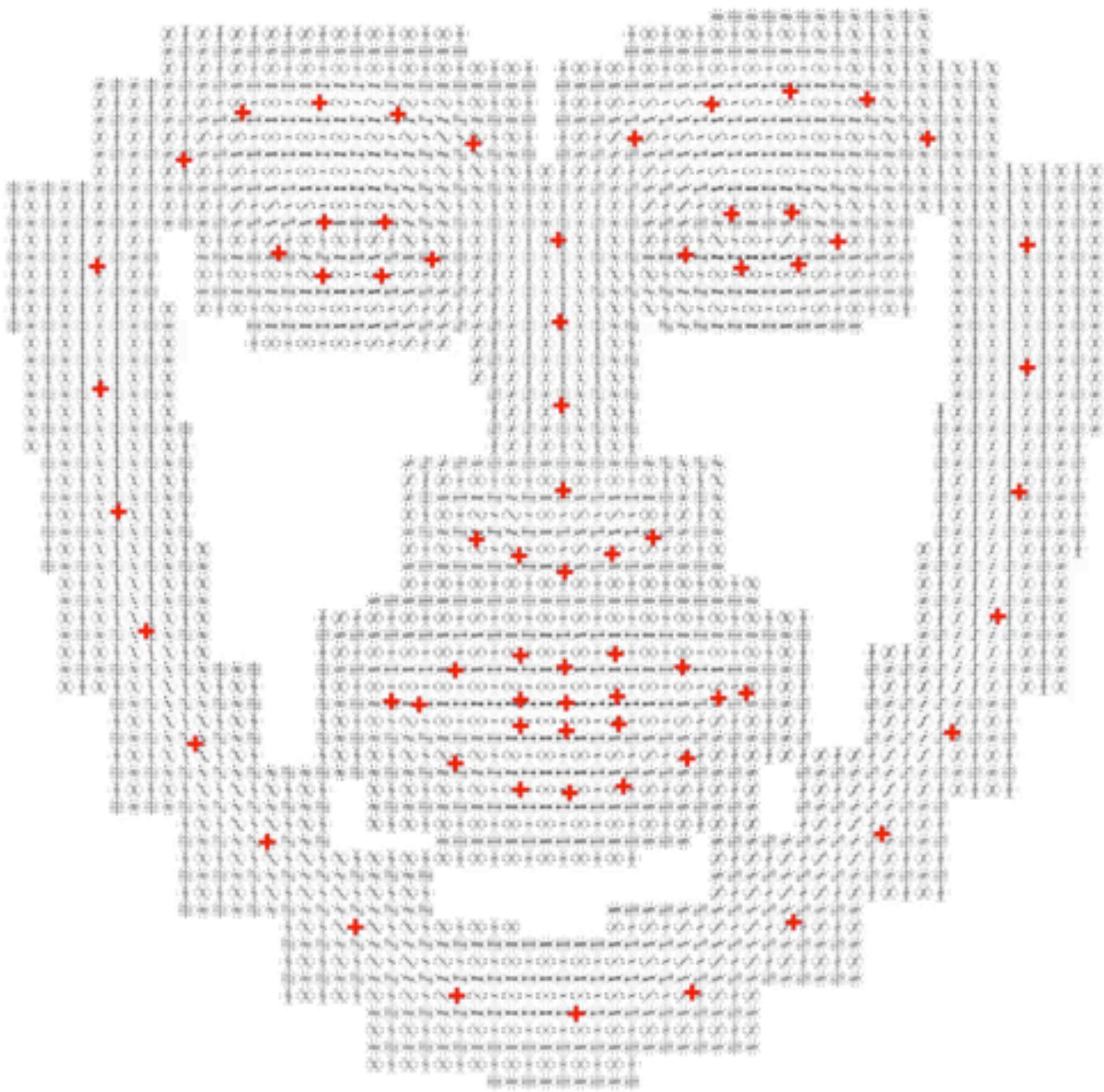
$+\mathbf{A}_2(\mathbf{x})$

$+\mathbf{A}_3(\mathbf{x})$

$$\mathcal{A}(\mathbf{x};\boldsymbol{\lambda}) = \mathbf{A}_0(\mathbf{x}) + \sum_{i=1}^{m} \mathbf{A}_i(\mathbf{x})\lambda_i$$

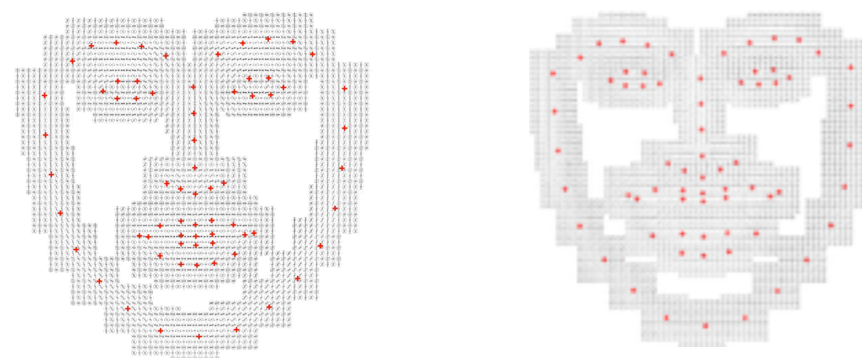
Local Appearance Model (LAM)

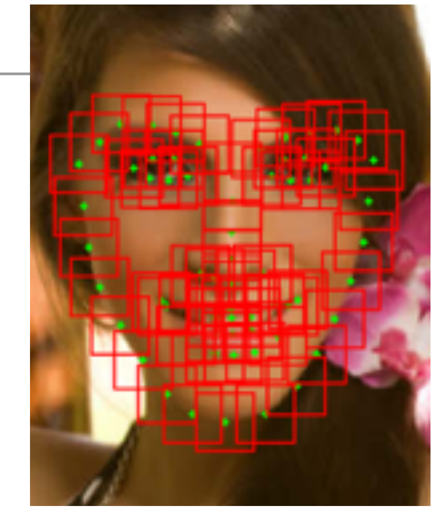
- Combined Parametric Model
  - Shape Regularization
  - Local Appearance
    (w/ HoG Features)
- Model Optimization/Fitting
  - Linear Warp Function
  - LK Framework
  - Cascaded Regression



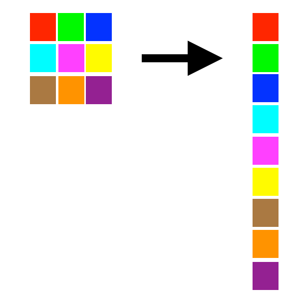
$$\mathcal{M}(\mathbf{p}, \boldsymbol{\lambda}) \equiv \underbrace{\mathcal{W}(\mathbf{s}; \mathbf{p})}_{\text{Shape + Pose}} \bigcup \underbrace{\mathcal{A}(\mathbf{x}; \boldsymbol{\lambda})}_{\text{Appearance}}$$

Simultaneous Forwards Additive (SFA)





$\mathbf{I}(\mathbf{x})$



Goal

$$\arg\min_{\mathbf{p},\boldsymbol{\lambda}} \|\underbrace{\mathbf{A}_0 + \mathbf{A}\boldsymbol{\lambda}}_{\text{Face Model}} - \underbrace{\mathbf{I}(\mathcal{W}(\mathbf{p}))}_{\text{Warped Instance}}\|^2$$

Iteratively solve for small updates

$$\arg\min_{\Delta\mathbf{p},\Delta\boldsymbol{\lambda}} \|\mathbf{A}_0 + \mathbf{A}(\boldsymbol{\lambda} + \Delta\boldsymbol{\lambda}) - \mathbf{I}(\mathcal{W}(\mathbf{p} + \Delta\mathbf{p}))\|^2$$

Solution

$$\begin{bmatrix} \Delta\mathbf{p} \\ \Delta\boldsymbol{\lambda} \end{bmatrix} = \mathbf{H}_{\mathbf{FA}}^{-1}\mathbf{J}_{\mathbf{FA}}^{T}\left[\mathbf{A}_0 + \mathbf{A}\boldsymbol{\lambda} - \mathbf{I}(\mathcal{W}(\mathbf{p}))\right]$$

Jacobian

$$\mathbf{J}_{\mathbf{FA}} = \left(\overbrace{\boxed{\nabla\mathbf{I}}}^{\text{Image Gradients}}\overbrace{\boxed{\frac{\partial\mathcal{W}(\mathbf{p})}{\partial\mathbf{p}}}}^{\text{Jacobian of the Warp}}, \mathbf{A}\right)$$

Hessian

$$\mathbf{H}_{\mathbf{FA}} = \mathbf{J}_{\mathbf{FA}}^{T}\mathbf{J}_{\mathbf{FA}}$$

Gauss Newton Approximation

Parameters Update

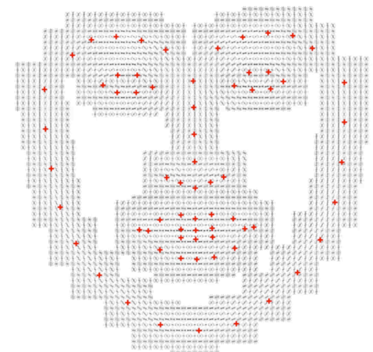
Shape Parameters

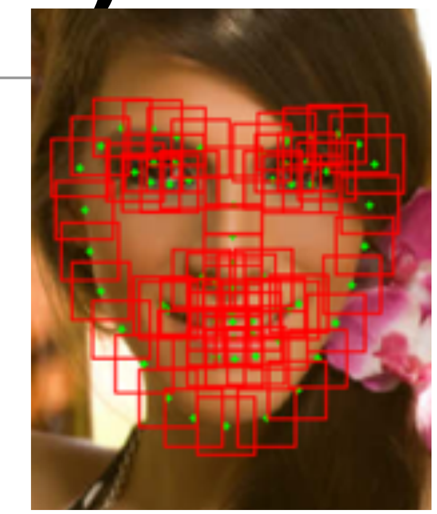
$$\mathbf{p} \leftarrow \mathbf{p} + \Delta\mathbf{p}$$

Appearance Parameters

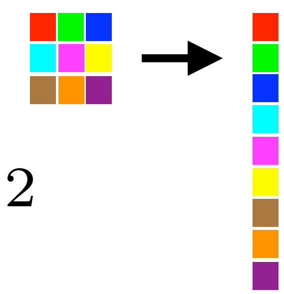
$$\boldsymbol{\lambda} \leftarrow \boldsymbol{\lambda} + \Delta\boldsymbol{\lambda}$$

Simultaneous Inverse Compositional (SIC)





$\mathbf{I}(\mathbf{x})$



Goal

$$\arg\min_{\mathbf{p},\boldsymbol{\lambda}} \left\| \mathbf{A}_0 + \mathbf{A}\boldsymbol{\lambda} - \mathbf{I}(\mathcal{W}(\mathbf{p})) \right\|^2$$

Face Model — Warped Instance

Iteratively solve for small updates

$$\arg\min_{\Delta\mathbf{p},\Delta\boldsymbol{\lambda}} \left\| \mathbf{A}_0(\mathcal{W}(\Delta\mathbf{p})) + \mathbf{A}(\mathcal{W}(\Delta\mathbf{p}))(\boldsymbol{\lambda} + \Delta\boldsymbol{\lambda}) - \mathbf{I}(\mathcal{W}(\mathbf{p})) \right\|^2$$

Solution

$$\begin{bmatrix} \Delta\mathbf{p} \\ \Delta\boldsymbol{\lambda} \end{bmatrix} = -\mathbf{H}_{\mathbf{IC}}^{-1}\mathbf{J}_{\mathbf{IC}}^{T}\left[\mathbf{A}_0 + \mathbf{A}\boldsymbol{\lambda} - \mathbf{I}(\mathcal{W}(\mathbf{p}))\right]$$

Jacobian

Appearance Model Gradients — Jacobian of the Warp

$$\mathbf{J}_{\mathbf{IC}} = \left(\boxed{(\nabla\mathbf{A}_0 + \nabla\mathbf{A}\boldsymbol{\lambda})} \boxed{\frac{\partial\mathcal{W}(\mathbf{0})}{\partial\mathbf{p}}},\ \mathbf{A} \right)$$

Hessian

$$\mathbf{H}_{\mathbf{IC}} = \mathbf{J}_{\mathbf{IC}}^{T}\mathbf{J}_{\mathbf{IC}}$$

Gauss Newton Approximation

Parameters Update

Shape Parameters

$$\mathcal{W}(\mathbf{s},\mathbf{p}) \leftarrow \mathcal{W}(\mathbf{s},\mathbf{p}) \circ \mathcal{W}(\mathbf{s},\Delta\mathbf{p})^{-1}$$

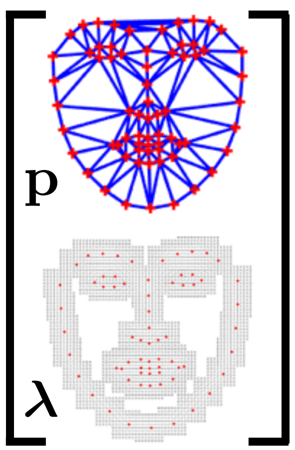
$$\mathbf{p} \leftarrow \mathbf{p} - \Delta\mathbf{p}$$

Appearance Parameters

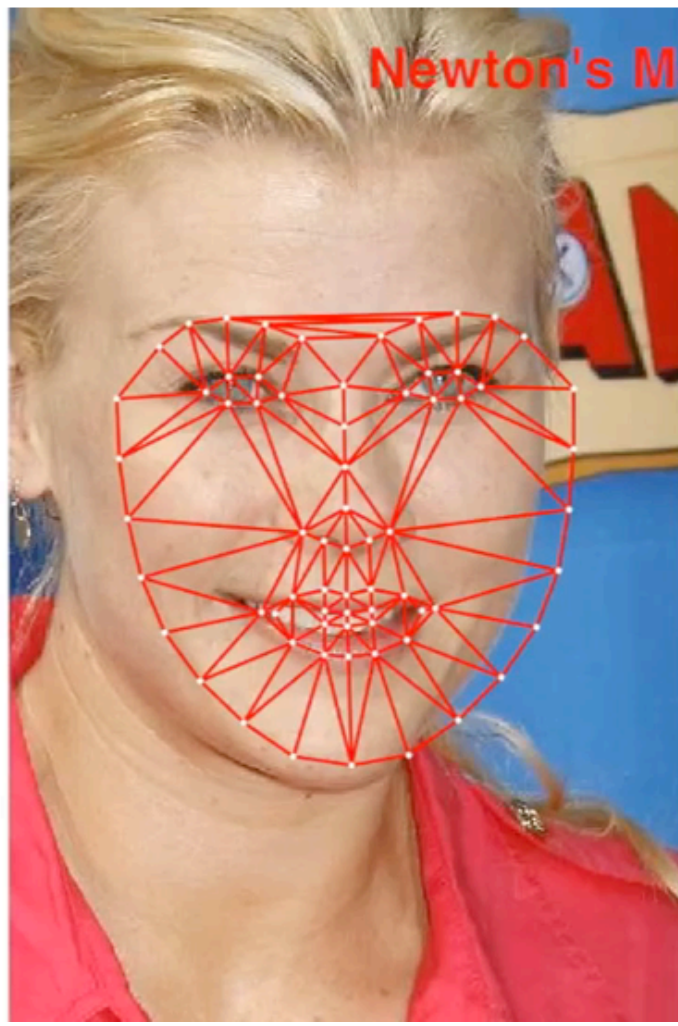
$$\boldsymbol{\lambda} \leftarrow \boldsymbol{\lambda} + \Delta\boldsymbol{\lambda}$$

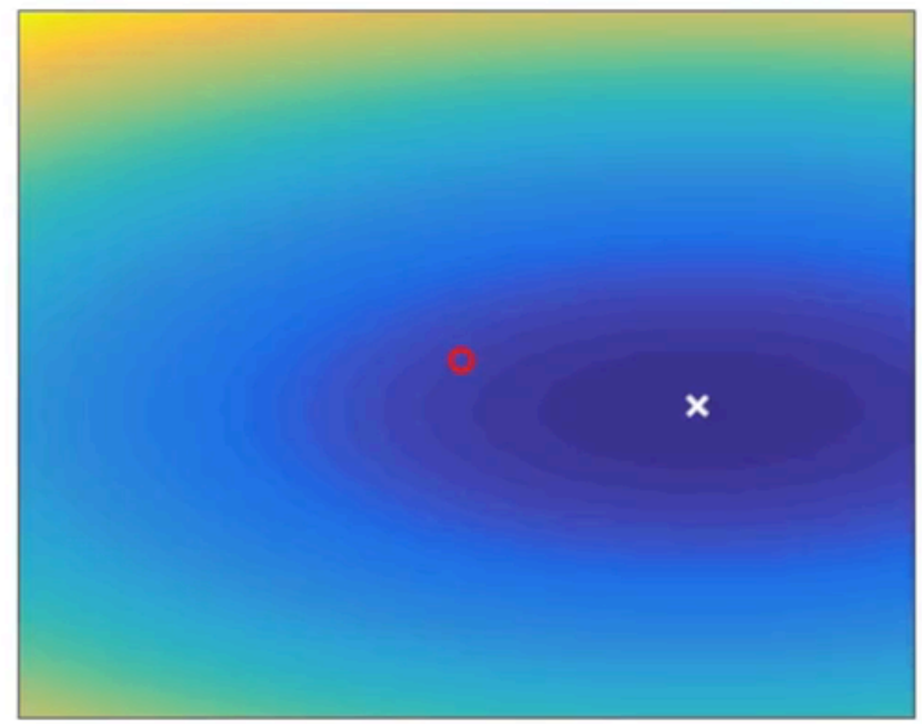
Simultaneous Cascaded Regression (SCR)

Regression with both shape and appearance structure



Newton's Method Optimization





Cost Function

Simultaneous Inverse Compositional (SIC) vs Simultaneous Cascaded Regression (SCR)

Level 1 → Level 2 → Level 3 → • • • Level K

$$\begin{bmatrix} \mathbf{p} \\ \boldsymbol{\lambda} \end{bmatrix}^{k} = \begin{bmatrix} \mathbf{p} \\ \boldsymbol{\lambda} \end{bmatrix}^{k-1} + \mathbf{R}^{k-1}\left(\mathbf{I}(\mathcal{W}(\mathbf{p}^{k-1})) - \mathbf{A}_0 - \mathbf{A}\boldsymbol{\lambda}^{k-1}\right), \quad k = 1, \ldots, K$$

Shape + Appearance parameters

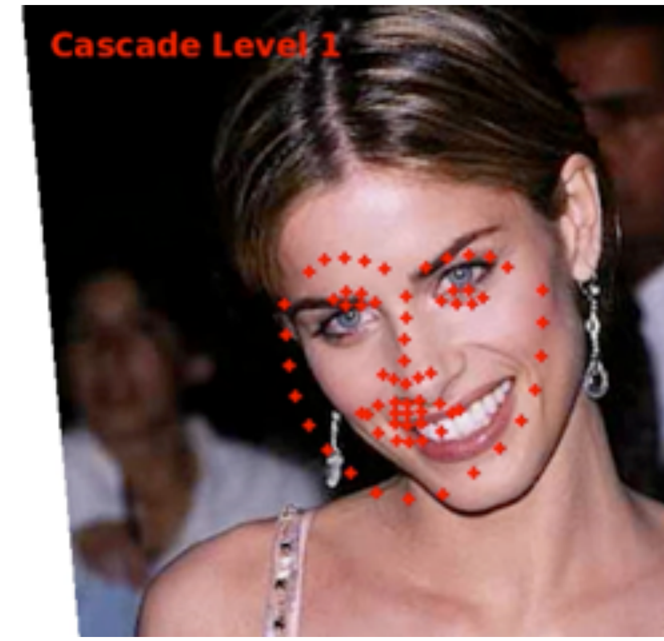
Features extracted at previous level

Features generated by the Model

SCR - Learning Regression Matrices

Estimate average Jacobian under multiple initializations

$$\arg\min_{\mathbf{J}_{\mathbf{S}}^k} \sum_{i=1}^{N} \int p(\mathbf{r}') \left\| \mathbf{A}_0 + \mathbf{A}\boldsymbol{\lambda}_i^k + \mathbf{J}_{\mathbf{S}}^k \Delta\mathbf{r}_i^k - \mathbf{I}_i(\mathcal{W}(\mathbf{p}_i^k)) \right\|^2 \partial\mathbf{r}'$$



Deviation from Ground Truth

$$\Delta\mathbf{r}_i^k = \begin{bmatrix} \mathbf{p}_i^k - \mathbf{p}_* \\ \boldsymbol{\lambda}_i^k - \boldsymbol{\lambda}_* \end{bmatrix}$$

k - cascade level
i - training image
j - virtual sample

Discrete approximation

$$\arg\min_{\mathbf{J}_{\mathbf{S}}^k} \sum_{i=1}^{N} \sum_{j=1}^{M} \left\| \mathbf{A}_0 + \mathbf{A}\boldsymbol{\lambda}_{ij}^k + \mathbf{J}_{\mathbf{S}}^k \Delta\mathbf{r}_{ij}^k - \mathbf{I}_i(\mathcal{W}(\mathbf{p}_{ij}^k)) \right\|^2$$

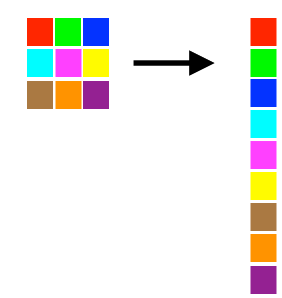
Solution by Ridge Regression

$$\mathbf{J}_{\mathbf{S}}^k = \left(\Delta\mathbf{r}\Delta\mathbf{r}^T + \lambda_1 \mathbf{I}_d\right)^{-1} \Delta\mathbf{r}\ \mathbf{E}^T$$

E: Data matrix w/ entries

$$\mathbf{E}_{ij} = \mathbf{I}_i(\mathcal{W}(\mathbf{p}_{ij}^k)) - \mathbf{A}_0 - \mathbf{A}\boldsymbol{\lambda}_{ij}^k$$

Advantage: do not require to invert a large data matrix



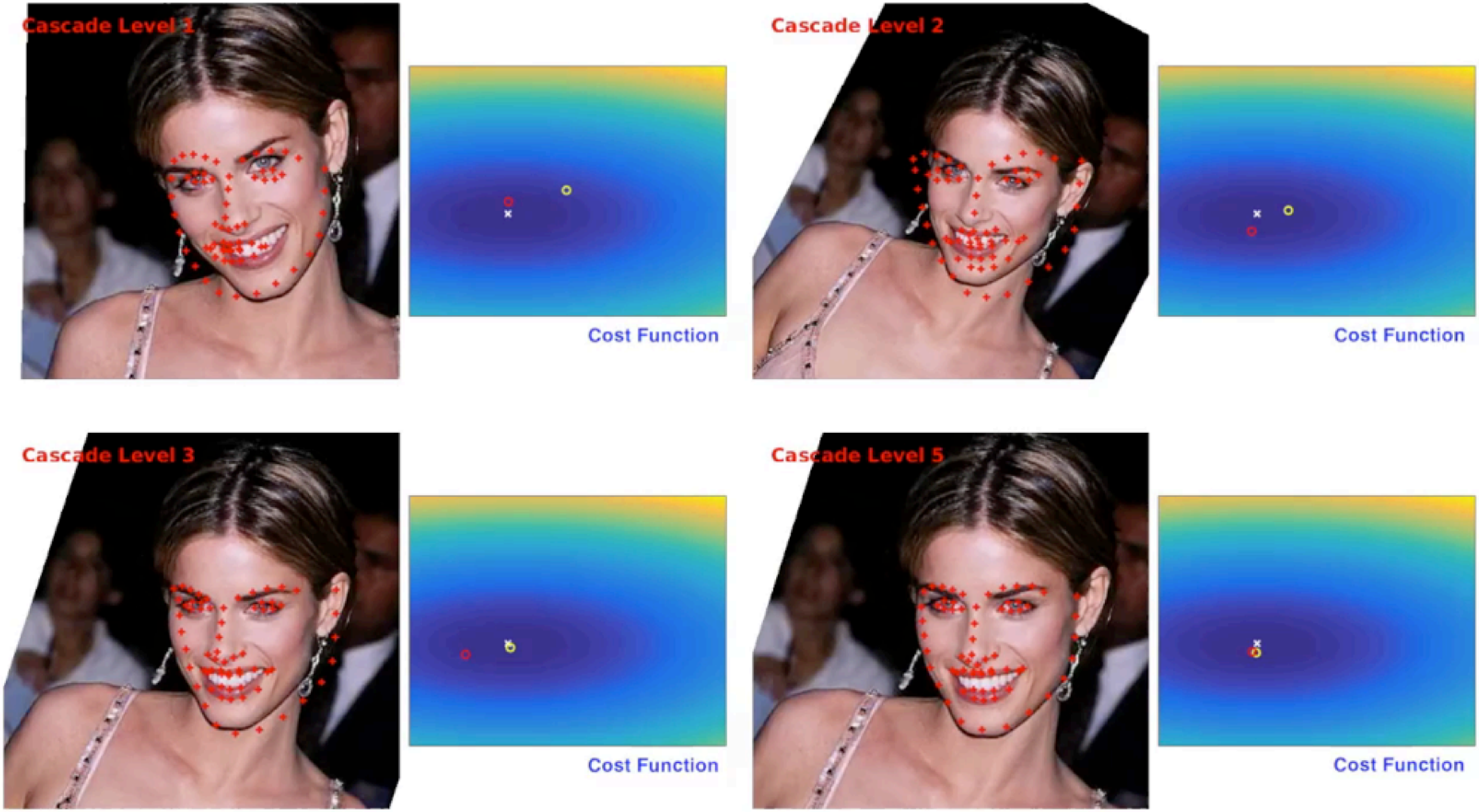
Update matrix

$$\mathbf{R}^k = \left((\mathbf{J}_{\mathbf{S}}^k)^T \mathbf{J}_{\mathbf{S}}^k + \lambda_2 \mathbf{I}_d\right)^{-1} (\mathbf{J}_{\mathbf{S}}^k)^T$$

Cascade update

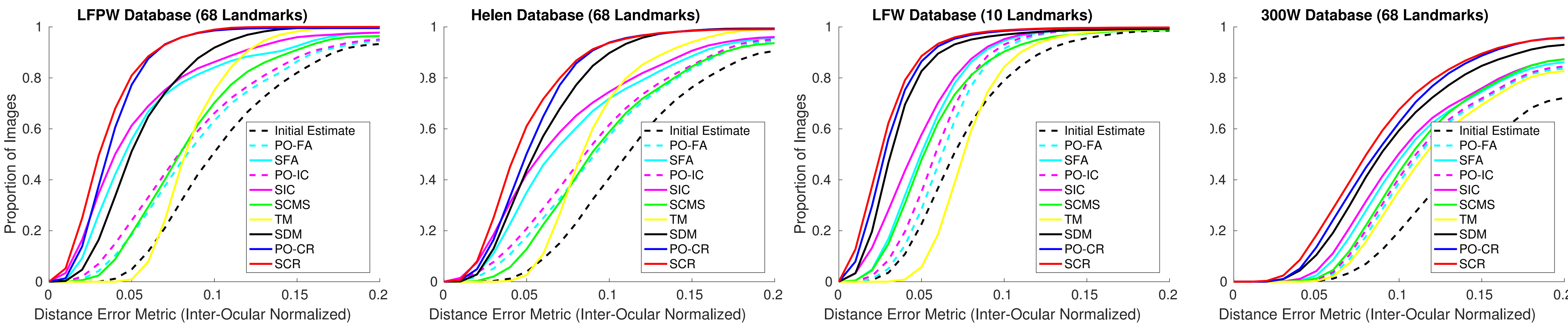
$$\Delta\mathbf{r}^k = \mathbf{R}^k \left(\mathbf{I}(\mathcal{W}(\mathbf{p}^k)) - \mathbf{A}_0 - \mathbf{A}\boldsymbol{\lambda}^k\right)$$
$$\mathbf{r}^{k+1} = \mathbf{r}^k + \Delta\mathbf{r}^k$$

Cascaded Regression Learning



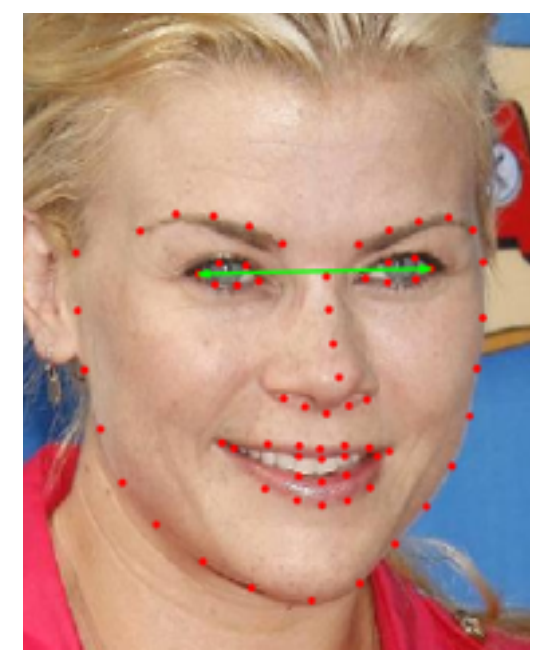
Evaluation Results

Cumulative error distribution function (CDF)



Method / AUC	LFPW	HELEN	LFW	300W
Initial Estimate	46.4	41.6	61.7	27.2
PO-FA	53.6	51.3	67.3	38.2
SFA	70.0	60.2	73.0	42.3
PO-IC	56.1	53.8	69.4	39.1
SIC	73.1	63.5	75.6	43.9
SCMS	56.9	50.7	70.7	40.9
TM	56.5	54.8	60.1	36.7
SDM	72.2	69.7	81.5	50.3
PO-CR	80.4	72.5	84.1	53.3
SCR	**82.6**	**74.8**	**85.5**	**55.5**

Area Under Curve (AUC)

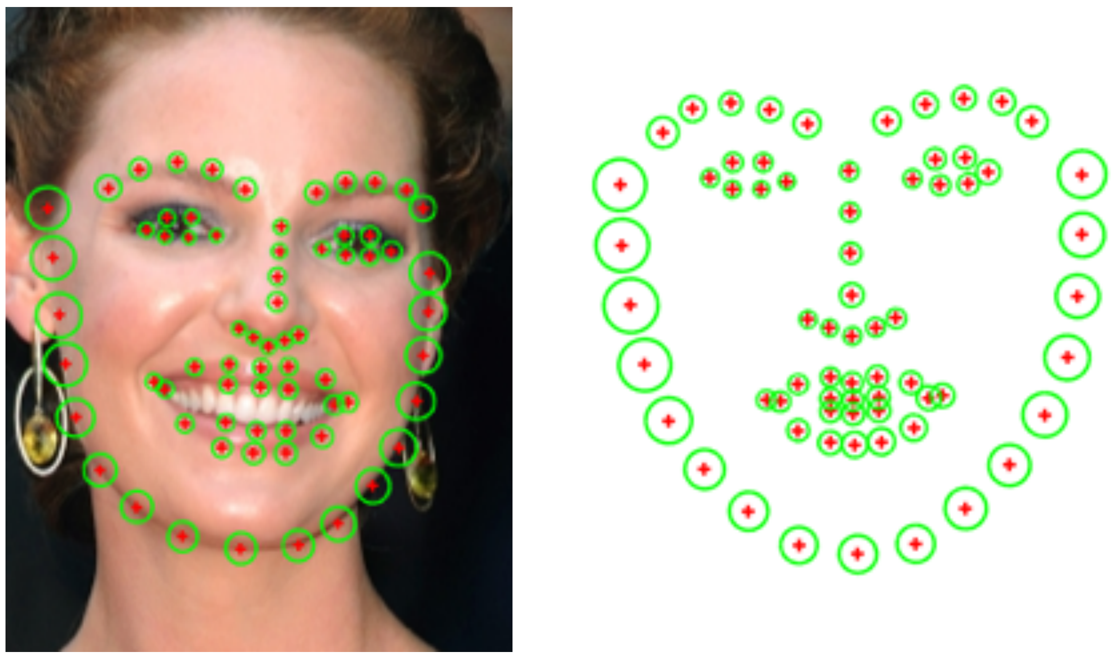


Inter-ocular normalized error

$$e_m(\mathbf{s}) = \frac{1}{v\, d_{\text{eyes}}} \sum_{i=1}^{v} \|\mathbf{s}_i - \mathbf{s}_i^*\|$$

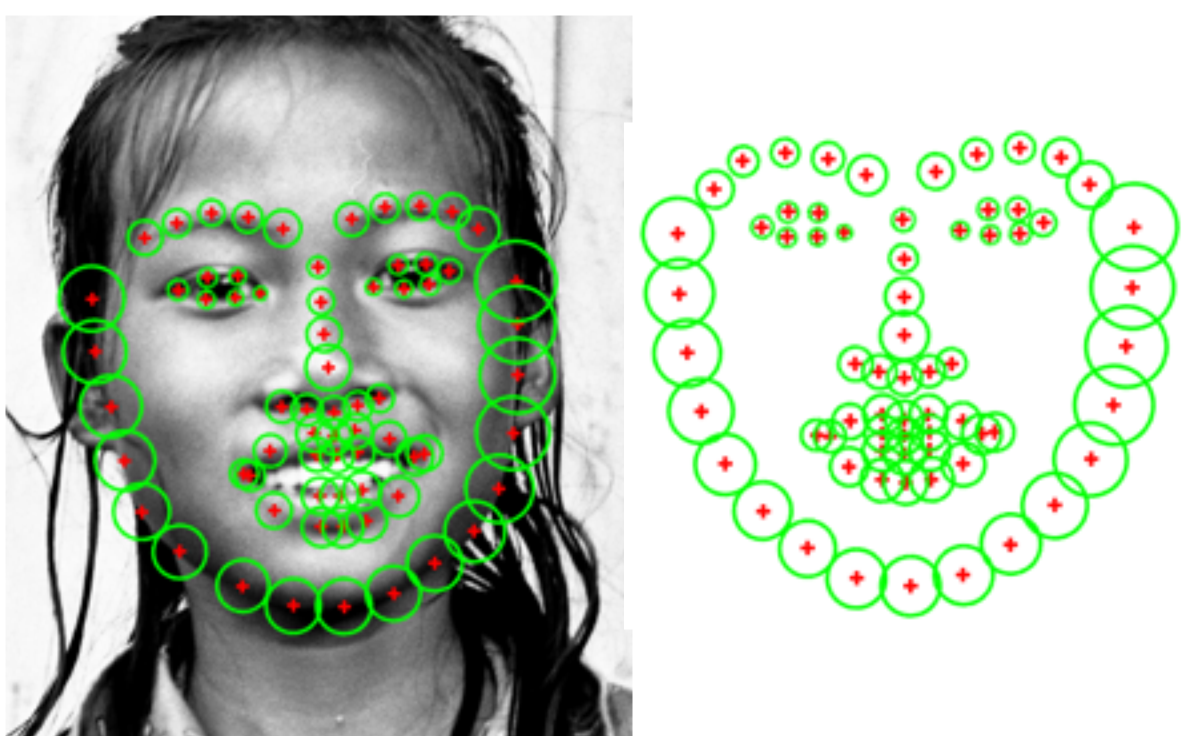
Landmark Fitting Error Standard Deviation

LFPW Database

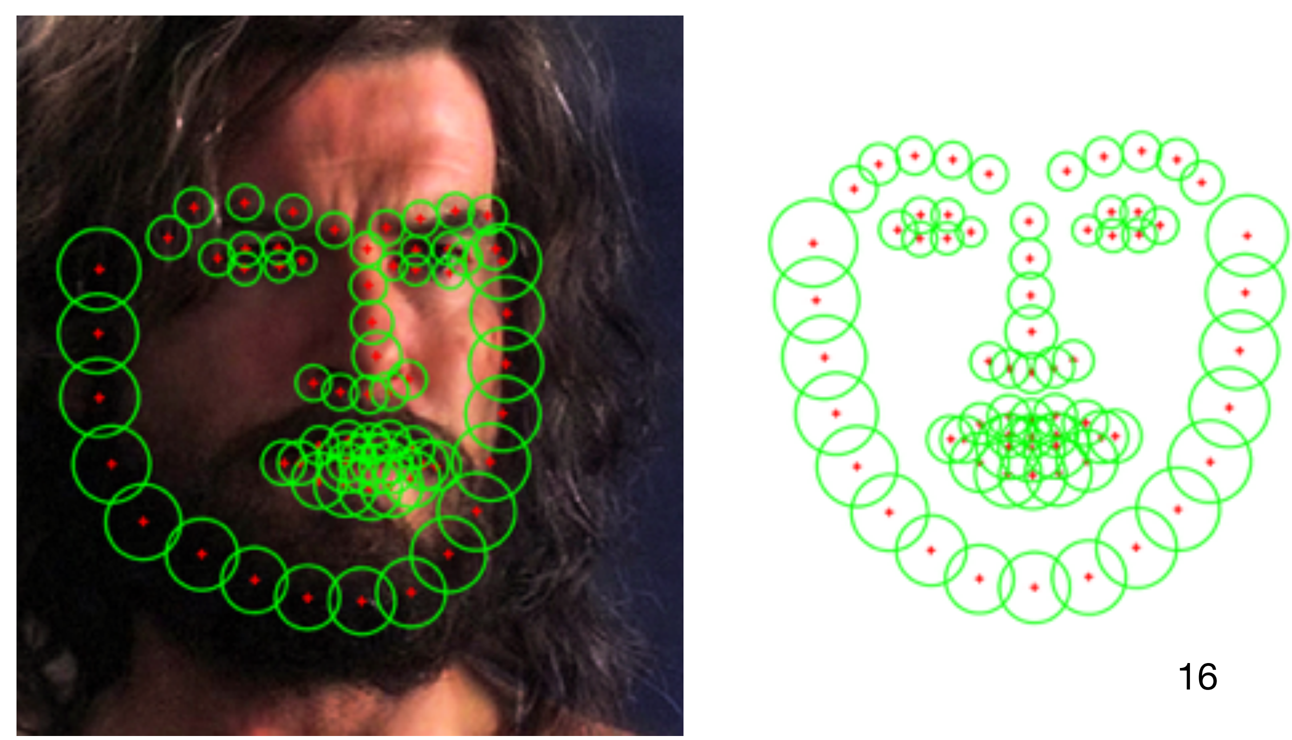


LFW Database

HELEN Database

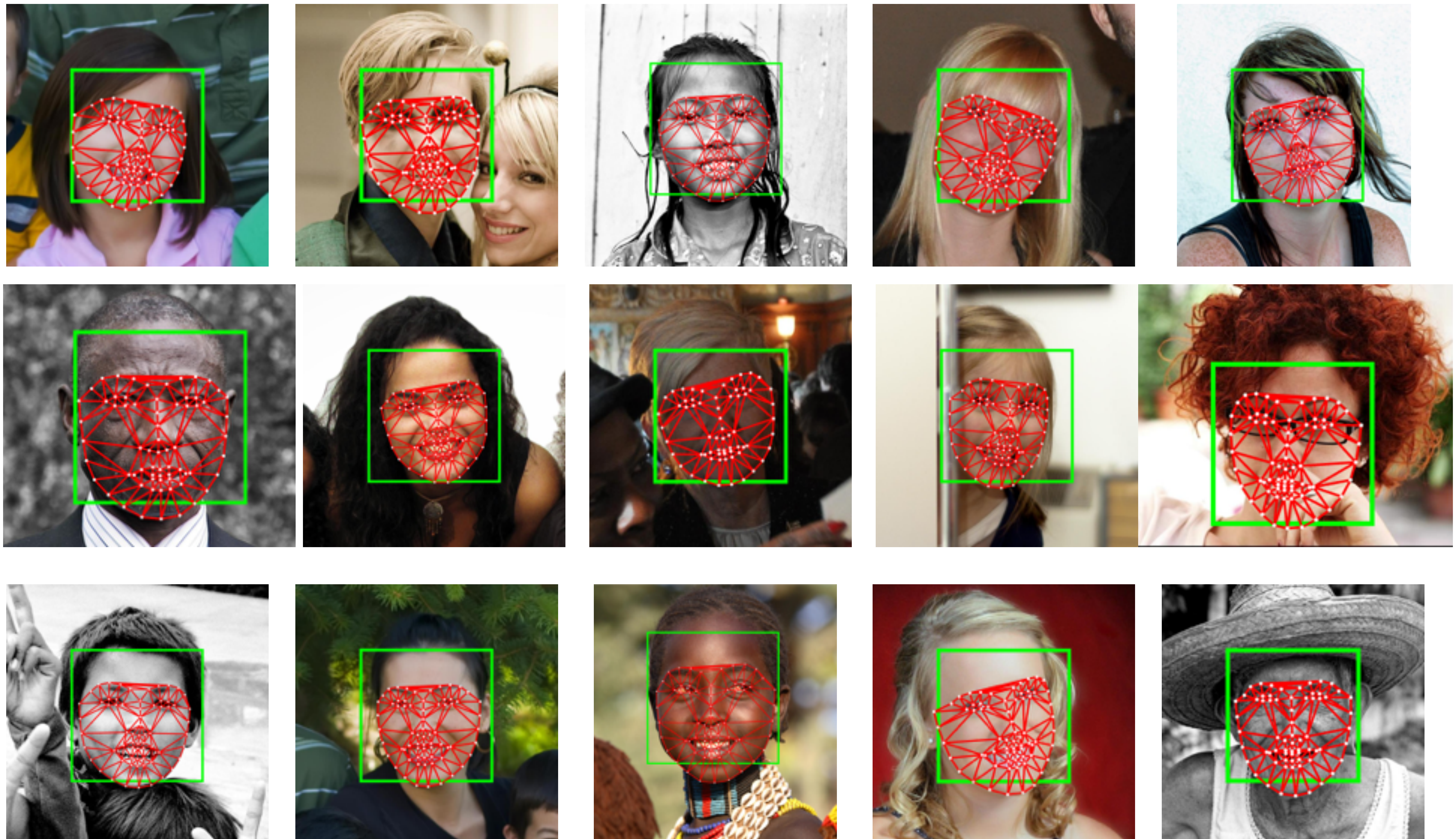


300W Database



Qualitative Results (LFPW Database)

Qualitative Results (HELEN Database)



SCR Fitting Video

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Conclusions

- Facial landmark localization w/ deformable face model
- Simultaneous Algorithm: Cascaded Regression Extension
  - Regression w/ both shape and appearance structure
  - Learning stage w/o inverting a large data matrix
- Evaluation Results (LFPW, HELEN, LFW, 300W datasets)
- Acknowledgements

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Questions?

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SCR Fitting Video

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