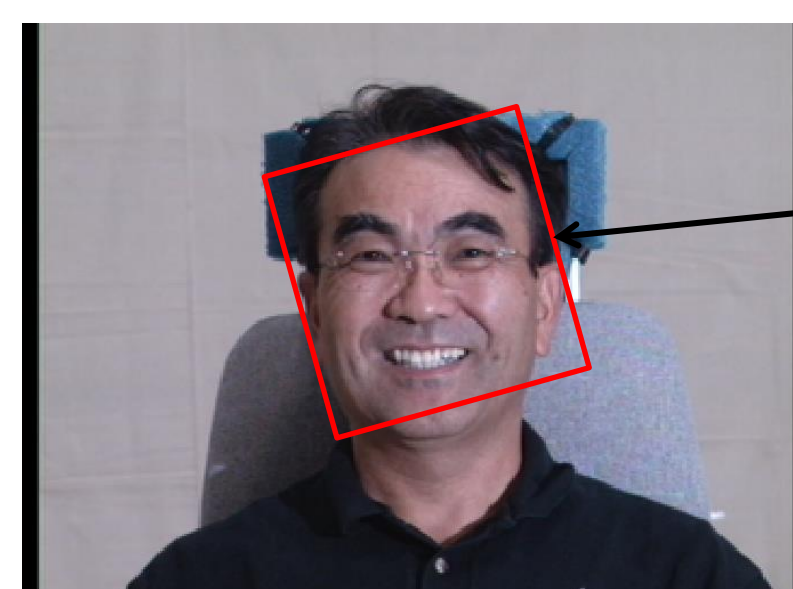


## MOTIVATION

### Generative Methods

- Template Matching (e.g., Lucas-Kanade 81)



Image

Pixels to align

Template

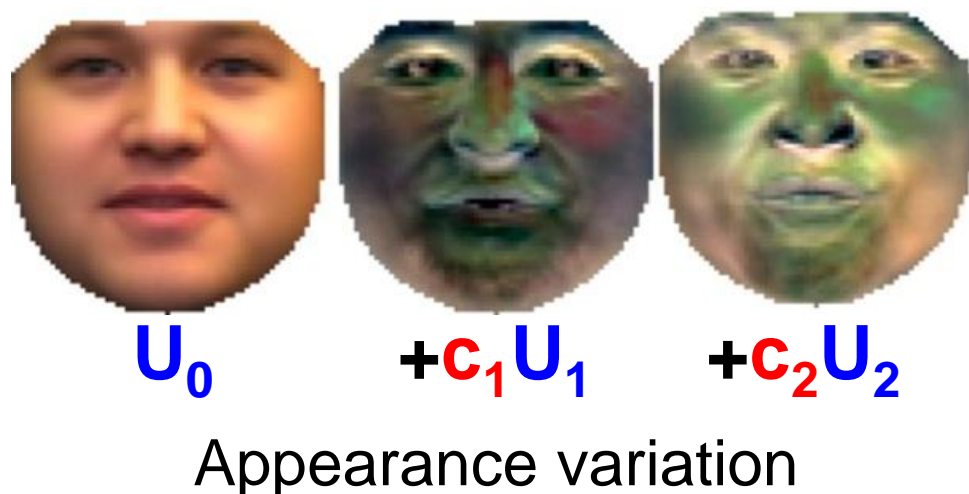
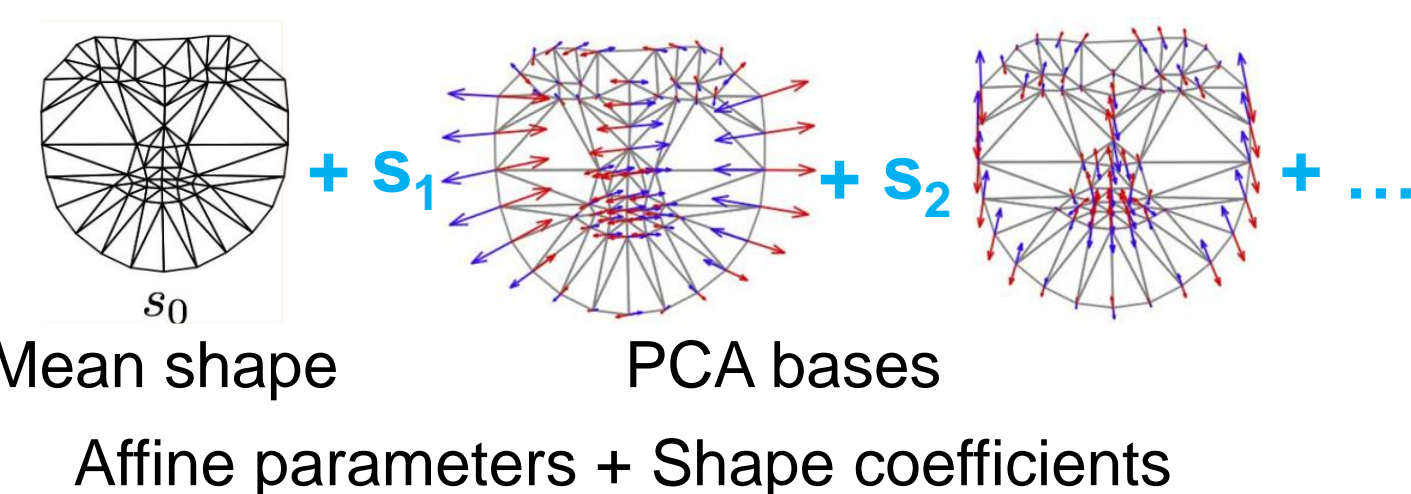


$$f_{TM}(\mathbf{p}) = \|\mathbf{d}(\mathbf{f}(\mathbf{x}, \mathbf{p})) - \mathbf{d}_{template}\|^2$$

Geometric transformation

Motion parameters

- Active Appearance Models (e.g., Cootes et al 98, Mathews & Baker 04, De la Torre et al. 02-08)

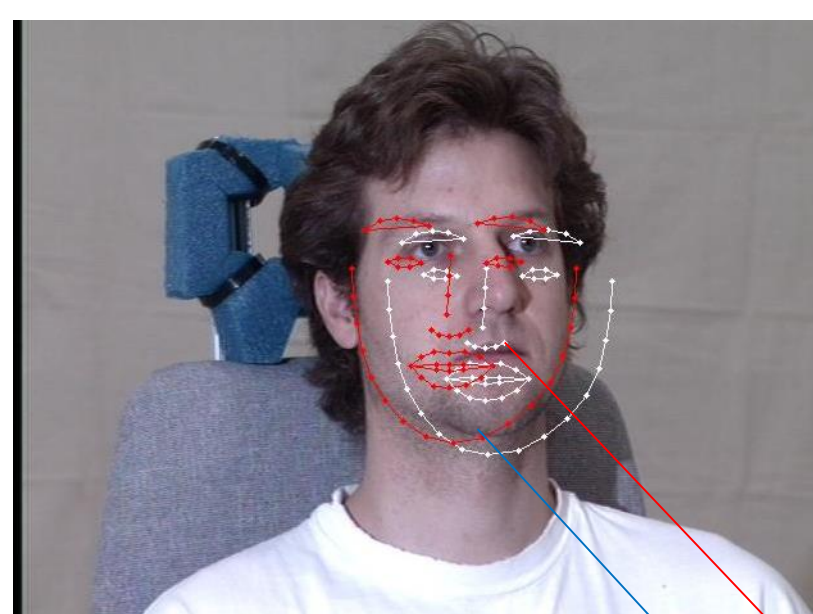


$$f_{AAM}(\mathbf{p}, \mathbf{c}) = \|\mathbf{d}(\mathbf{f}(\mathbf{x}, \mathbf{p})) - \mathbf{U}\mathbf{c}\|^2$$

- Problems: prone to local minima

### Discriminative Methods

(e.g., Saraghi & Goecke '09, Liu '09, Sauer et al. '11, Saraghi '11, Cao et al. '12, Ribera & Martinez '12))



- What are discriminative methods minimizing?
- Is there any relation between discriminative and traditional image alignment methods?
- How to learn discriminative methods effectively?

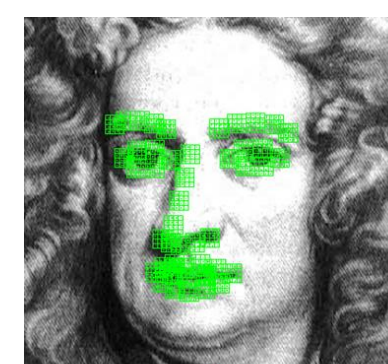
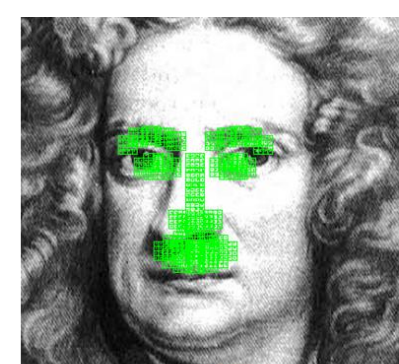
$$\Delta \mathbf{p}_1 \leftarrow \text{features}(\mathbf{d}(\mathbf{f}(\mathbf{x}, \mathbf{p}_0 + \Delta \mathbf{p}_1)))$$

$$\Delta \mathbf{p}_2 \leftarrow \text{features}(\mathbf{d}(\mathbf{f}(\mathbf{x}, \mathbf{p}_0 + \Delta \mathbf{p}_2)))$$

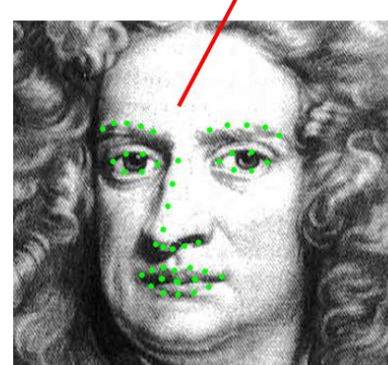
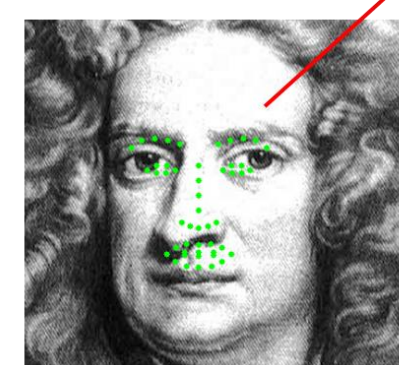
Perturbation of motion parameters

## SUPERVISED DESCENT METHOD

### Objective Function



$$f_{SDM}(\Delta \mathbf{x}) = \|\mathbf{h}(\mathbf{d}(\mathbf{x}_0 + \Delta \mathbf{x})) - \mathbf{h}(\mathbf{d}(\mathbf{x}_*))\|^2$$



- SDM vs. TM vs. AAM

$$f_{SDM}(\Delta \mathbf{x}) = \|\mathbf{h}(\mathbf{d}(\mathbf{x}_0 + \Delta \mathbf{x})) - \boldsymbol{\phi}_*\|^2$$

$$f_{TM}(\mathbf{p}) = \|\mathbf{d}(\mathbf{f}(\mathbf{x}, \mathbf{p})) - \mathbf{d}_{template}\|^2$$

$$f_{AAM}(\mathbf{p}, \mathbf{c}) = \|\mathbf{d}(\mathbf{f}(\mathbf{x}, \mathbf{p})) - \mathbf{U}\mathbf{c}\|^2$$

- No model of shape or appearance
  - asymmetric facial gestures
  - no coupling between landmarks (e.g., brows and mouth)
- Richer image descriptors (e.g., SIFT)

### How to Optimize

Newton update

$$\mathbf{x}_k = \mathbf{x}_{k-1} - \mathbf{H}^{-1} \mathbf{J}_f$$

$$= \mathbf{x}_{k-1} + 2\mathbf{H}^{-1} \mathbf{J}_h^T (\boldsymbol{\phi}_* - \boldsymbol{\phi}_{k-1})$$

$$\boldsymbol{\phi}_* = \mathbf{h}(\mathbf{d}(\mathbf{x}_*)) \quad \boldsymbol{\phi}_{k-1} = \mathbf{h}(\mathbf{d}(\mathbf{x}_{k-1}))$$

SDM update

$$\mathbf{x}_k = \mathbf{x}_{k-1} + \mathbf{R}_{k-1} \boldsymbol{\phi}_{k-1} + \mathbf{b}_{k-1}$$

Generic descent direction

### Learning SDM

SDM learns a sequence of  $\{\mathbf{R}_k, \mathbf{b}_k\}$  such that the succession of  $\mathbf{x}_k$  will converge to  $\mathbf{x}_*$  for all images in the training data

Problems:

- Hessian is expensive to invert
- Hessian is not positive definite in all domain
- $\mathbf{h}$  is a non-differentiable image operator
- In testing we do not know  $\boldsymbol{\phi}_*$

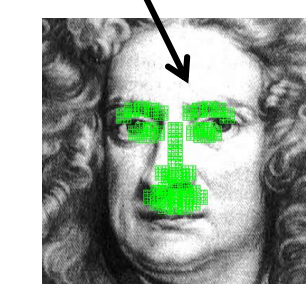
Solutions:

- $2\mathbf{H}^{-1} \mathbf{J}_h^T$  is learnt from data
- $\boldsymbol{\phi}_*$  is learnt through a bias term  $\mathbf{b}_{k-1}$

For example, learning  $\mathbf{R}_0, \mathbf{b}_0$

$$\argmin_{\mathbf{R}_0, \mathbf{b}_0} \sum_{\mathbf{d}^i} \sum_{\mathbf{x}_0^i} \|\Delta \mathbf{x}_*^i - \mathbf{R}_0 \boldsymbol{\phi}_0^i - \mathbf{b}_0\|^2$$

$$\Delta \mathbf{x}_*^i = \mathbf{x}_*^i - \mathbf{x}_0^i$$



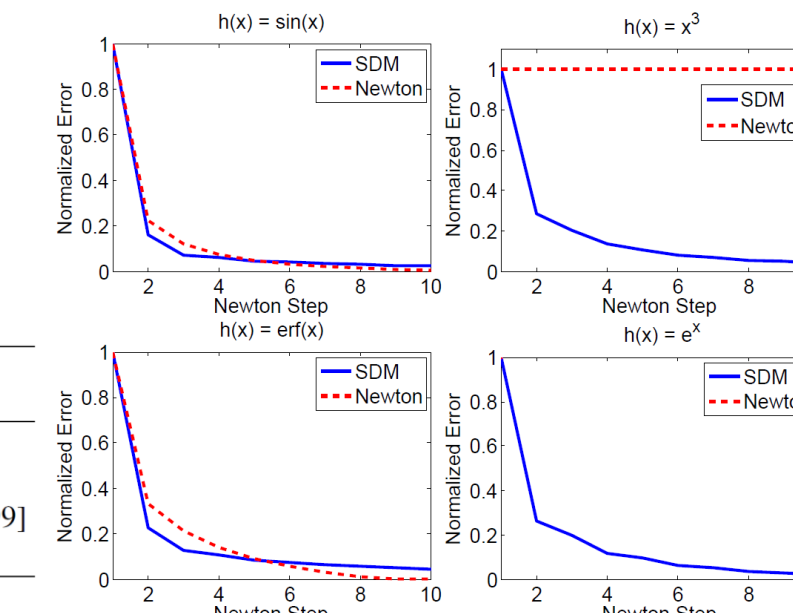
## RESULTS

### Analytic Functions

Problem:  
 $\min_x f(x) = (h(x) - y^*)^2$

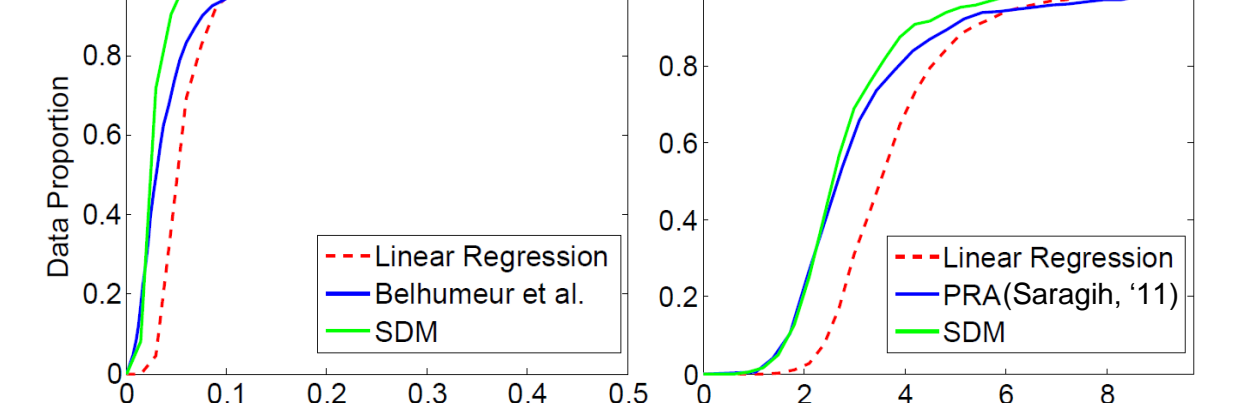
Experimental setup:

Function	Training Set	Test Set
$h(x)$	$y$	$x = h^{-1}(y)$
$\sin(x)$	$[-1:0.2:1]$	$\arcsin(y)$
$x^3$	$[-27:3:27]$	$y^{\frac{1}{3}}$
$\text{erf}(x)$	$[-0.99:0.11:0.99]$	$\text{erf}^{-1}(y)$
$e^x$	$[1:3:28]$	$\log(y)$



### Comparison with Previous Methods

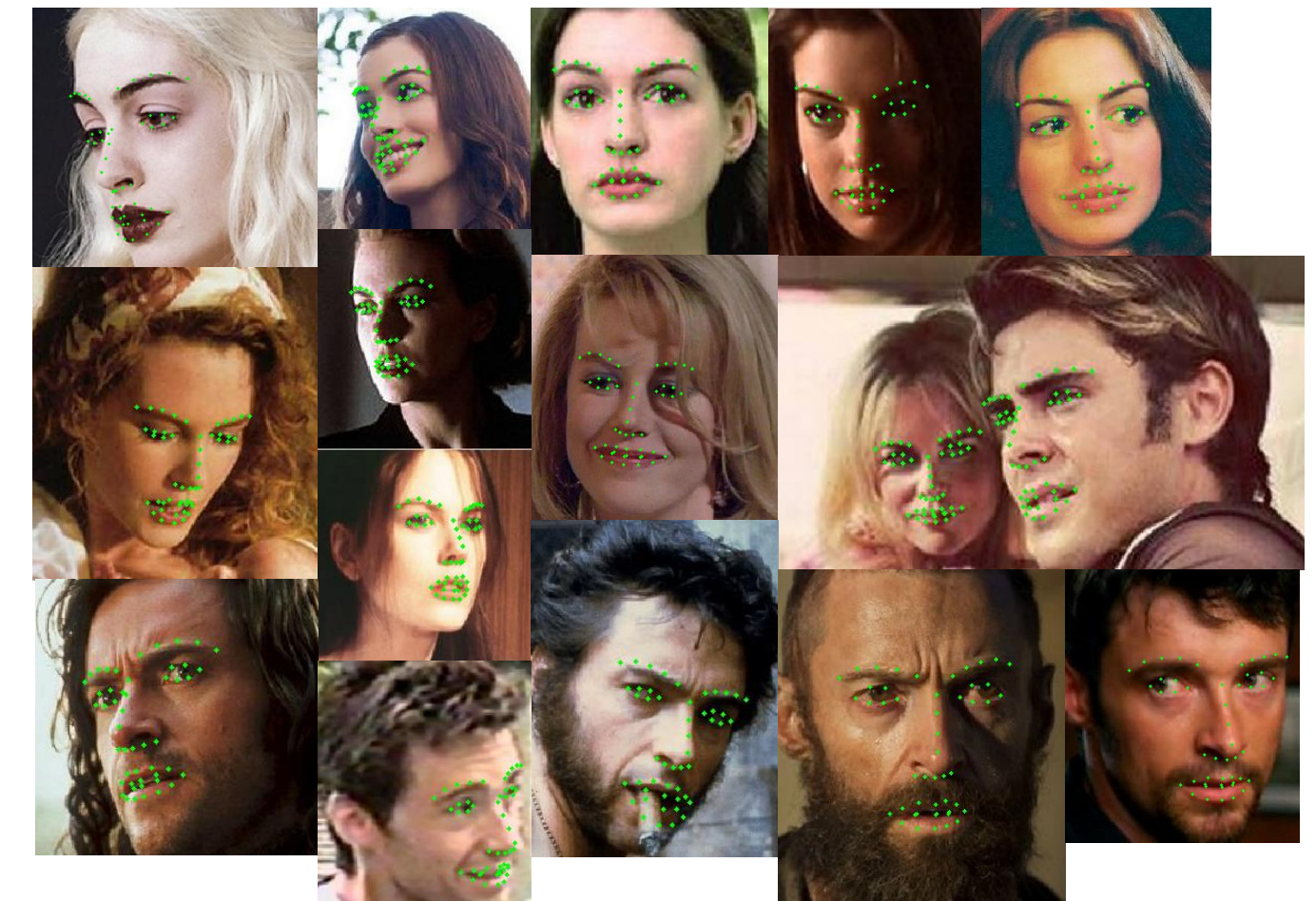
Alignment Accuracy on LFW Dataset



### Expression



### "faces in the wild"



### Cartoon and Drawings

