

# Supervised Descent Method and its Applications to Face Alignment

Xuehan Xiong, Fernando De la Torre (CVPR-2013, extensions: submitted to TPAMI)

Zoltán Szabó

Gatsby Unit, Tea Talk

March 16, 2015

# Motivation

- Computer vision: many tasks boil down to continuous nonlinear optimization.
- Our focus: facial feature detection/tracking.



# Newton's method (and its variants)

- Task:  $\min_{\mathbf{x}} f(\mathbf{x})$ ,  $f \in C^2$ .
- Newton's method: locally quadratic approximation,
  - $\mathbf{x}_0$ : given.
  - Second order Taylor expansion ( $k = 0, 1, 2, \dots$ ) around  $\mathbf{x}_k$ :

$$f(\mathbf{x}_k + \Delta\mathbf{x}) \approx f(\mathbf{x}_k) + \mathbf{J}_f(\mathbf{x}_k)^T(\Delta\mathbf{x}) + \frac{1}{2}(\Delta\mathbf{x})^T \mathbf{H}(\mathbf{x}_k)(\Delta\mathbf{x}) \Rightarrow$$

$$\Delta\mathbf{x}_{k+1} = -\mathbf{H}^{-1}(\mathbf{x}_k)\mathbf{J}_f(\mathbf{x}_k),$$

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \Delta\mathbf{x}_{k+1}.$$

# Newton's method: pro & contra

- Advantages:

- If it converges  $\Rightarrow$  quadratic rate ( $q = 2$ )

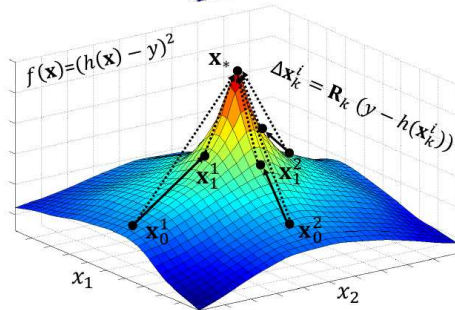
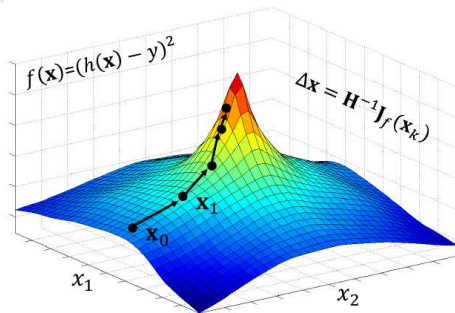
$$\lim_{k \rightarrow \infty} \frac{\|\mathbf{x}_k - \mathbf{x}_*\|}{\|\mathbf{x}_{k-1} - \mathbf{x}_*\|^q} = L > 0.$$

- If  $\mathbf{x}_0$  is "close enough" to  $\mathbf{x}_*$   $\Rightarrow$  convergence.

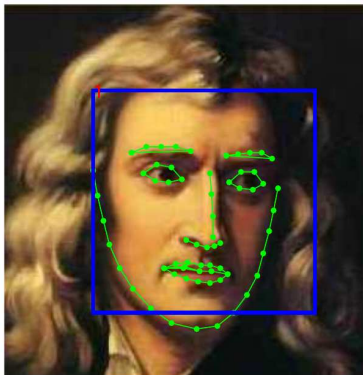
- Disadvantages (in CV):

- $f$ : non-differentiable (SIFT)  $\rightarrow$  numerical  $\mathbf{J}_f$ ,  $\mathbf{H}$ : slow.
- Linear equation: expensive (quasi too).

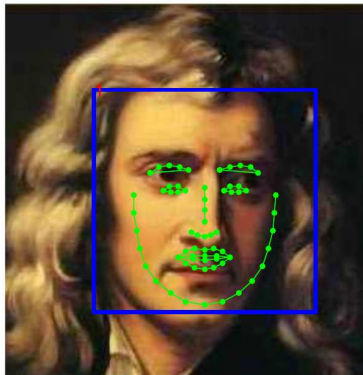
# Optimization idea (z-axis: reversed)



# Face alignment: $\mathbf{x}_0$ – initial estimation, $\mathbf{x}_*$ – manual labels



(a)  $\mathbf{x}_*$



(b)  $\mathbf{x}_0$

# Face alignment: formulation

- Image:  $\mathbf{d}$ .
- Landmark locations ( $p$ ):  $\mathbf{x} = [x_1; y_1; \dots; x_p; y_p] \in \mathbb{R}^{2p}$ .
- Feature extraction function (SIFT):  $\mathbf{h}$ .
- Features around the landmarks:  $\mathbf{h}(\mathbf{x}; \mathbf{d}) \in \mathbb{R}^{128p}$ .
- Task: for given  $\mathbf{x}_0$

$$g(\Delta \mathbf{x}) = f(\mathbf{x}_0 + \Delta \mathbf{x}) = \|\mathbf{h}(\mathbf{x}_0 + \Delta \mathbf{x}; \mathbf{d}) - \phi_*\|_2^2 \rightarrow \min_{\Delta \mathbf{x}},$$

$$\phi_* = \mathbf{h}(\mathbf{x}_*; \mathbf{d}).$$

- Task:

$$f(\mathbf{x}_0 + \Delta\mathbf{x}) = \|\mathbf{h}(\mathbf{x}_0 + \Delta\mathbf{x}; \mathbf{d}) - \phi_*\|_2^2 \rightarrow \min_{\Delta\mathbf{x}}.$$

- By the Newton trick (+chain rule):

$$\Delta\mathbf{x}_1 = -\mathbf{H}^{-1}(\mathbf{x}_0)\mathbf{J}_f(\mathbf{x}_0) = -2\mathbf{H}^{-1}(\mathbf{x}_0)\mathbf{J}_h^T(\mathbf{x}_0)(\phi_0 - \phi_*),$$

$$\phi_0 = \mathbf{h}(\mathbf{x}_0; \mathbf{d}),$$

$$\phi_* = \mathbf{h}(\mathbf{x}_*; \mathbf{d}).$$



# Face alignment

- Task:

$$f(\mathbf{x}_0 + \Delta \mathbf{x}) = \|\mathbf{h}(\mathbf{x}_0 + \Delta \mathbf{x}; \mathbf{d}) - \phi_*\|_2^2 \rightarrow \min_{\Delta \mathbf{x}}.$$

- By the Newton trick (+chain rule):

$$\Delta \mathbf{x}_1 = -\mathbf{H}^{-1}(\mathbf{x}_0) \mathbf{J}_f(\mathbf{x}_0) = -2\mathbf{H}^{-1}(\mathbf{x}_0) \mathbf{J}_h^T(\mathbf{x}_0) (\phi_0 - \phi_*),$$

$$\phi_0 = \mathbf{h}(\mathbf{x}_0; \mathbf{d}),$$

$$\phi_* = \mathbf{h}(\mathbf{x}_*; \mathbf{d}).$$

- Idea [ $\mathbf{H} := \mathbf{H}(\mathbf{x}_0)$ ,  $\mathbf{J}_h := \mathbf{J}_h(\mathbf{x}_0)$ ]:

$$\begin{aligned} \Delta \mathbf{x}_1 &= -2\mathbf{H}^{-1} \mathbf{J}_h^T (\phi_0 - \phi_*) = \left[ -2\mathbf{H}^{-1} \mathbf{J}_h^T \right] \phi_0 + \left[ 2\mathbf{H}^{-1} \mathbf{J}_h^T \phi_* \right] \\ &= \mathbf{R}_0 \phi_0 + \mathbf{b}_0 \Rightarrow \text{optimize for } (\mathbf{R}_0, \mathbf{b}_0) \text{ based on samples.} \end{aligned}$$

- The algorithm is unlikely to converge in 1 iteration.
- Cascade of regressors:

$$\Delta \mathbf{x}_1 = \mathbf{R}_0 \phi_0 + \mathbf{b}_0,$$

— — — —

$$\Delta \mathbf{x}_k = \mathbf{R}_{k-1} \phi_{k-1} + \mathbf{b}_{k-1}, \text{ where}$$

$\phi_{k-1} = \mathbf{h}(\mathbf{x}_{k-1}; \mathbf{d})$  : features at the previous landmarks.

# Face alignment: optimization ( $k = 0$ )

- Given:
  - set of images:  $\{\mathbf{d}^i\}_{i=1}^N$ ,
  - hand-labelled landmarks:  $\{\mathbf{x}_*^i\}_{i=1}^N$ ,
  - initial estimates:  $\{\mathbf{x}_0^i\}_{i=1}^N \Rightarrow$
- Optimal updates, extracted features:

$$\Delta \mathbf{x}_{*0}^i = \mathbf{x}_*^i - \mathbf{x}_0^i, \quad \phi_0^i = \mathbf{h}(\mathbf{x}_0^i; \mathbf{d}^i).$$

- Objective:

$$J(\mathbf{R}_0, \mathbf{b}_0) = \frac{1}{N} \sum_{i=1}^N \left\| \Delta \mathbf{x}_{*0}^i - \mathbf{R}_0 \phi_0^i - \mathbf{b}_0 \right\|_2^2 \rightarrow \min_{\mathbf{R}_0, \mathbf{b}_0}.$$

# Face alignment: optimization (general $k$ )

- Update the landmark estimates ( $\mathbf{x}_k$ ):

$$\Delta \mathbf{x}_k^i = \mathbf{R}_{k-1} \phi_{k-1}^i + \mathbf{b}_{k-1} \quad (i = 1, \dots, N).$$

- Compute optimal updates ( $\forall i$ ), extract features:

$$\Delta \mathbf{x}_{*k}^i = \mathbf{x}_{*k}^i - \mathbf{x}_k^i, \quad \phi_k^i = \mathbf{h}(\mathbf{x}_k^i; \mathbf{d}^i).$$

- Objective:

$$J(\mathbf{R}_k, \mathbf{b}_k) = \frac{1}{N} \sum_{i=1}^N \left\| \Delta \mathbf{x}_{*k}^i - \mathbf{R}_k \phi_k^i - \mathbf{b}_k \right\|_2^2 \rightarrow \min_{\mathbf{R}_k, \mathbf{b}_k}.$$

Numerical experience: convergence in 4 – 5 steps.

# Face alignment: training, testing

- Training  $\Rightarrow \{\mathbf{R}_k, \mathbf{b}_k\}$ .
- Testing:
  - test image:  $\tilde{\mathbf{d}}$ ,
  - initial estimate:  $\mathbf{x}_0$ ,
  - extract features:  $\phi_0 = \mathbf{h}(\mathbf{x}_0; \tilde{\mathbf{d}})$ ,
  - iteratively compute  $\Delta \mathbf{x}_k$ , the features at  $\mathbf{x}_k$  ( $k = 1, \dots$ ):

$$\Delta \mathbf{x}_k = \mathbf{R}_{k-1} \phi_{k-1} + \mathbf{b}_{k-1},$$

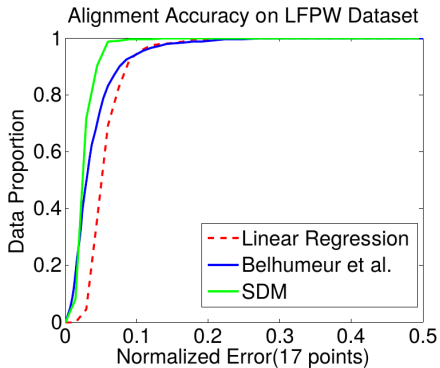
$$\phi_k = \mathbf{h}(\mathbf{x}_k; \tilde{\mathbf{d}}).$$

# Facial feature detection: 2 "face in the wild" datasets

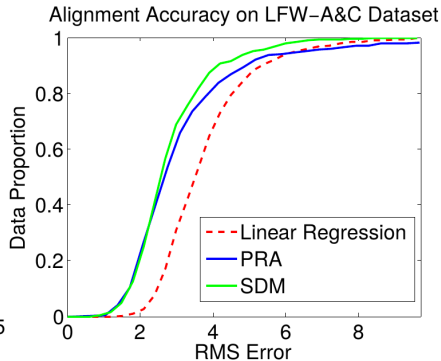


Last row: 10 worst cases.

# Facial feature detection: cumulative error distribution curves



(a)

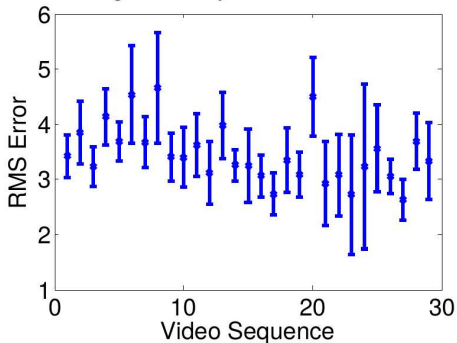


(b)

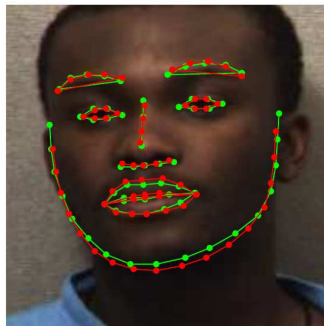
# Facial feature tracking

- Initialization = landmark estimate from the previous frame.
- (a): average RMSE-s on 29 videos, (b): RMSE=5.03 demo.

Tracking Accuracy on RU-FACS Dataset



(a)



(b)



- Focus: continuous nonlinear optimization.
- Newton's method: expensive.
- Idea:
  - supervised Newton method,
  - learn cascade of affine regressors based on samples.
- Application:
  - facial feature detection,
  - face tracking.

Thank you for the attention!

