Sparse representation of active appearance model texture maps

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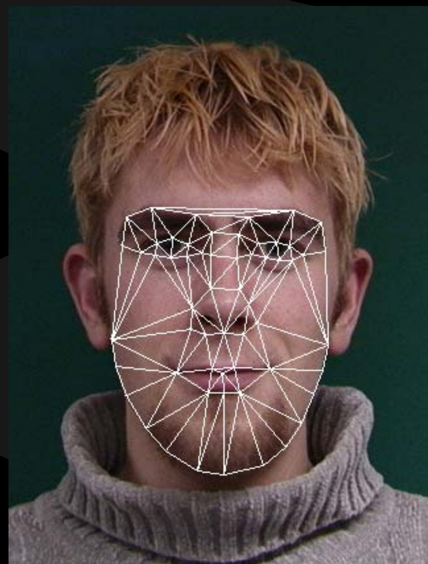
DTU Informatics

IMM face database

- 37 face images annotated with 58 landmarks
- 24042 downloads (2010.08.18) since 2002


Training image


Annotation


Model mesh


Shape-compensation

A face tracking blunder

- Face tracking

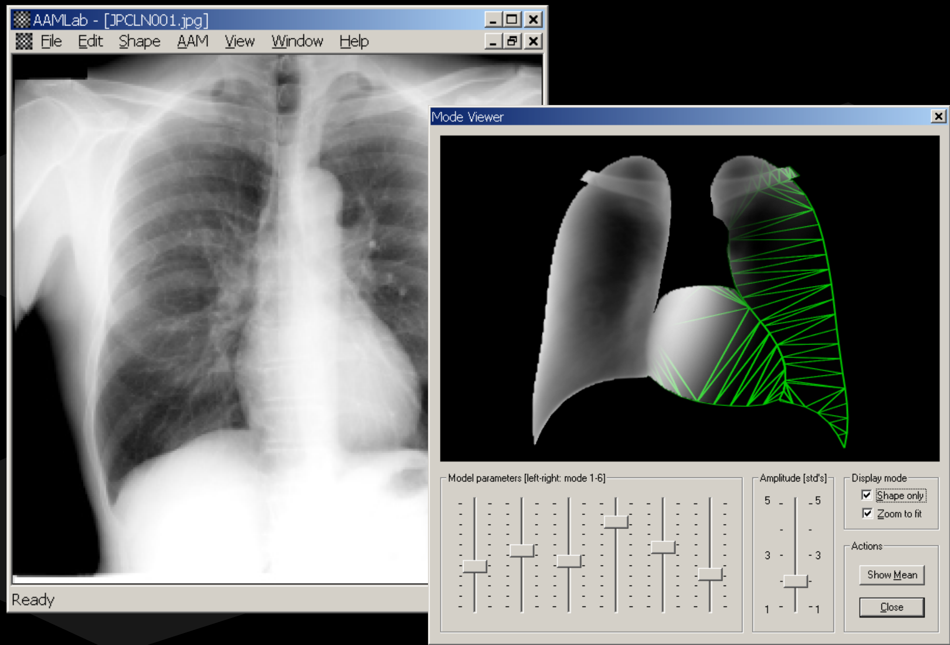
DTU Technical University of Denmark

The AAM-API

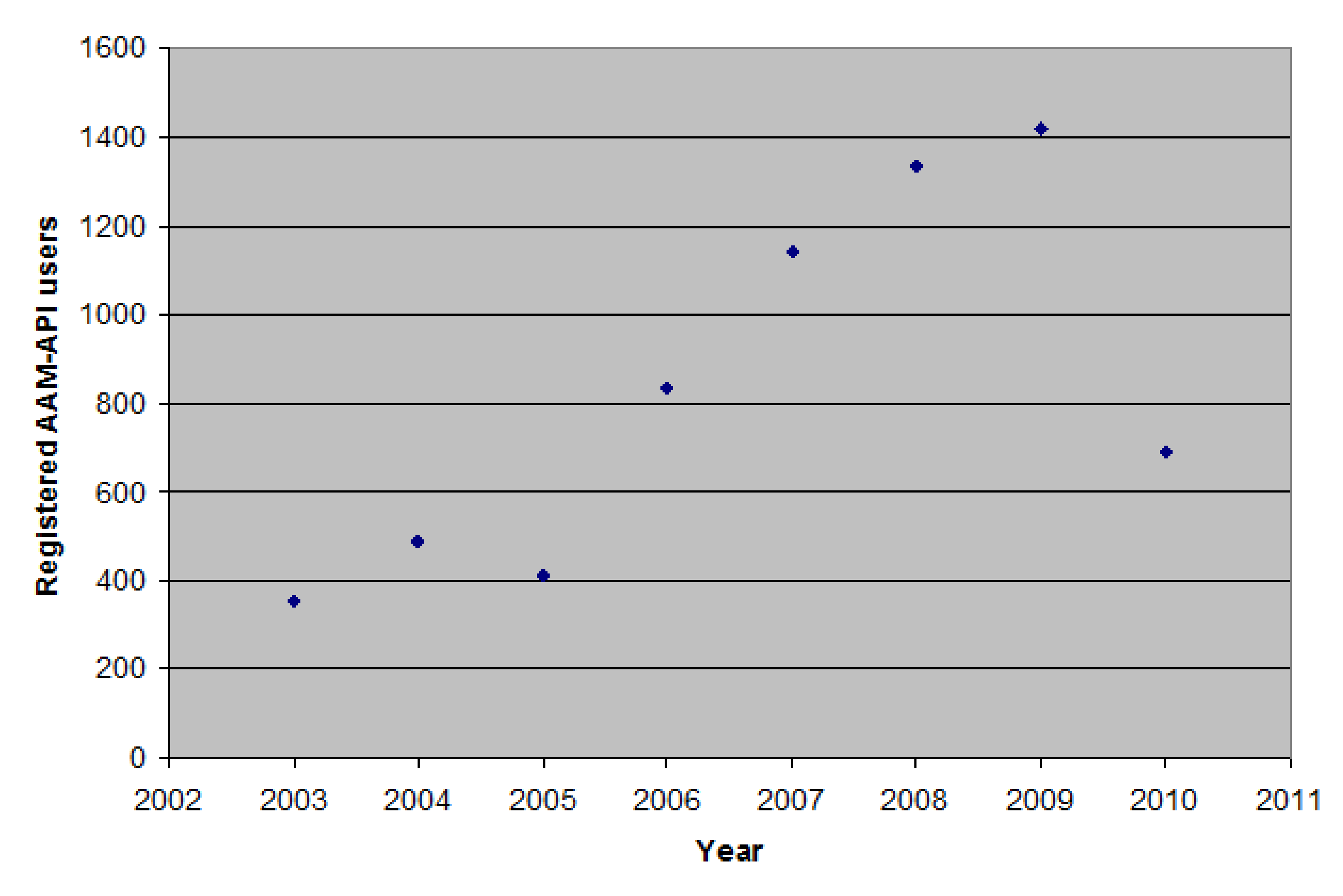
M. B. Stegmann, B. K. Ersbøll, R. Larsen, *FAME – A flexible appearance modelling environment*, IEEE Transactions on Medical Imaging, vol. 22(10), pages 1319–1331, 2003

- Our wide-spread, open source C++ AAM implementation
  - Fraunhofer Institute
  - Massachusetts Institute of Technology
  - Harvard University
  - Carnegie Mellon
  - Intel
  - Siemens
  - Microsoft
  - Hewlett-Packard
  - Ericsson
  - Panasonic
  - Honeywell
  - Sanyo
  - Mitsubishi
  - Toyota
  - NASA
  - NIH
- C++ / Console / GUI interfaces
- Publicly available reference test data

Download from http://www.imm.dtu.dk/~aam/



6677 – 2010.07.04



Active Appearance Model segmentation

Appearance Model

Landmark coordinates: s (~100)
Pixel intensities: t (~100.000)

$$E\{\boldsymbol{s}\} = \bar{\boldsymbol{s}} + \boldsymbol{\Phi}_s \boldsymbol{\theta}$$
$$E\{\boldsymbol{t}\} = \bar{\boldsymbol{t}} + \boldsymbol{\Phi}_t \boldsymbol{\theta}$$

Eigenvectors: Φ (~100.000×20)
Parameters: θ (~20)

SO(2): ψ (4)

Active part

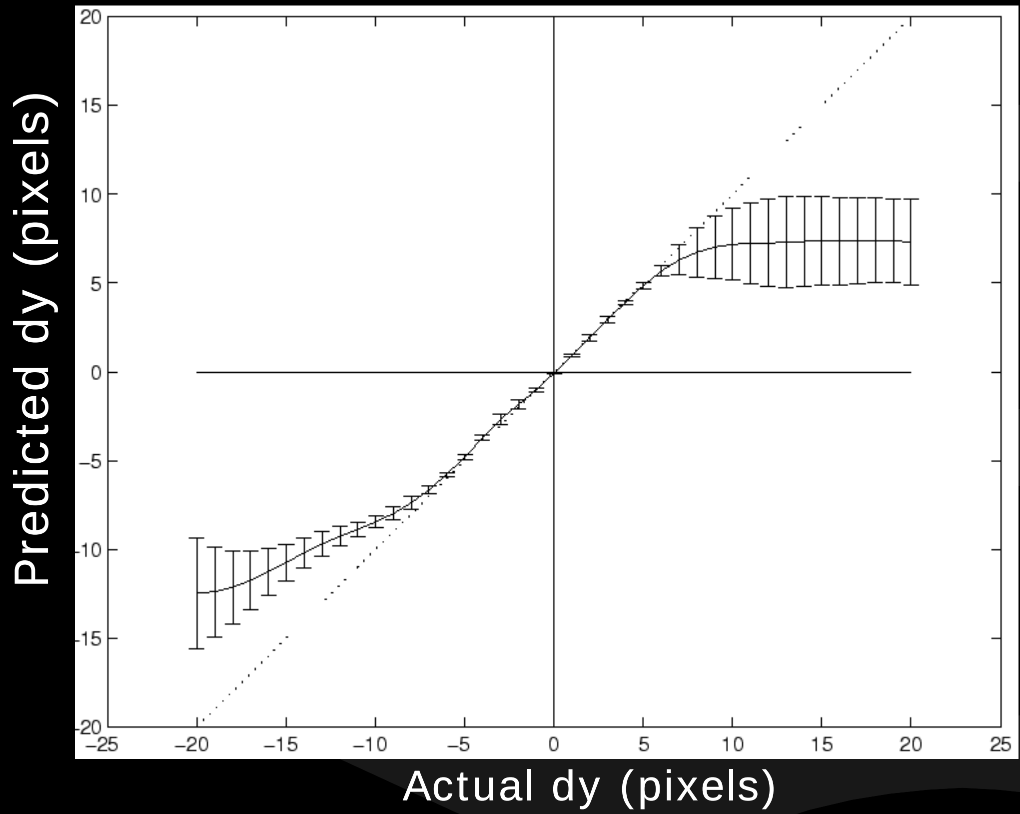
$$\Delta \boldsymbol{t} = \boldsymbol{X} \begin{bmatrix} \Delta\psi \\ \Delta\boldsymbol{\theta} \end{bmatrix}$$

Jacobian: X (~100.000×24)

$$\begin{bmatrix} \widehat{\Delta\theta} \\ \widehat{\Delta\psi} \end{bmatrix} = \left(\boldsymbol{X}^T\boldsymbol{X}\right)^{-1}\boldsymbol{X}^T\Delta\boldsymbol{t} = \boldsymbol{Q}\Delta\boldsymbol{t}.$$

Q (~24×100.000)

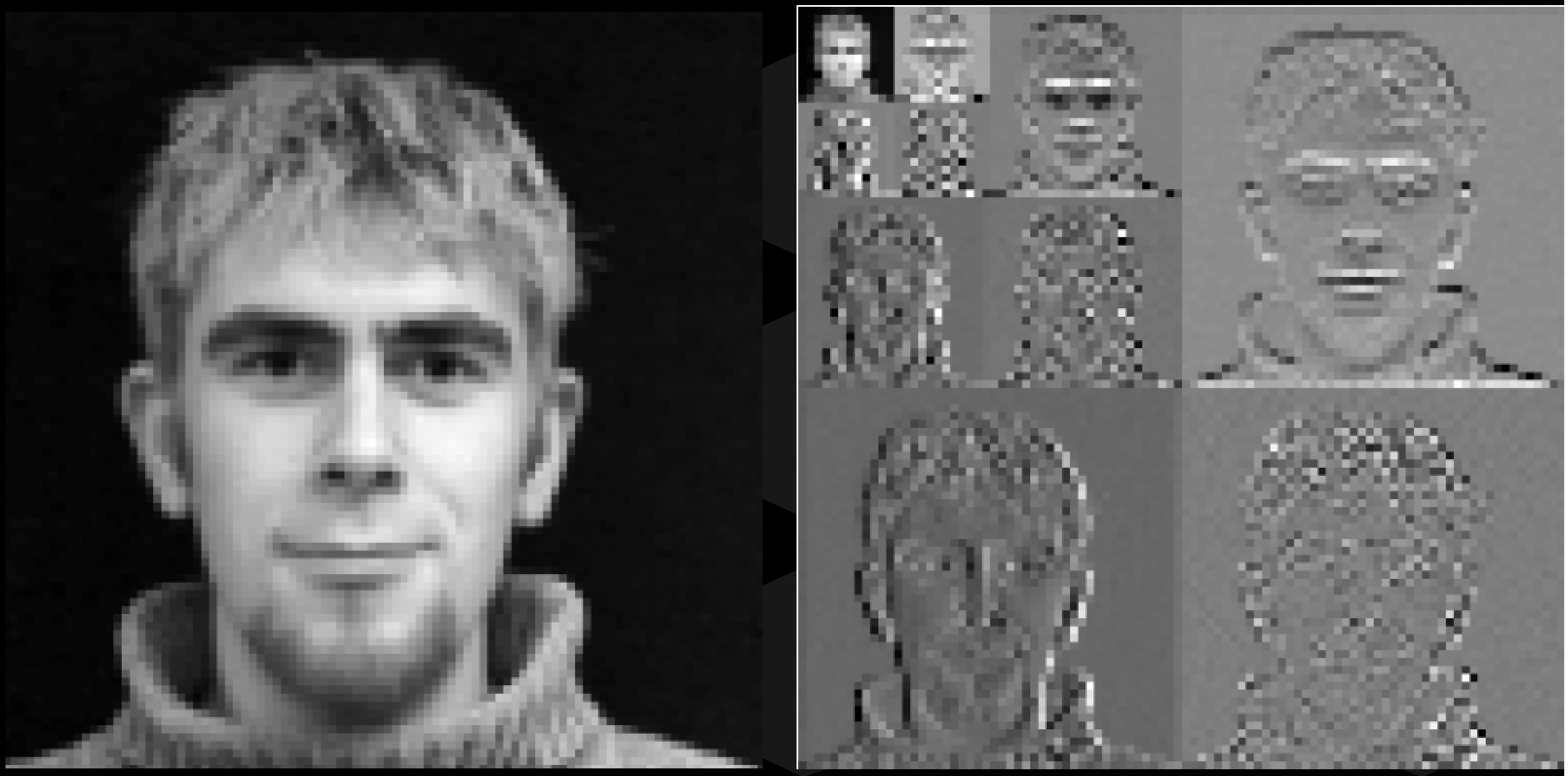
Parameter update



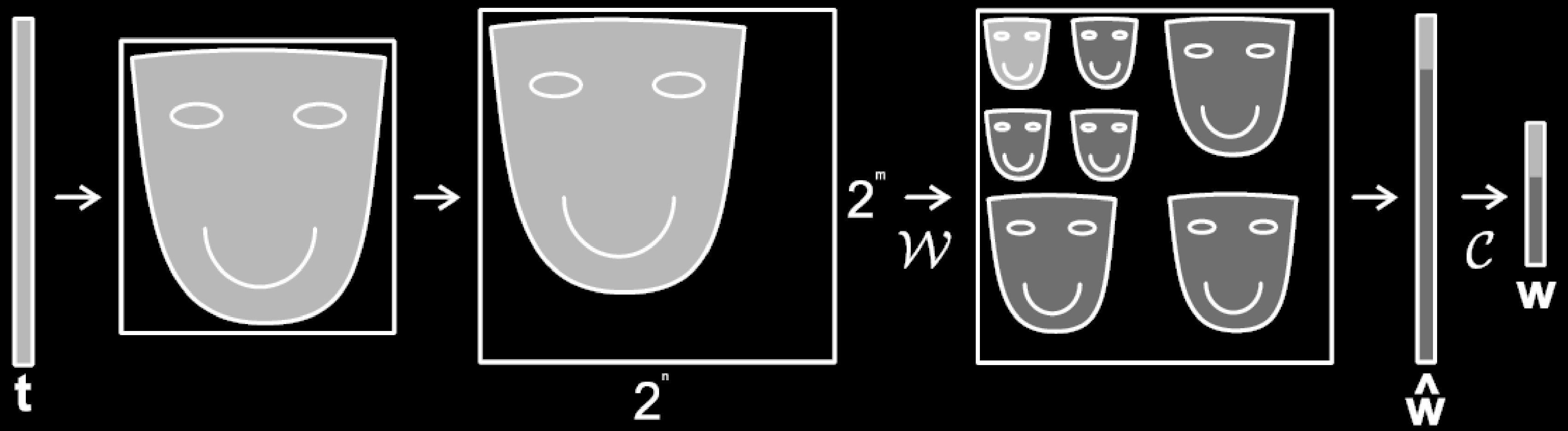
Intensity vector truncation using pre-determined dictionaries

$$\begin{bmatrix} \widehat{\Delta\theta} \\ \widehat{\Delta\psi} \end{bmatrix} = \left(\boldsymbol{X}^T \boldsymbol{X} \right)^{-1} \boldsymbol{X}^T \Delta \boldsymbol{t} = \boldsymbol{Q} \Delta \boldsymbol{t}.$$

Wavelet decomposition



Wavelet texture pipeline

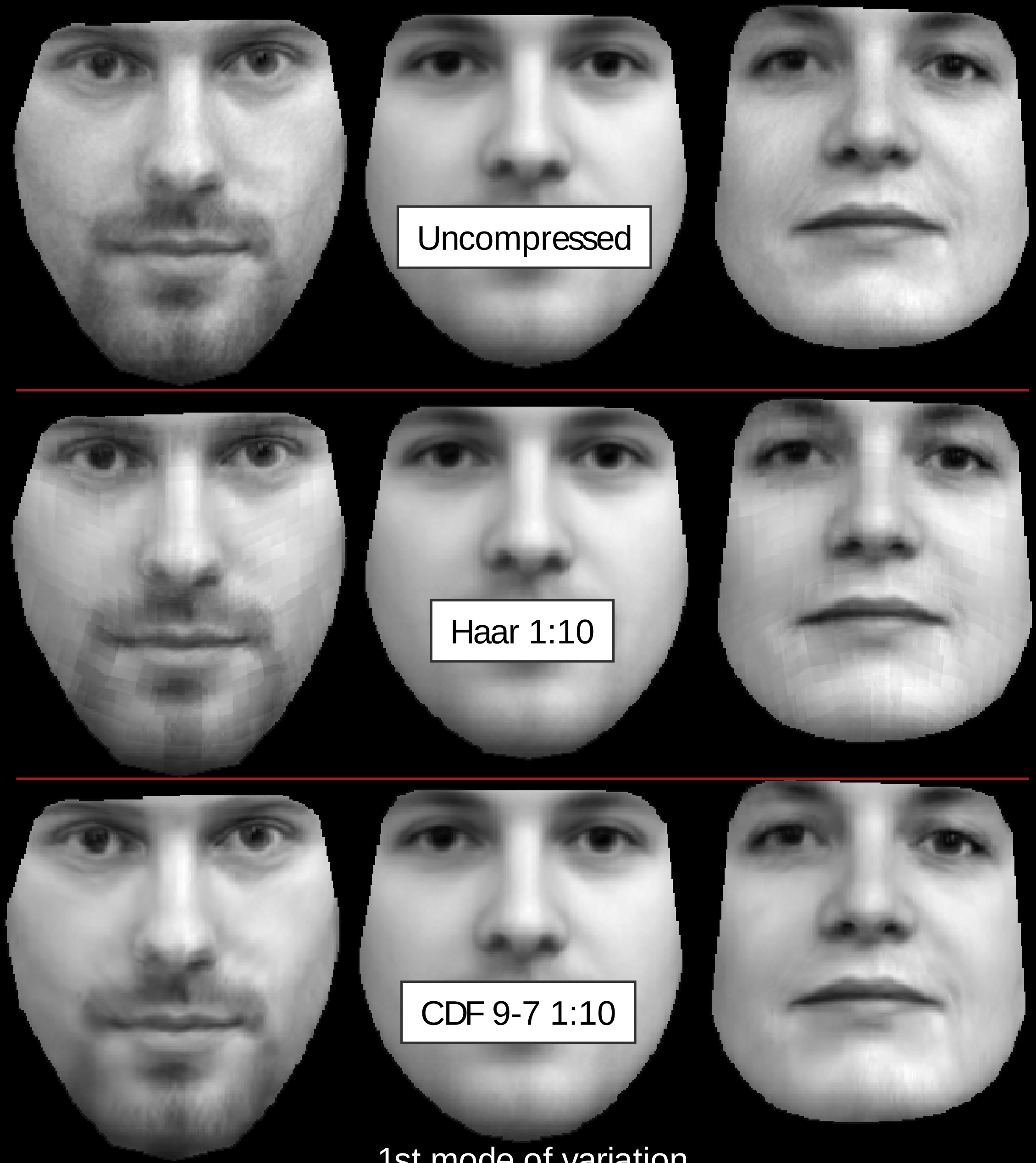


Retain coefficients that represent the largest variance across the training set

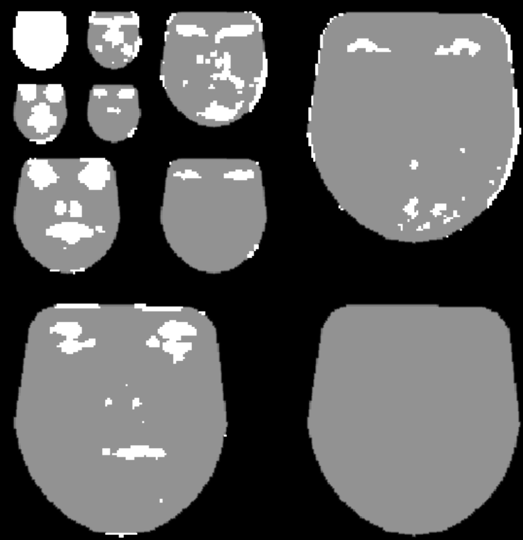
$$\hat{\sigma}_j^2 = \frac{1}{I} \sum_{i=1}^{I} (w_{ij} - \overline{w}_{\cdot j})^2,$$

Wavelet-based AAMs

[Wolstenholme & Taylor, MICCAI 1999]

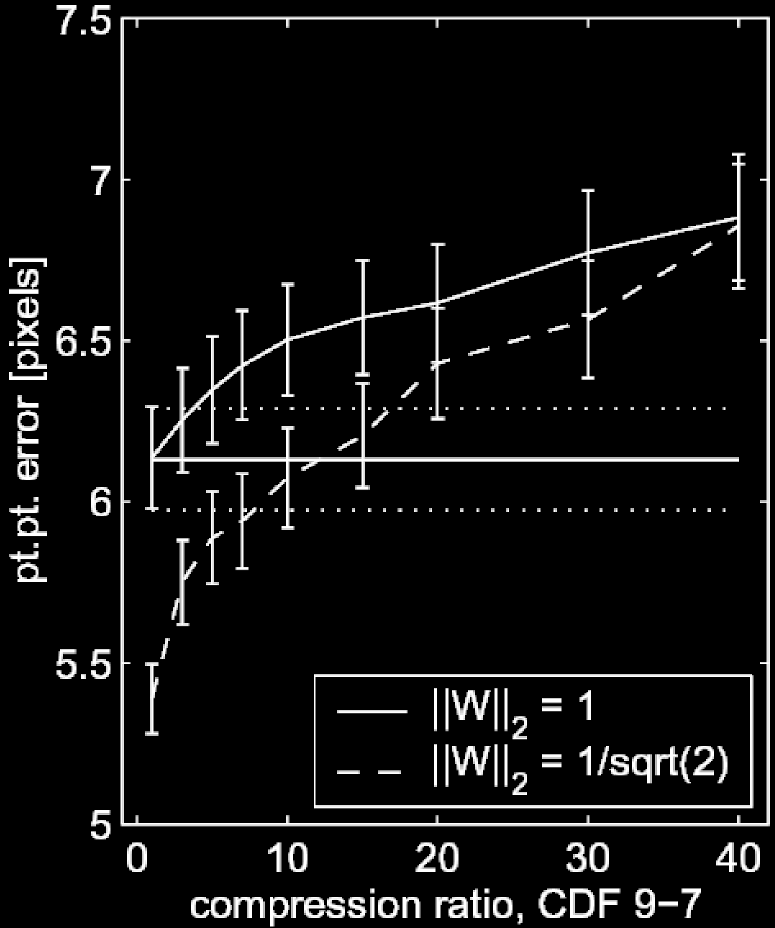


1st mode of variation



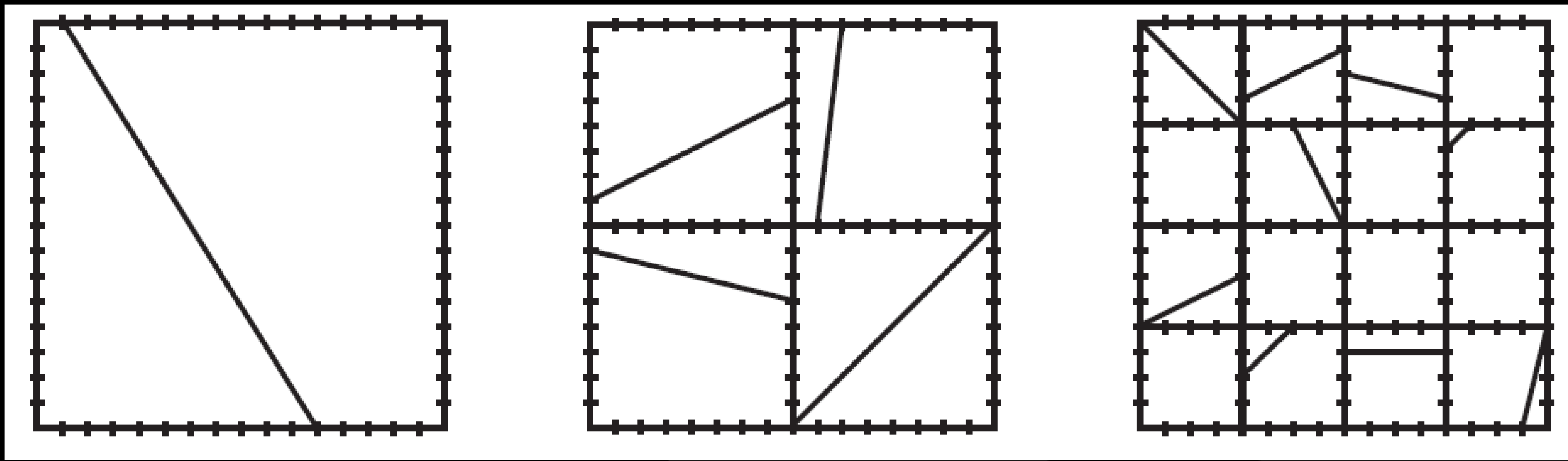
Selected wavelet coefficients

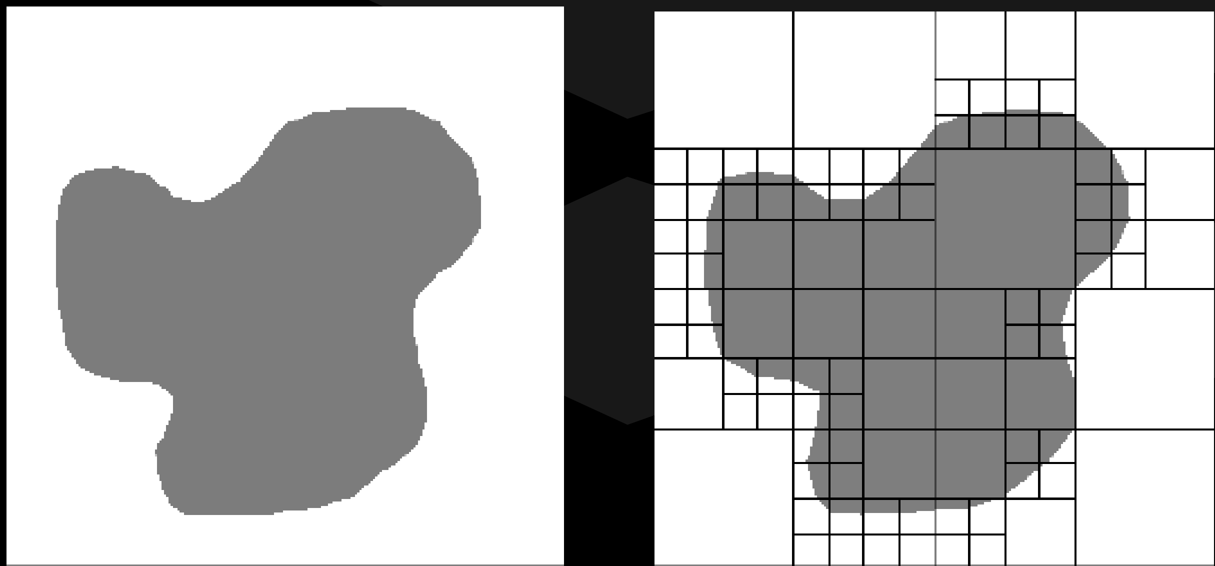
Cross-validation of registration accuracy



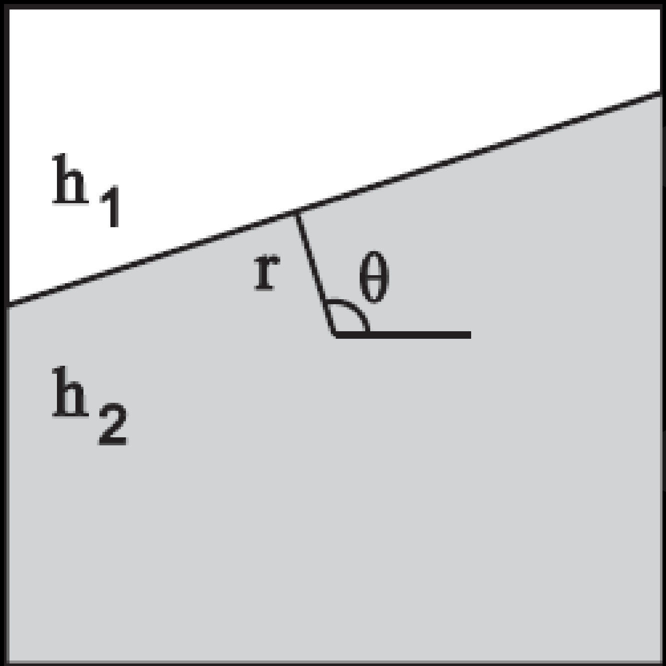
Landmark error [AAM, CDF 9-7 , CDF 9-7 weighted]

Wedgelet dictonary (Donoho, 1997)

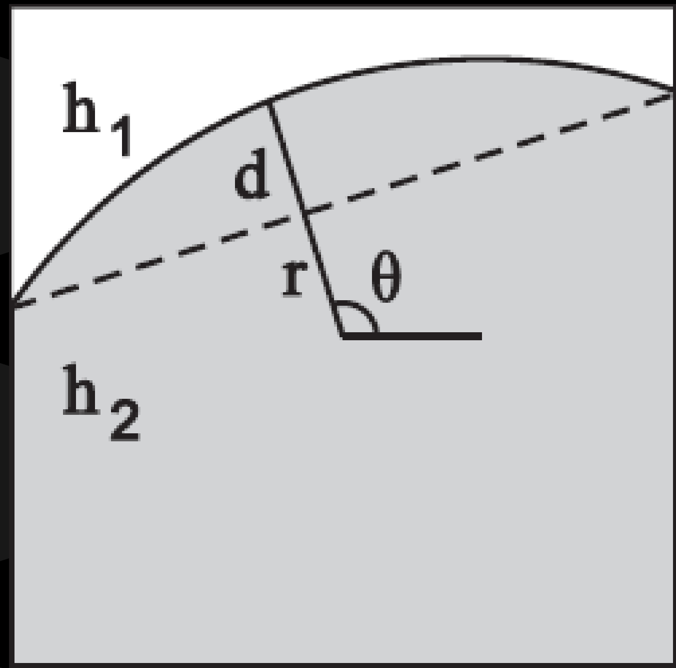




Parametrization

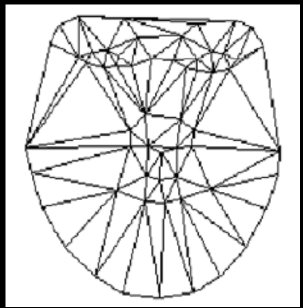


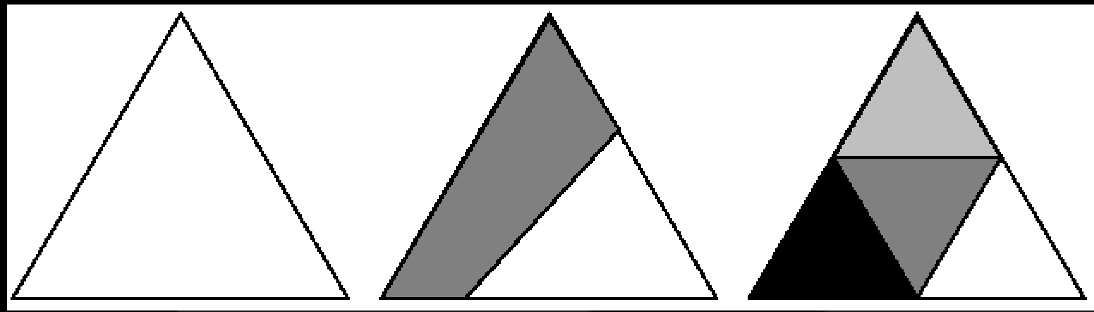
wedgelet

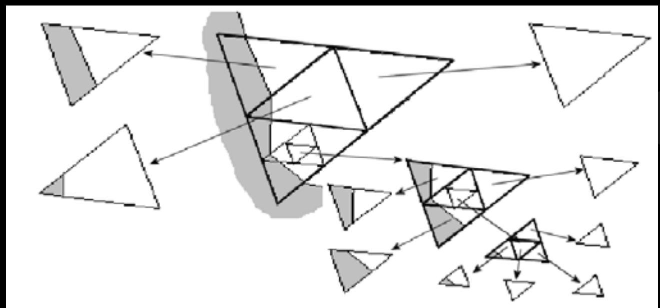


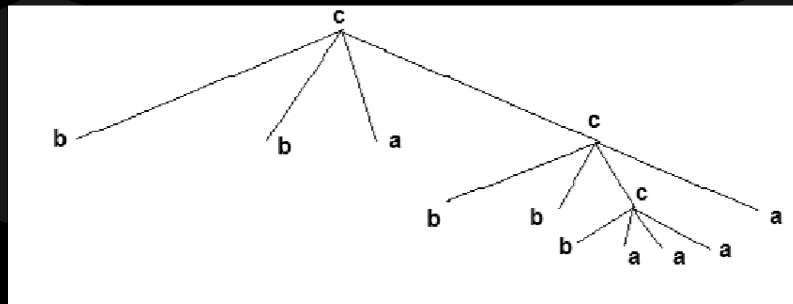
Extended wedgelet, (Lisowska, 2004)

Triangulated wedgelets









$$f_i(\boldsymbol{x}_l) = \sum_r \mu_{ir} I\{\boldsymbol{x}_l \in r\}$$

$$\hat{\mu}_{ir} = \mathrm{ave}(y_{il} | \boldsymbol{x}_l \in r)$$

Fitting the wedgelet quadtree

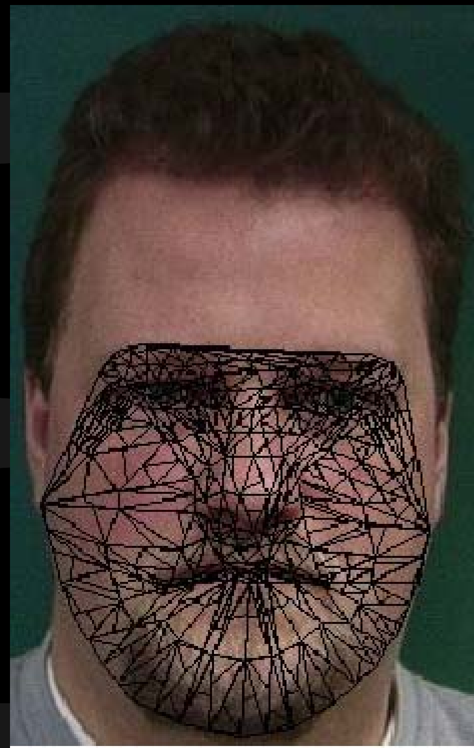
- Bottom-up
- A each level compare (degenerate, non-degenerate, interior)
- Cross validation
- Complexity penalized RSS

$$\mathrm{CPRSS}(\mathcal{P}, \lambda) = \sum_i \sum_l \|y_{il} - f_i(\boldsymbol{x}_l; \mathcal{P})\|^2 + \lambda^2 \mathrm{card}(\mathcal{P})$$

Wedgelet quadtrees

1:3

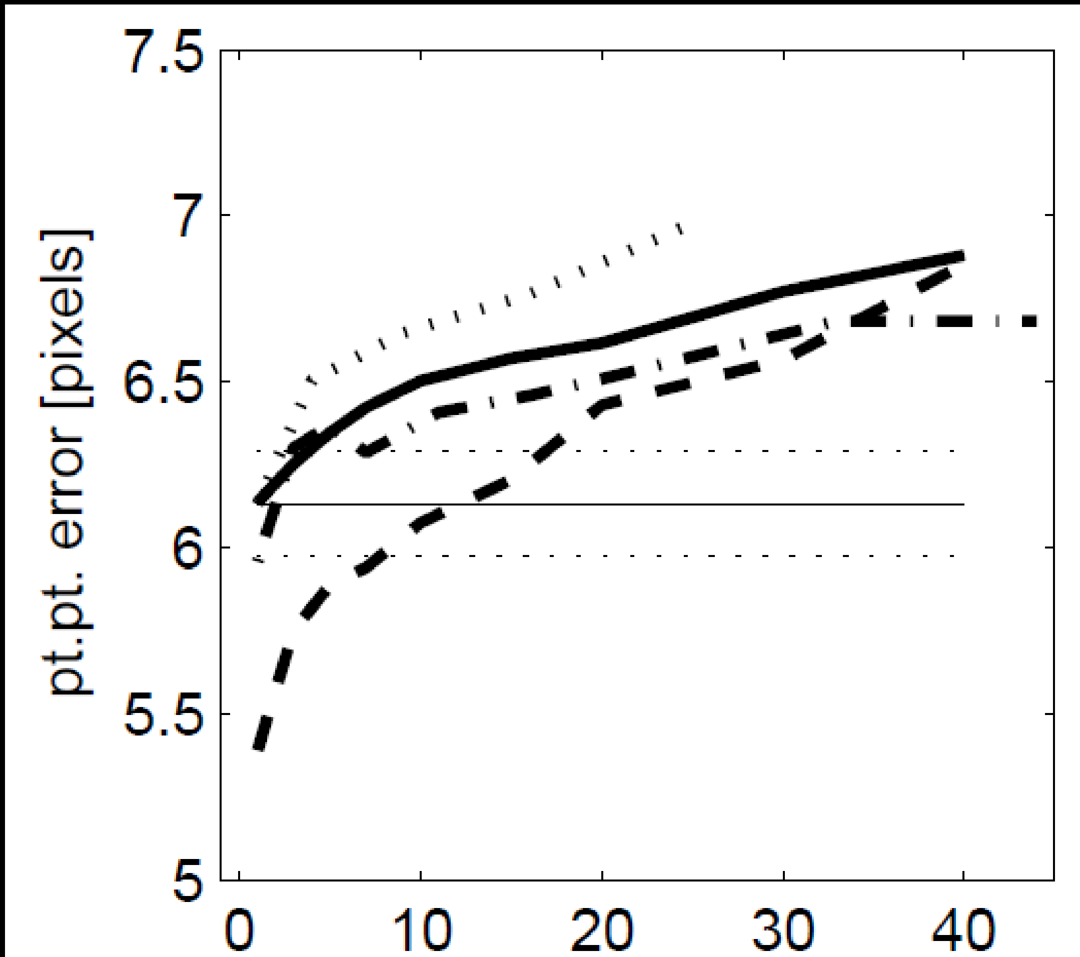
1:40



#super pixels / #pixels

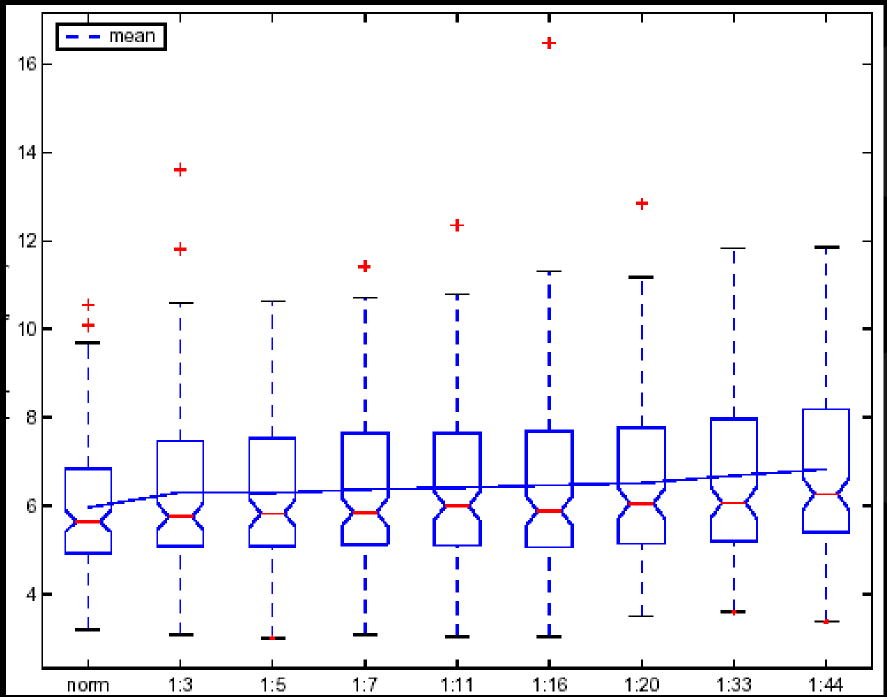
Wedgelet AAM fitting

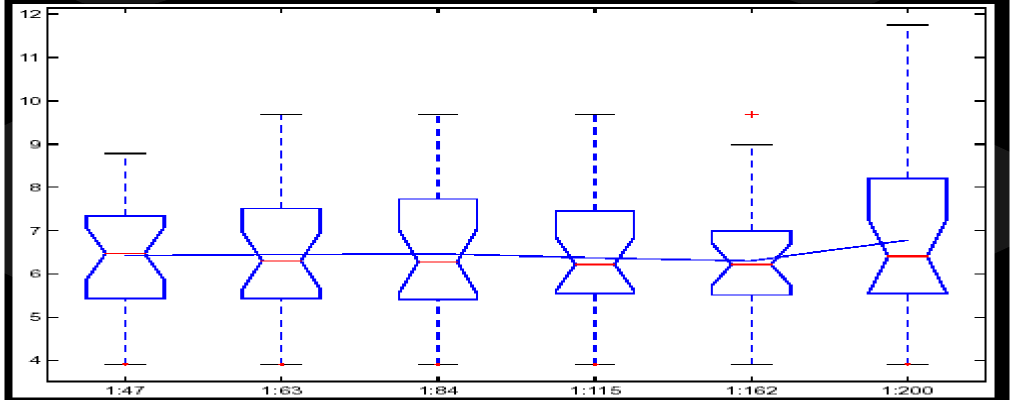
Segmentation accuracy



Solid: CDF 9-7
Dashed: CDF 9-7, weighted
Dot-dash: wedgelet
Dot: pixel subsampling

Segmentation accuracy, wedgelet





1:50 1:200

Conclusions

- 2D triangulated wedgelet transformation
- Applied to AAM
- Reduced computational load of inner loop AAM fitting by factor of ~200 with very limited loss of accuracy

- Regularized PCA (prefiltered data), explicitly building (piecewise) smoothness into AAM

fin

www.imm.dtu.dk/~aam

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