

Active Shape Model Unleashed with Multi-scale Local Appearance

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Three modifications to ASM

- **Shape** optimisation by energy minimisation
Enhance the performance with very limited training samples
- Adopt the subspace inverse gradient descent for local **feature searching**
Model and remove the variations of local appearance presented in the training data
- Multi-scale local features for a seamless coarse-to-fine **fitting**
Integrate landmark observations from multi-scale features

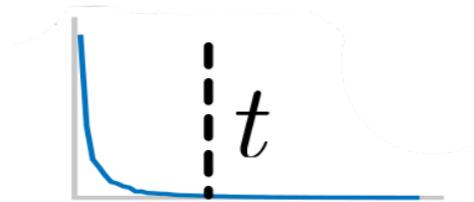
Active Shape Model

- Constrain the shape with statistical shape prior

$$P_s = [e_1, e_2, \dots]$$

1. Retain first t significant shape variations

$$P_s = [e_1, e_2, \dots, e_t]$$



$$s = \bar{s} + P_s b_s$$

2. Bound the shape variations b_s within certain s.d.

Active Shape Model

Constraint

■ 1. Retain first t significant shape variations

■ 2. Bound the shape variations b_s within certain s.d. of mean shape

Drawback:

■ Over constraint with high dimensional variations and limited training data

Active Shape Model

Constraint

- 1. Retain first t significant shape variations
- 2. Bound the shape variations b_s within certain s.d. of mean shape

Causes: (why)

1. Does not count the cost of cutting off minor components

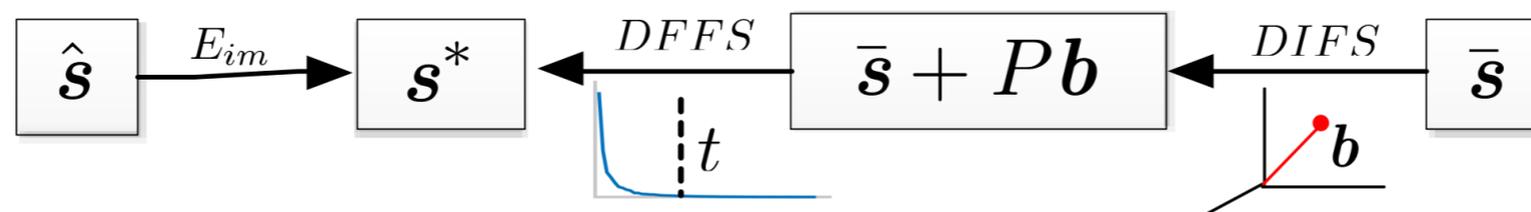
ASM assume the minor components are noises, but they could also be the shape details.

2. Shape variations outside the rigid boundary could still represent reasonable instances

Shape prior can not cover all the variations without adequate training samples, which is always the truth in medical images.

Shape optimisation by energy minimisation

Solution:



$$E(\mathbf{s}) = E_{shape}^{DIFS}(\mathbf{s})$$

Distance **In** feature space [1]:

Distances from the statistical mean shape

$$+ E_{shape}^{DFFS}(\mathbf{s})$$

Distance **From** feature space [1]:

Energy of the minor variations been cut off

$$+ \beta E_{image}(\mathbf{s})$$

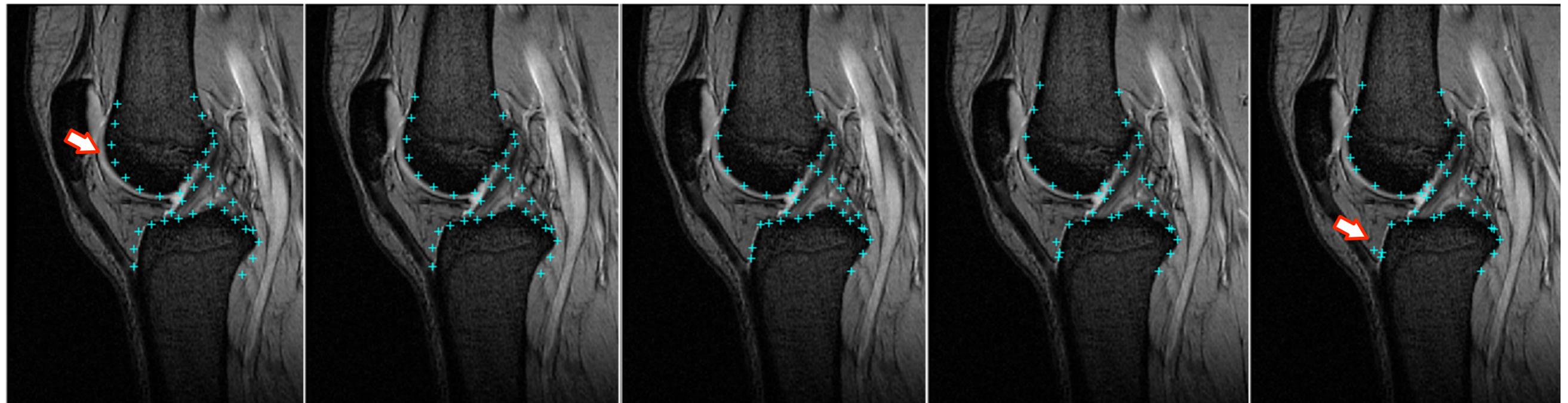
$$E_{image}(\mathbf{s}) = \sum_{j=1}^{2N} \frac{(x_j - \hat{x}_j)^2}{2\sigma_j^2},$$

[1] Moghaddam, Baback, and Alex Pentland. "Probabilistic visual learning for object representation." PAMI, 1997

Shape optimisation by energy minimisation

What is β

$$E(\mathbf{s}) = E_{shape}^{DIFS}(\mathbf{s}) + E_{shape}^{DFFS}(\mathbf{s}) + \beta E_{image}(\mathbf{s})$$



beta = 0.001

0.01

1

10

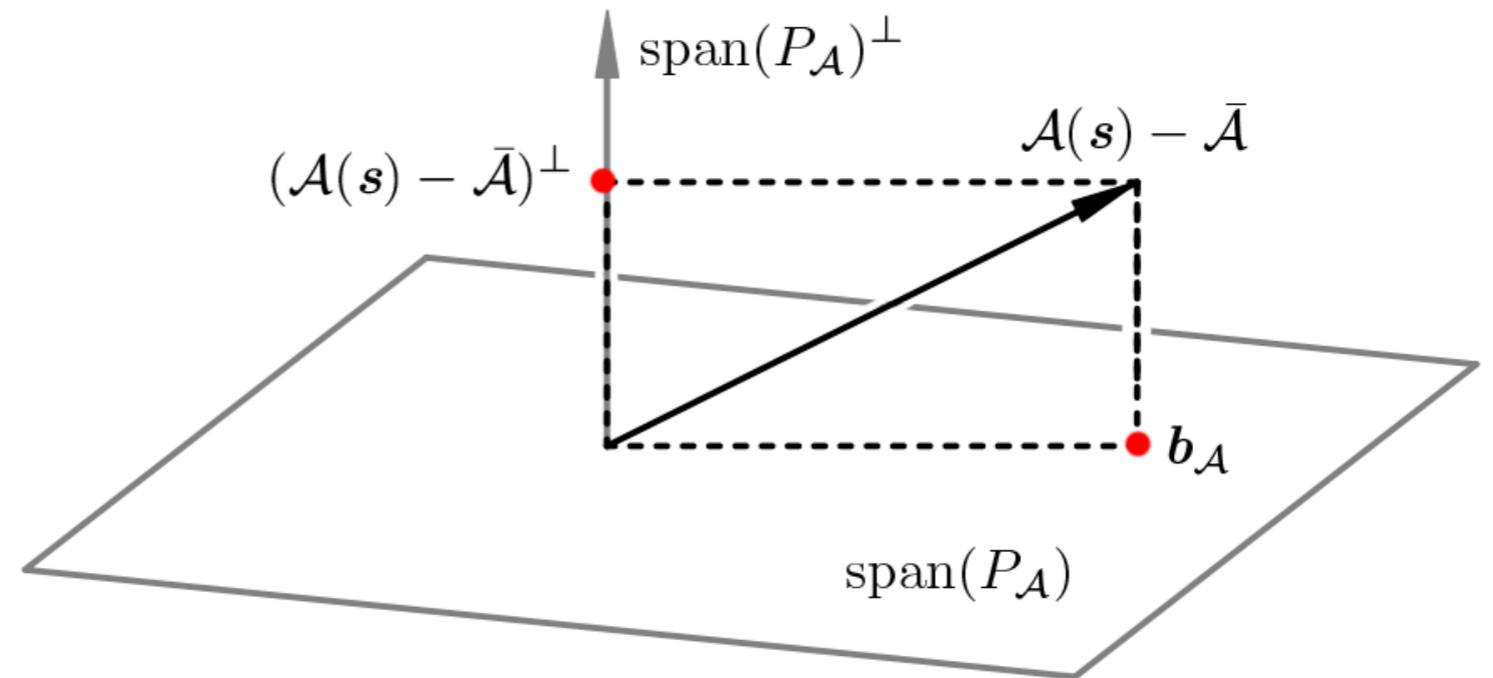
100

Lucas & Kanade algorithm for feature searching

Basic idea:

During training, the large appearance variations of local features can be modelled in an eigen-space.

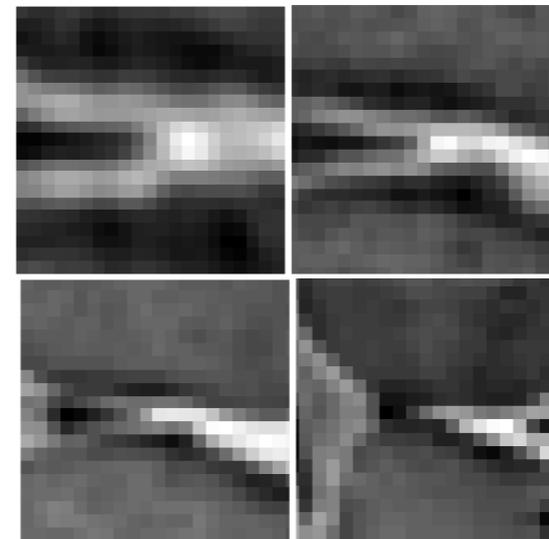
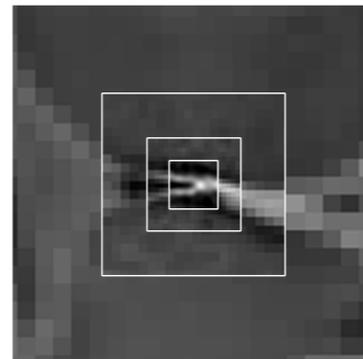
During testing, to remove the large appearance variations, the local features of the testing image is projected onto the orthogonal space of the eigen-space, which result in a more robust fitting



Multi-scale local features for a seamless fitting

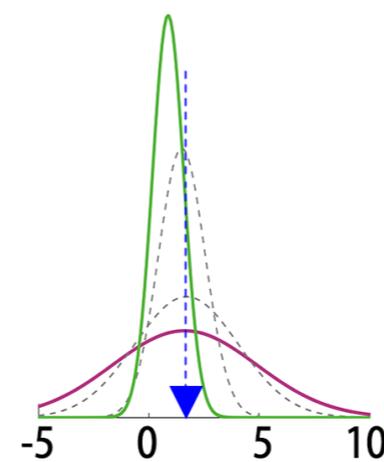
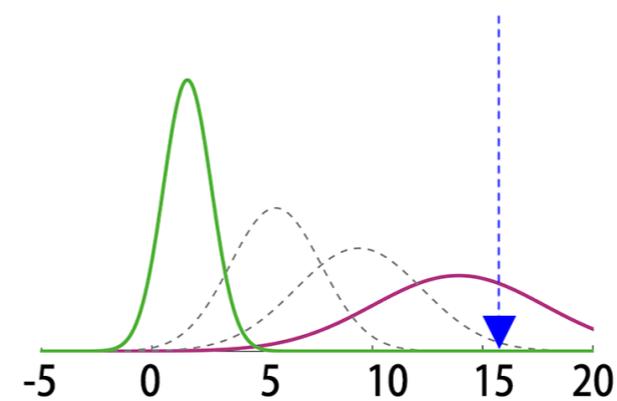
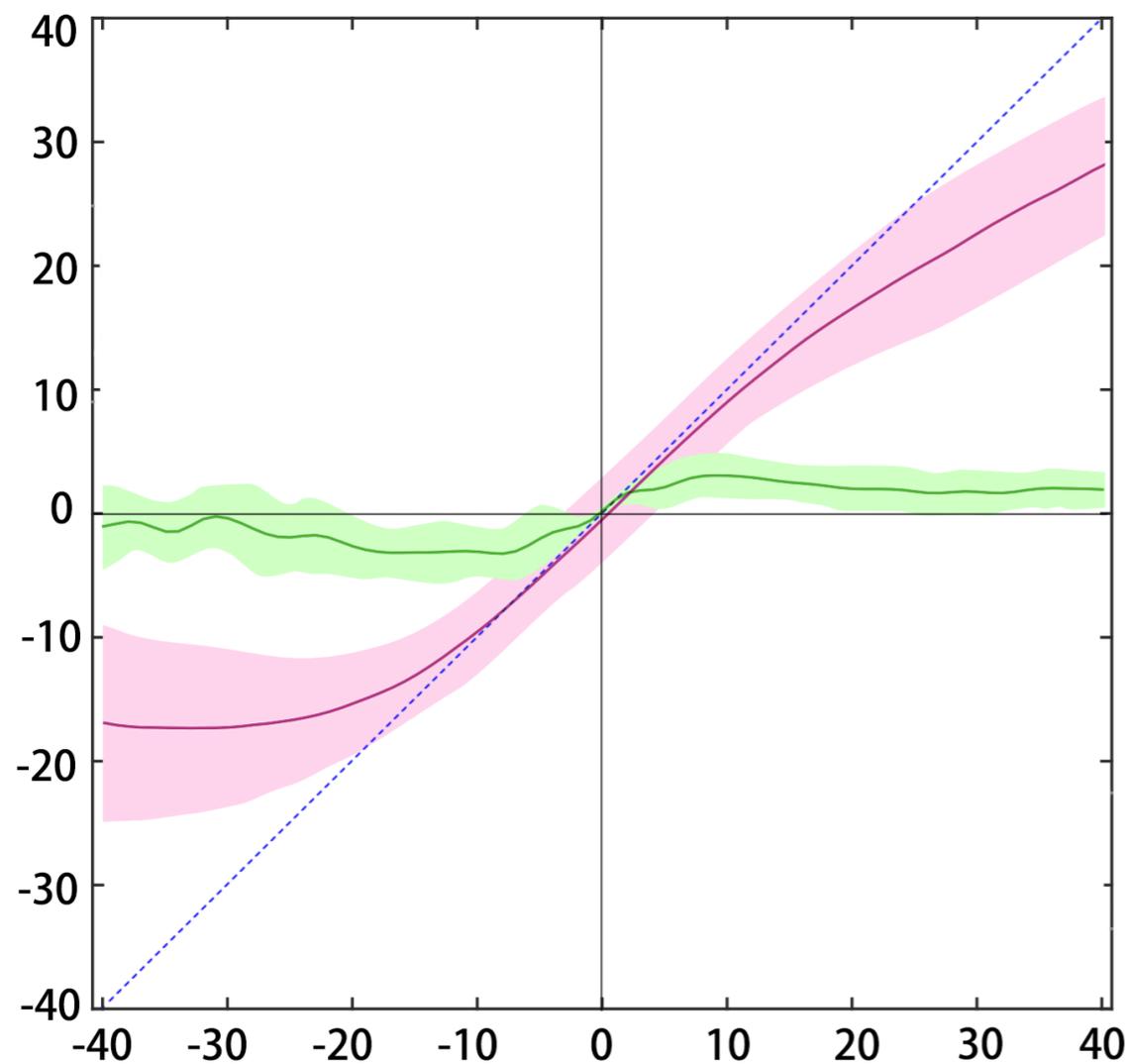
- **What** is multi-scale local features

A landmark can be described by local features at multiple scales, we combine them for a more comprehensive description



Convergence range and precision at multiple scales

■ Why multi-scale

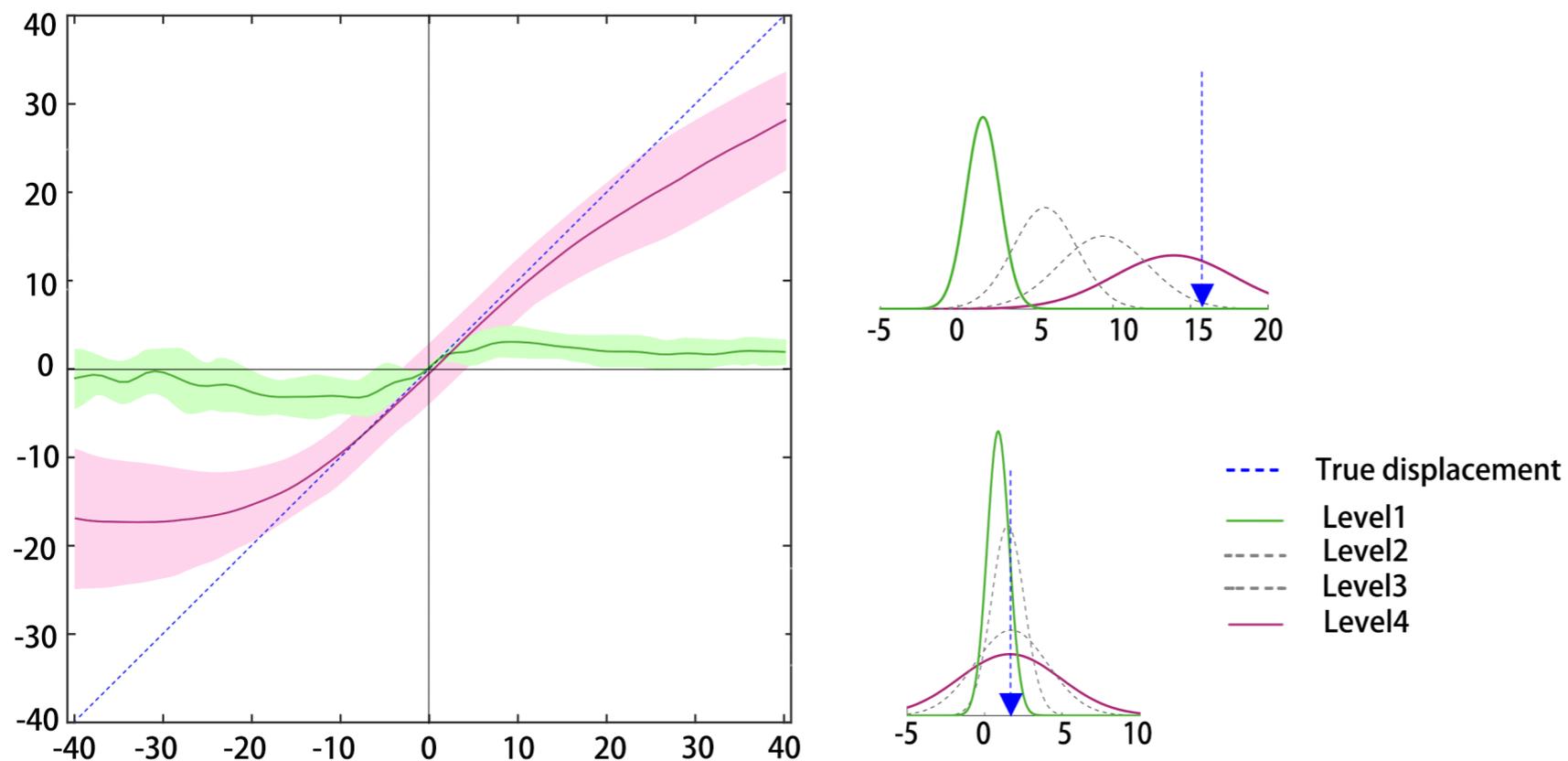


- True displacement
- Level1
- - - Level2
- - - Level3
- Level4

Combine multi-scale local features

■ Product of Gaussian

likelihood: $p(\Delta x) \sim \{\mathcal{N}(\Delta x_1, \sigma_1^2), \dots, \mathcal{N}(\Delta x_L, \sigma_L^2)\}$



Combine multi-scale local features

■ **How** to combine the multi-level observations

likelihood: $p(\Delta x) \sim \{\mathcal{N}(\Delta x_1, \sigma_1^2), \dots, \mathcal{N}(\Delta x_L, \sigma_L^2)\}$

$$E_{image}(\mathbf{s}) = \frac{1}{2}(\mathbf{s} - \hat{\mathbf{s}})^T \Sigma^{-1}(\mathbf{s} - \hat{\mathbf{s}})$$

$$E_{image}(\mathbf{s}) = \frac{1}{2} \sum_{l=1}^L (\mathbf{s} - \hat{\mathbf{s}}_l)^T \Sigma_l^{-1} (\mathbf{s} - \hat{\mathbf{s}}_l),$$

An optimal shape with respect to multiple observations of landmarks at multi-scales

Shape optimisation vs. standard shape constraint

	DtoTB (pixels)			DSC (%)		
	<i>Rect.</i> [1]	<i>Ellip.</i> [13]	<i>Our</i>	<i>Rect.</i> [1]	<i>Ellip.</i> [13]	<i>Our</i>
Vertebra						
$m = 40$	2.6±1.2	2.6±1.0	2.5±1.1	95.3±2.1	95.7±1.8	95.6±2.3
$m = 20$	3.1±1.3	2.9±1.1	2.7±1.0	94.3±3.1	94.1±2.2	95.0±3.5
$m = 10$	4.1±1.9	4.2±2.5	3.1±1.1	92.0±3.0	91.8±3.6	93.9±2.1
$m = 5$	7.7±2.6	7.7±2.9	5.0±1.7	84.1±6.4	84.2±6.7	88.7±4.0
Knee						
$m = 20$	2.7±1.2	2.7±1.3	2.2±0.7	97.4±1.3	97.6±1.2	97.9±0.7
$m = 10$	4.3±2.7	3.5±2.5	2.7±1.0	96.3±3.2	96.7±2.6	97.6±1.0
$m = 7$	5.5±3.0	3.7±2.5	3.0±1.3	94.3±4.9	96.3±2.5	97.3±1.1
$m = 5$	7.2±3.2	4.9±2.6	4.0±2.5	92.5±4.3	94.9±3.2	96.6±1.8

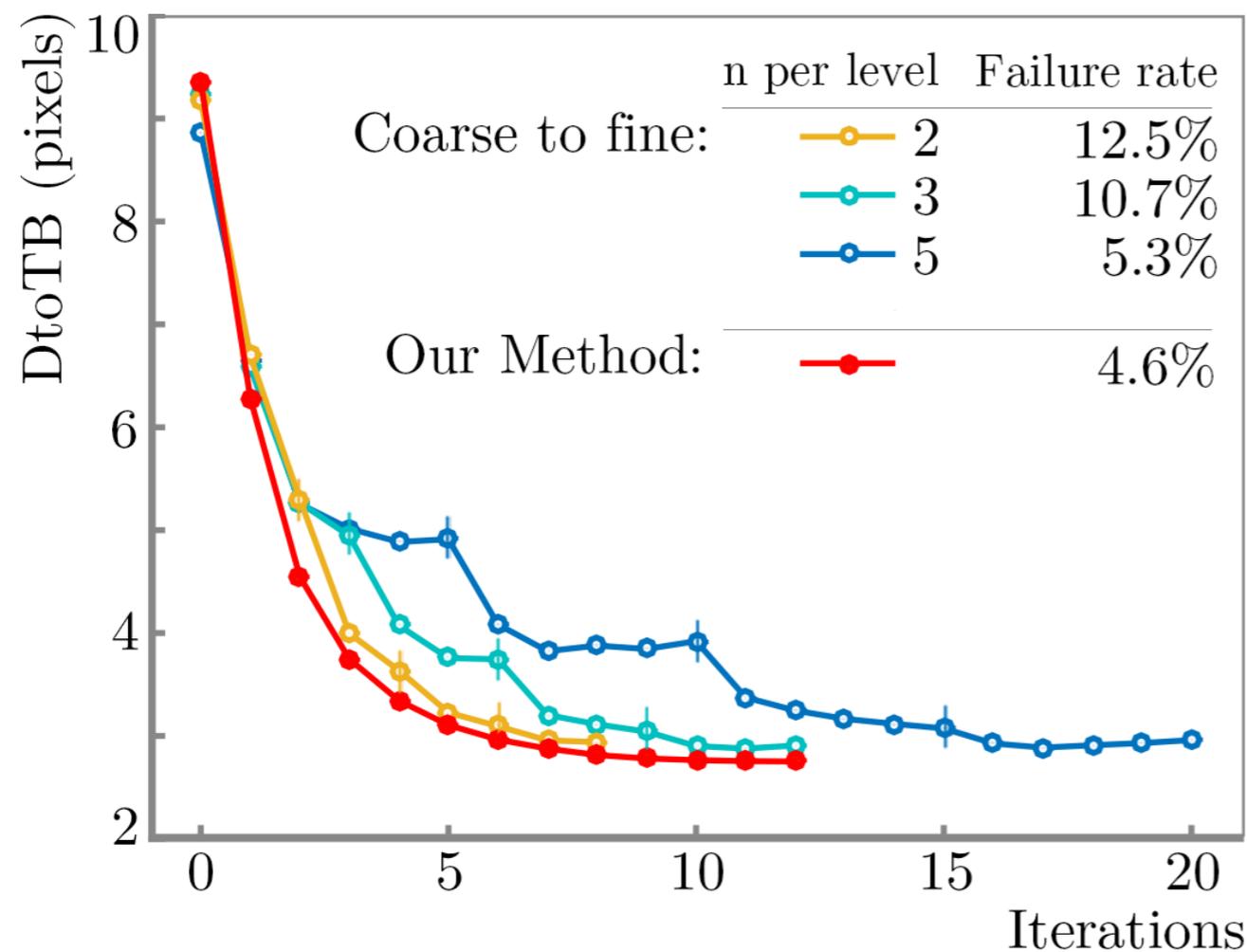
Performance of three methods on segmentation of vertebrae and knees, trained with reducing m samples

[1] Cootes, Timothy F., et al. "Active shape models-their training and application." *Computer vision and image understanding* 61.1 (1995): 38-59.

[13] Cerrolaza, Juan J., Arantxa Villanueva, and Rafael Cabeza. "Shape Constraint Strategies: Novel Approaches and Comparative Robustness." *BMVC*. 2011.

Multi-scale vs. coarse-to-fine

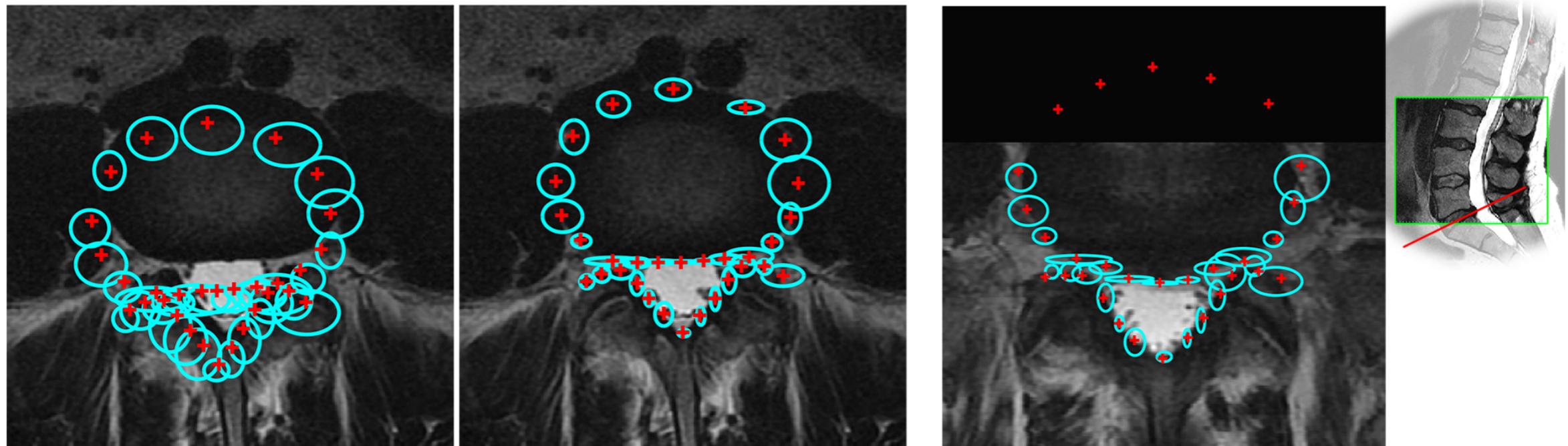
■ Convergence speed



Convergence speed and failure rate of multi-scale strategy compared with coarse-to-fine methods

Multi-scale vs. coarse-to-fine

■ Local feature variances and robustness



(a) Initial position

(b) Converged

(c) Partial occlusion

- Cyan ellipses show the variance of observations, red crosses show the optimal shape. Salient features have smaller variances therefore larger weights.

Conclusion

- Higher precision in local feature searching.
- Better performance with limited training samples.

Shape is optimal in a statistical sense taking both the shape prior and feature confidence into consideration. The detail of salient features is better preserved

- Seamless and rapid convergence process.

Converge faster with lower failure rate. Larger scale features keep the shape from local minima, while the smaller scales take effect as soon as it gets into the convergence range.

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Thank you