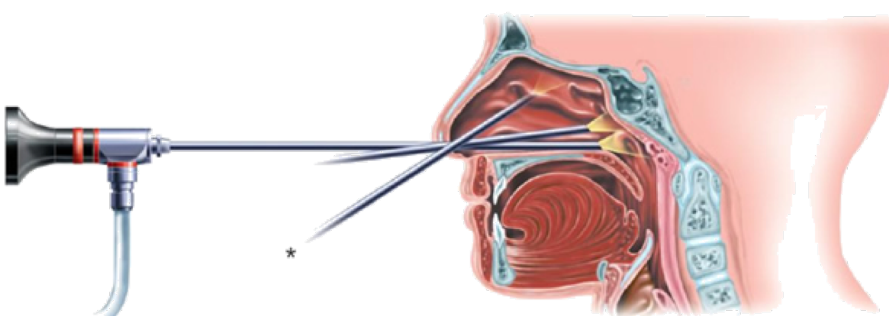
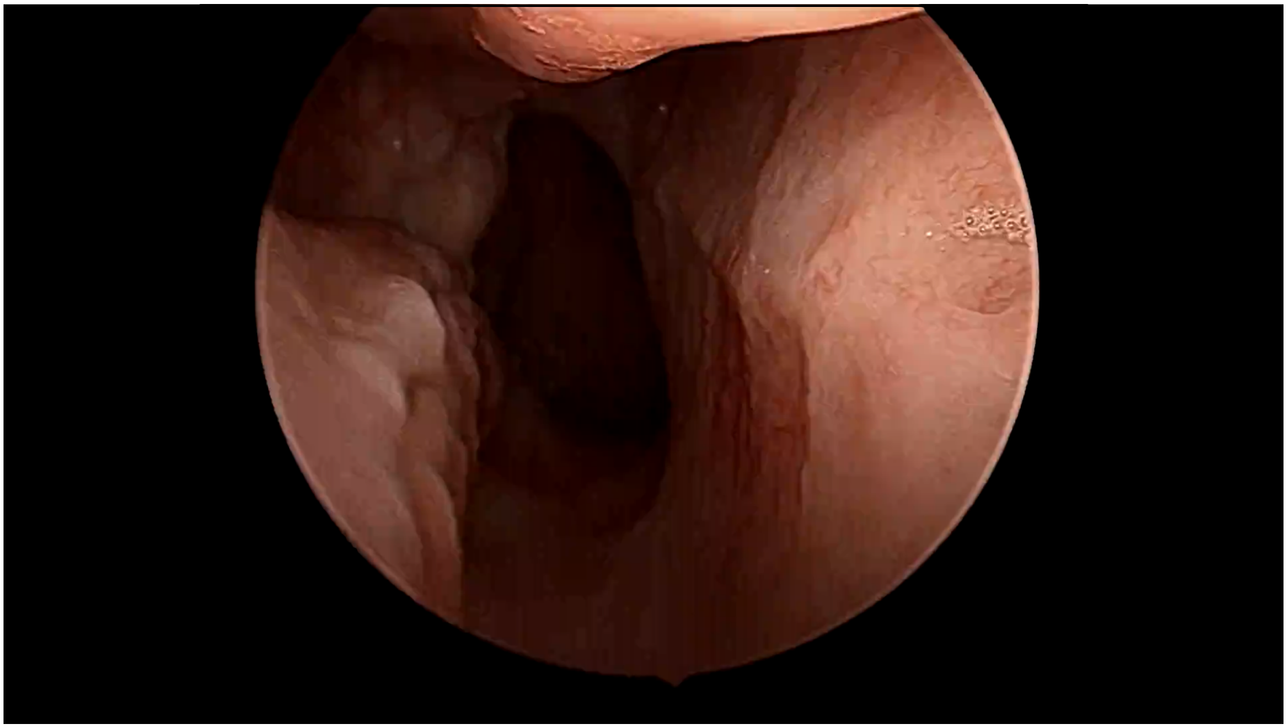
Enhanced endoscopic navigation using shape statistics in the absence of CT imaging

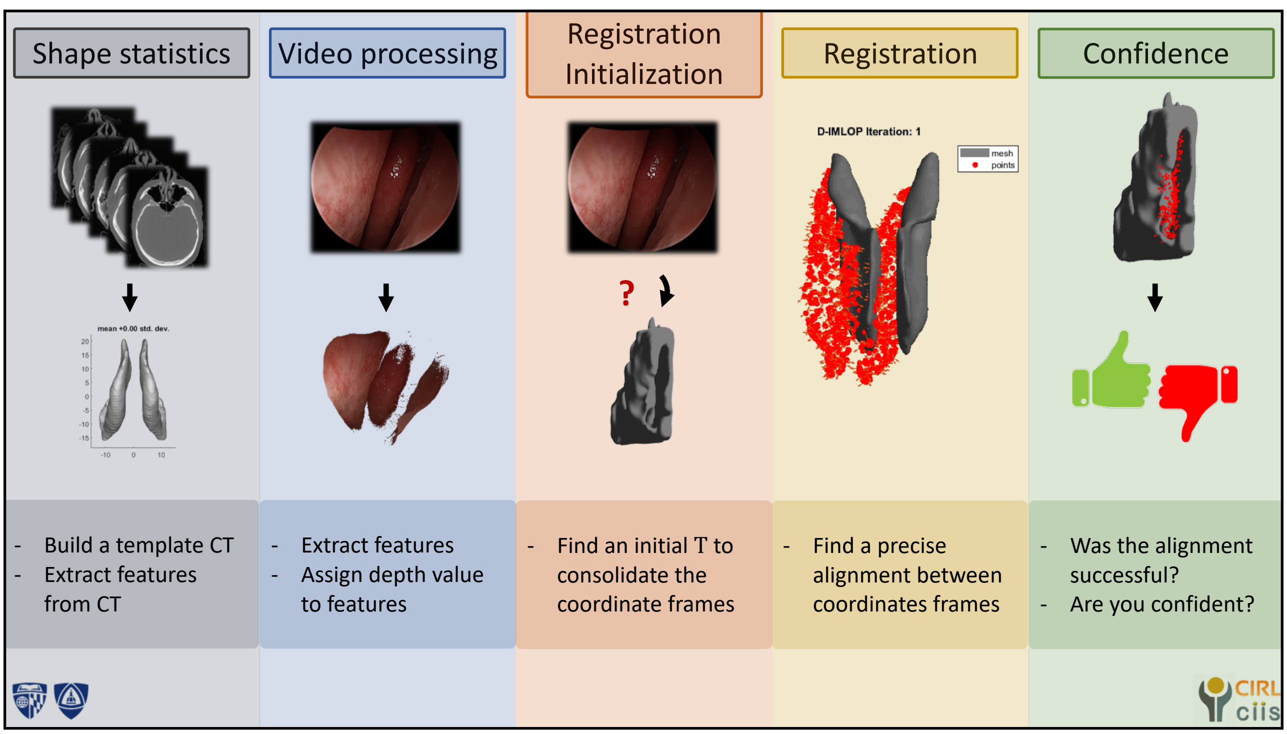
Ayushi Sinha
Provost's Postdoctoral Fellow, LCSR

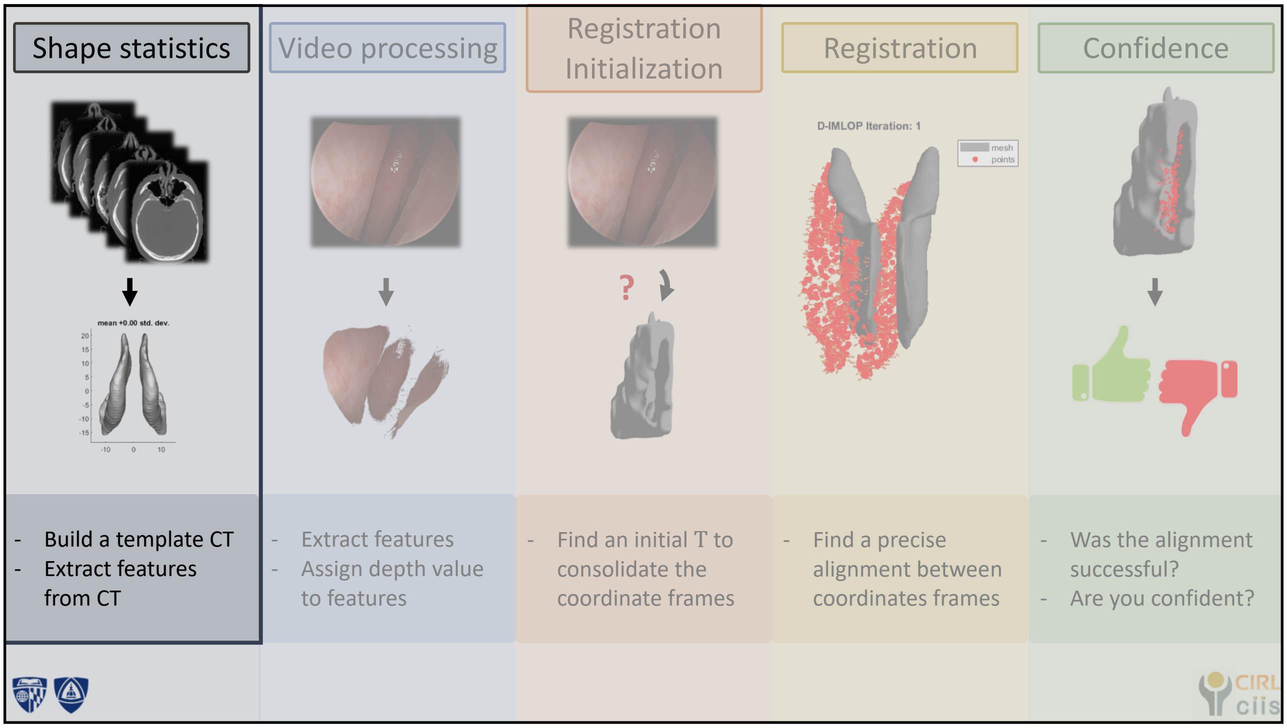
Minimally invasive surgeries though the nasal cavity



G. Scadding et al., *Diagnostic tools in Rhinology EAACI position paper*, Clinical and Translational Allergy, **1**(2), 2011




Shape statistics
Video processing
Registration Initialization
Registration
Confidence
D-IMLOP Iteration: 1
mesh
points
mean +0.00 std. dev.
?
- Build a template CT
- Extract features from CT
- Extract features
- Assign depth value to features
- Find an initial T to consolidate the coordinate frames
- Find a precise alignment between coordinates frames
- Was the alignment successful?
- Are you confident?
CIRL
ciis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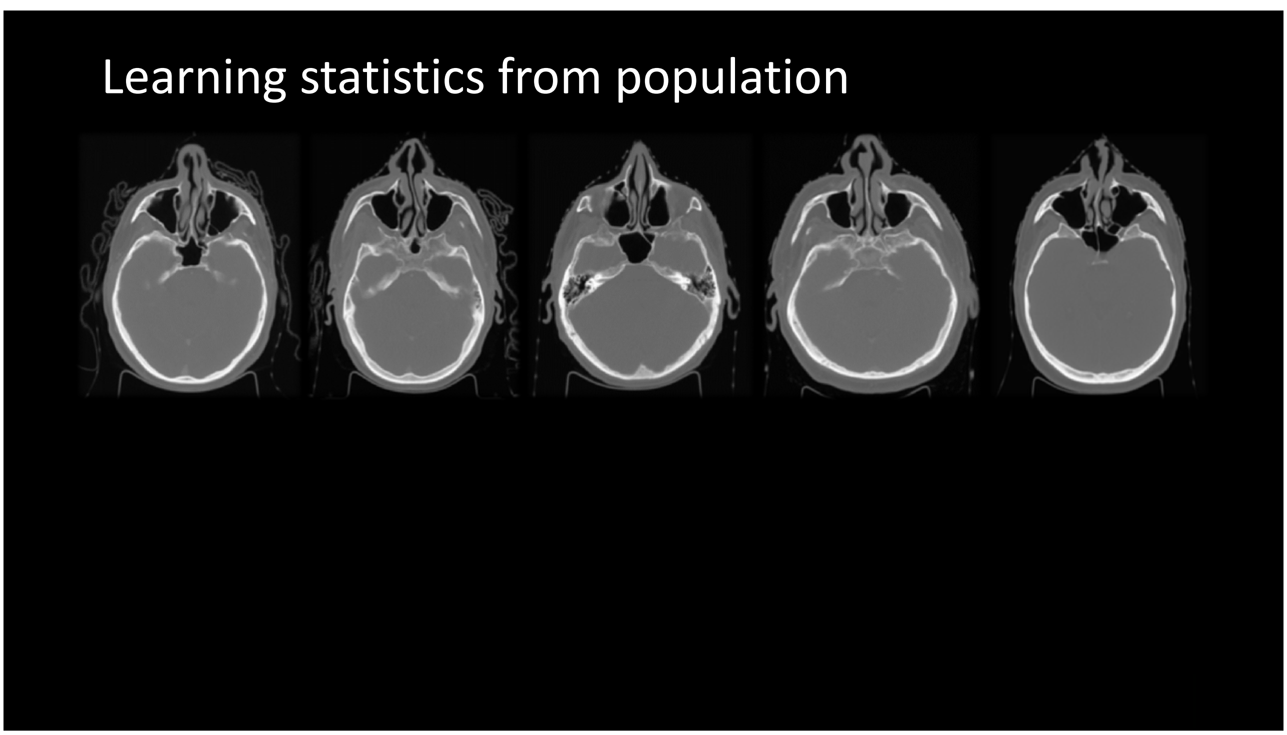
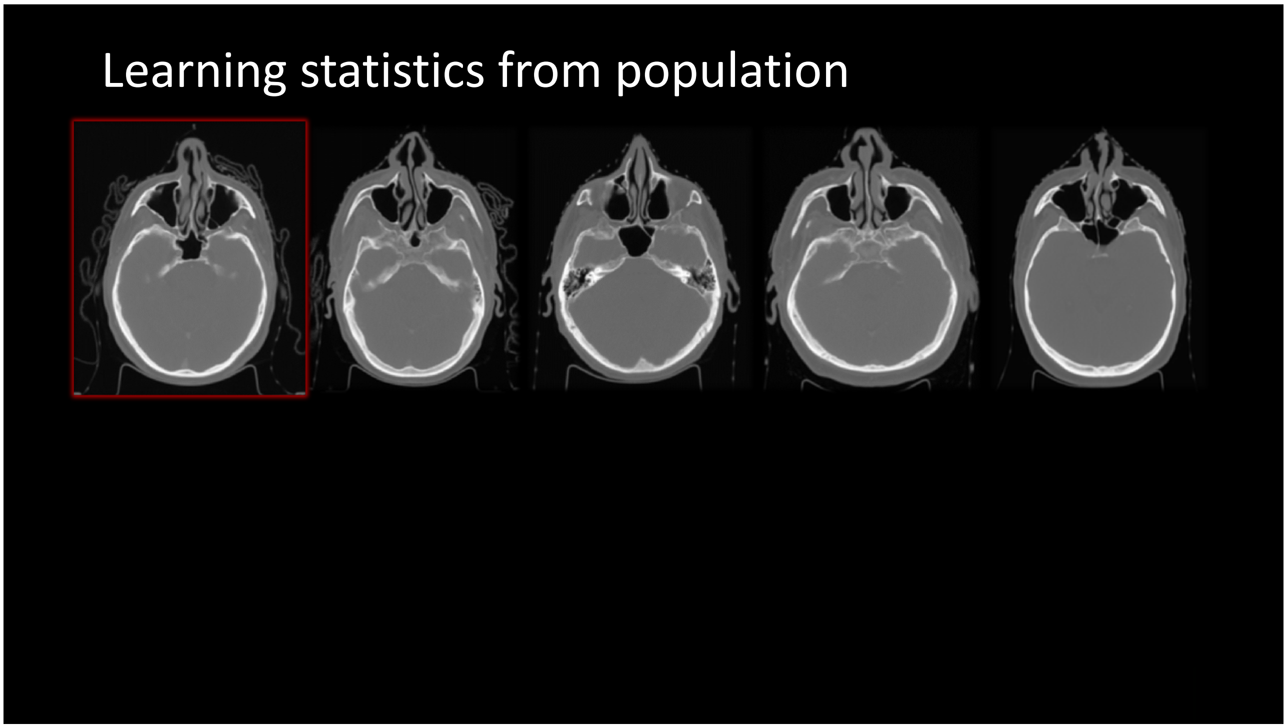

Learning statistics from population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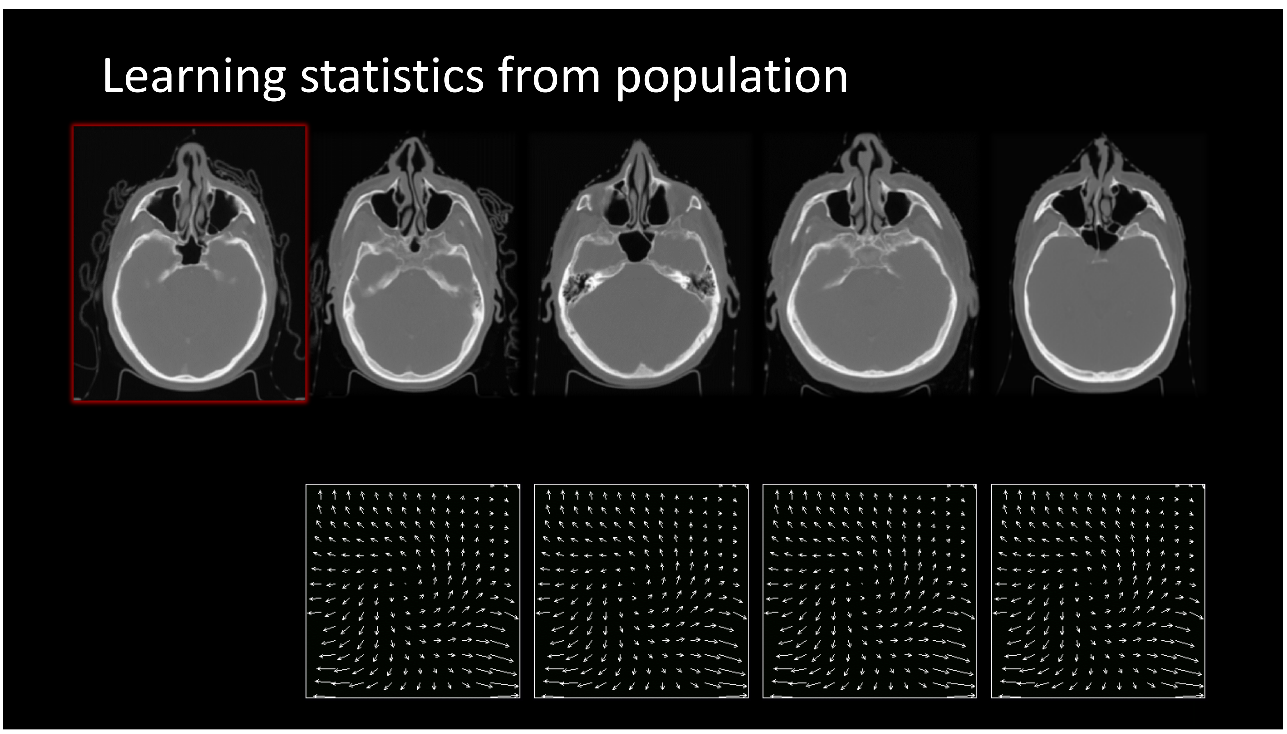
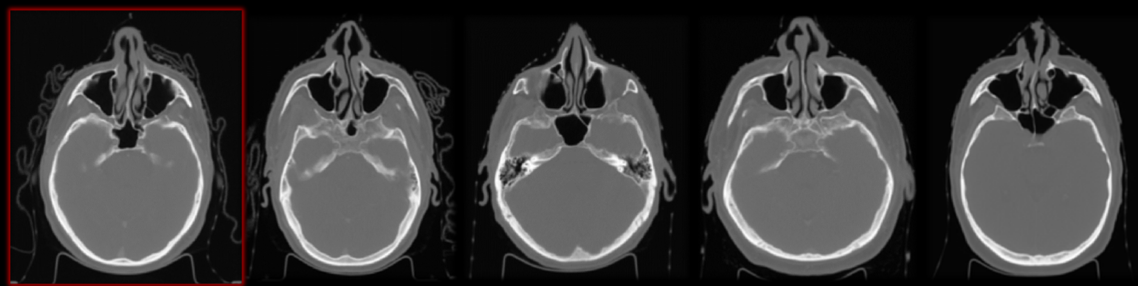
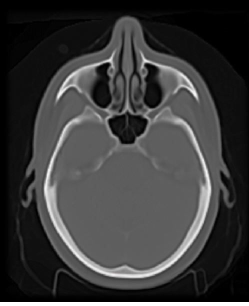

Learning statistics from population

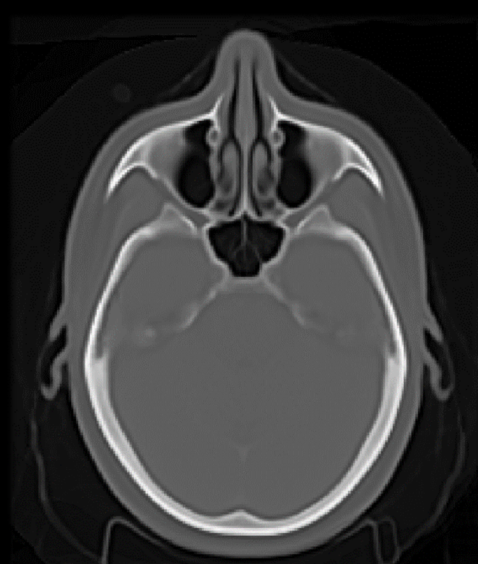
Learning statistics from population





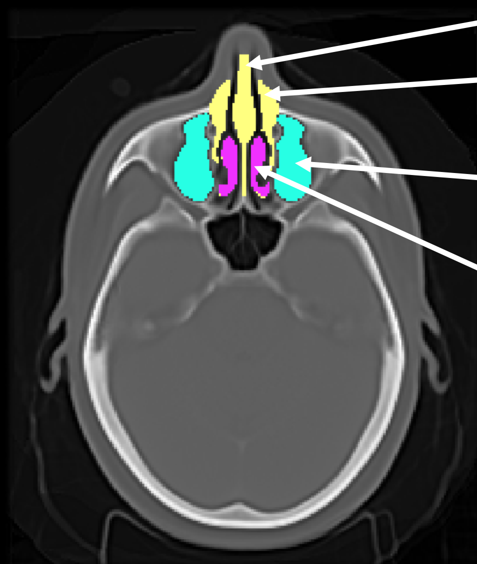
Template CT

Learning statistics from population



Template CT

Learning statistics from population



Template CT

Learning statistics from population

- Given shapes, $\mathbf{V} = [\mathbf{v}_1 \ \mathbf{v}_2 \ldots \mathbf{v}_{\mathbf{n}_v}]^\mathbf{T}$, with correspondences, we can compute the principal components:

- Mean:

$$\bar{\mathbf{V}} = \frac{1}{n_\mathbf{s}} \sum_{i=1}^{n_\mathbf{s}} \mathbf{V}_i$$

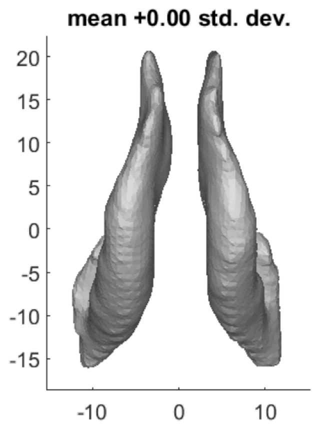
- Variance:

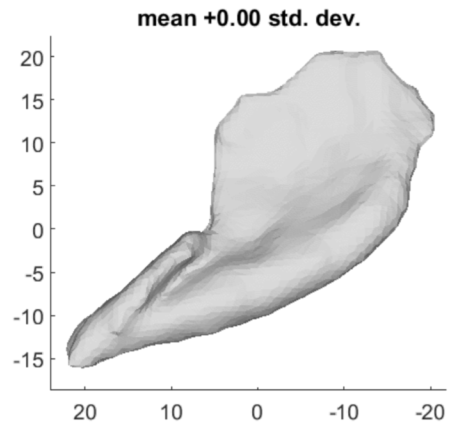
$$\boldsymbol{\Sigma} = \frac{1}{n_\mathbf{s}} \sum_{i=1}^{n_\mathbf{s}} (\mathbf{V}_i - \bar{\mathbf{V}})(\mathbf{V}_i - \bar{\mathbf{V}})^\mathbf{T}$$

$$\boldsymbol{\Sigma} = [\mathbf{m}_1 \ldots \mathbf{m}_{n_s}] \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_{n_s} \end{bmatrix} [\mathbf{m}_1 \ldots \mathbf{m}_{n_s}]^\mathbf{T}$$

Learning statistics from population

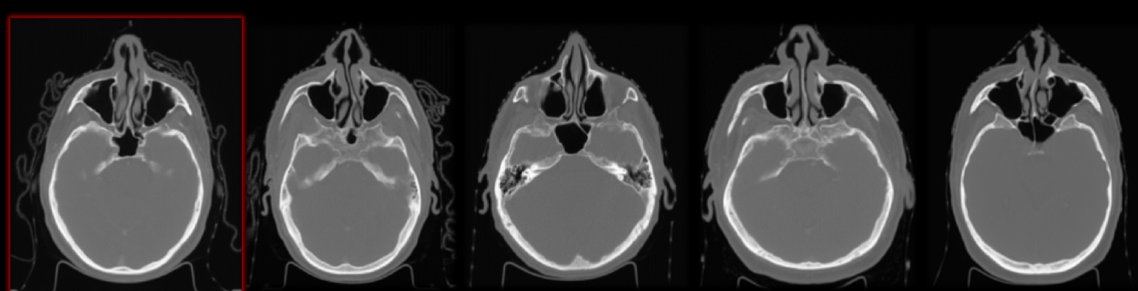
Built from ~50 CT scans

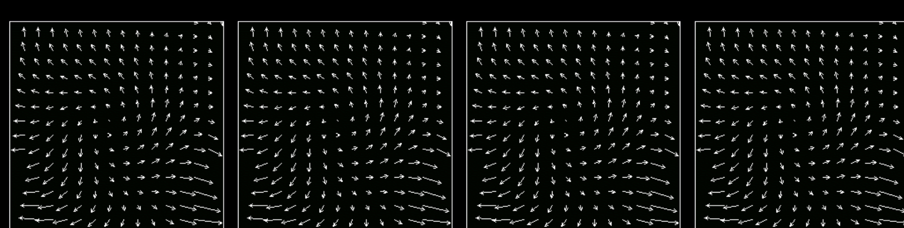




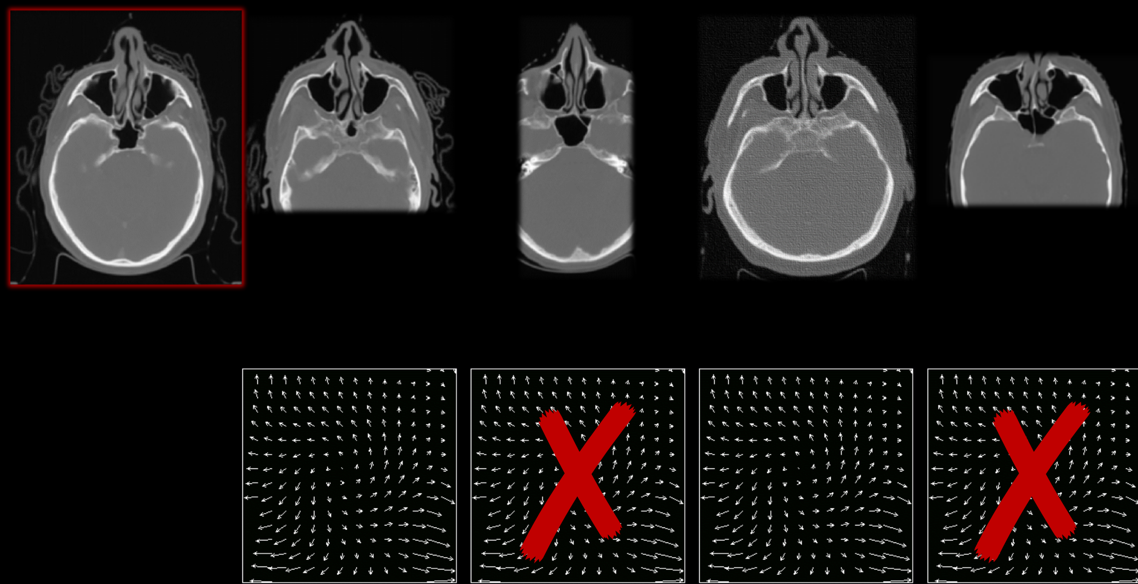
Can we scale up to **~5000** CT scans?

Learning statistics from population





Learning statistics from population



Did the registration work?

This CVPR2015 paper is the Open Access version, provided by the Computer Vision Foundation.
The authoritative version of this paper is available in IEEE Xplore.

Learning to Compare Image Patches via Convolutional Neural Networks

Sergey Zagoruyko
Universite Paris Est, Ecole des Ponts ParisTech
sergey.zagoruyko@imagine.enpc.fr

Nikos Komodakis
Universite Paris Est, Ecole des Ponts ParisTech
nikos.komodakis@enpc.fr

Abstract

In this paper we show how to learn directly from image data (i.e., without resorting to manually-designed features) a general similarity function for comparing image patches, which is a task of fundamental importance for many computer vision problems. To encode such a function, we opt for a CNN-based model that is trained to account for a wide variety of changes in image appearance. To that end, we explore and study multiple neural network architectures, which are specifically adapted to this task. We show that such an approach can significantly outperform the state-of-the-art on several problems and benchmark datasets.

1. Introduction

Comparing patches across images is probably one of the most fundamental tasks in computer vision and image anal-

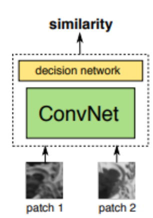
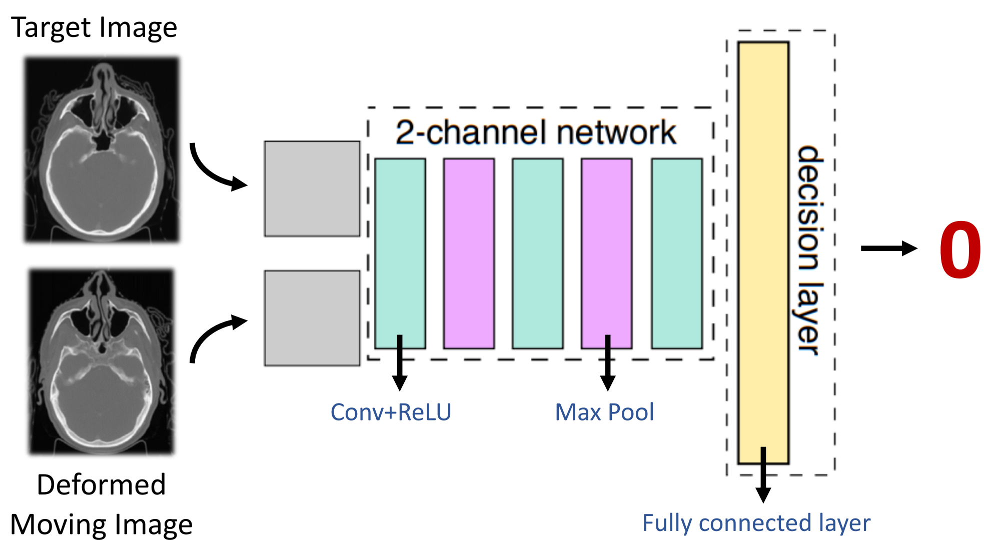


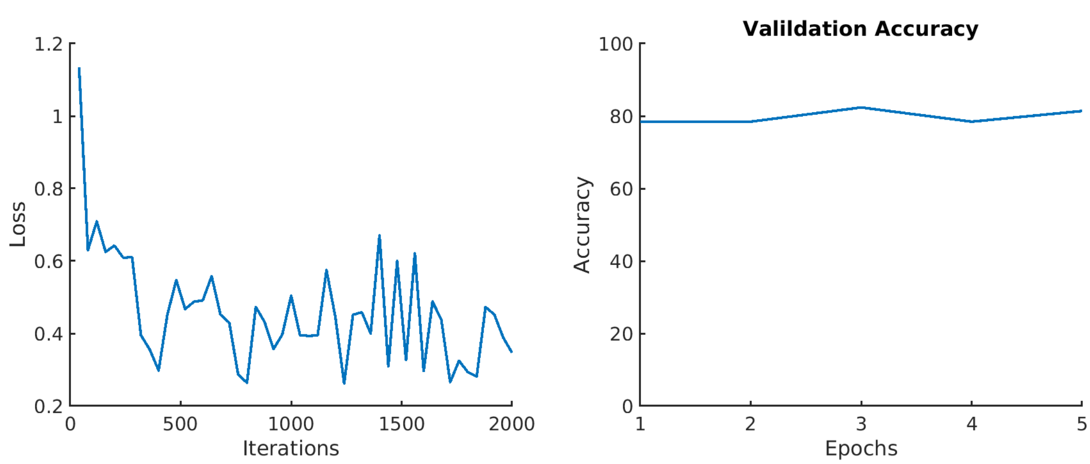
Figure 1. Our goal is to learn a general similarity function for image patches. To encode such a function, here we make use of and explore convolutional neural network architectures.

software) large datasets that contain patch correspondences between images [22]. This begs the following question: can

Did the registration work?

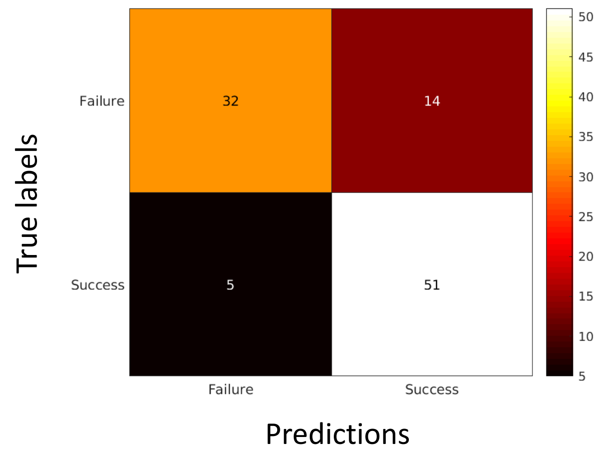


Did the registration work?



Test Accuracy = 81%

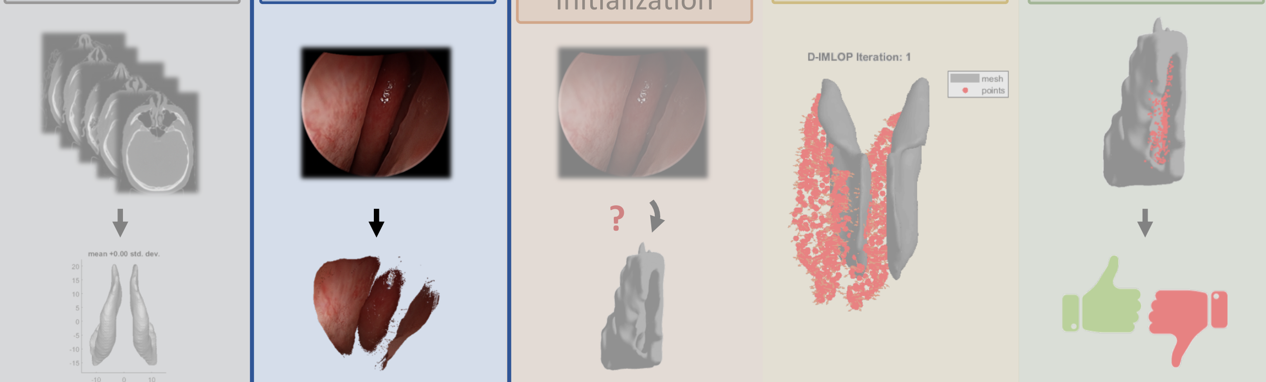
Did the registration work?



69.57% failure classification

91.07% success classification

Shape statistics	Video processing	Registration Initialization	Registration	Confidence



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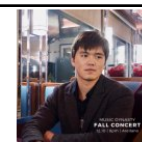
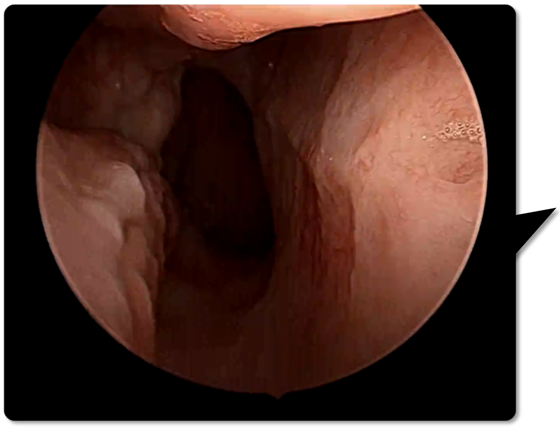
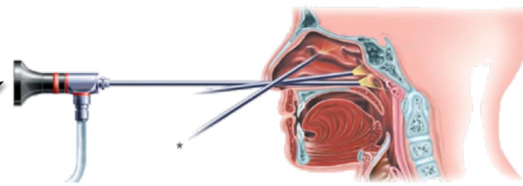
Feature extraction from video







G. Scadding et al., *Diagnostic tools in Rhinology EAACI position paper*, Clinical and Translational Allergy, 1(2), 2011

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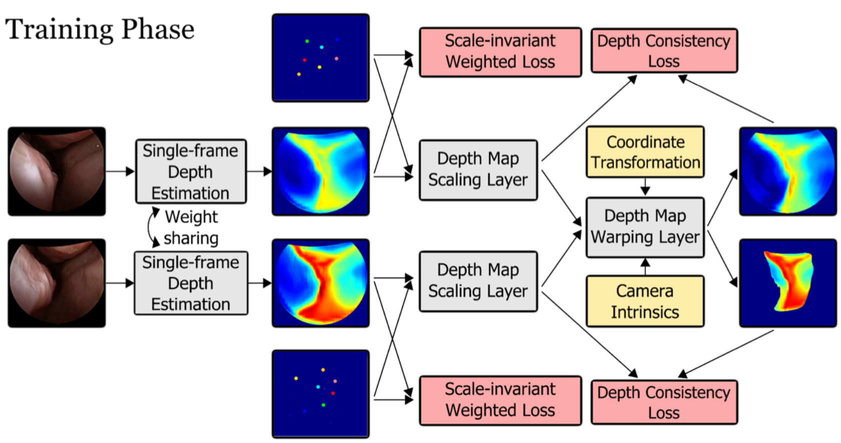
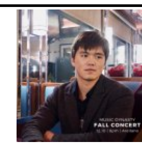
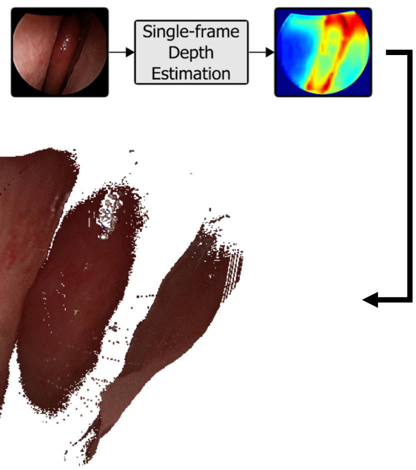


Feature extraction from video

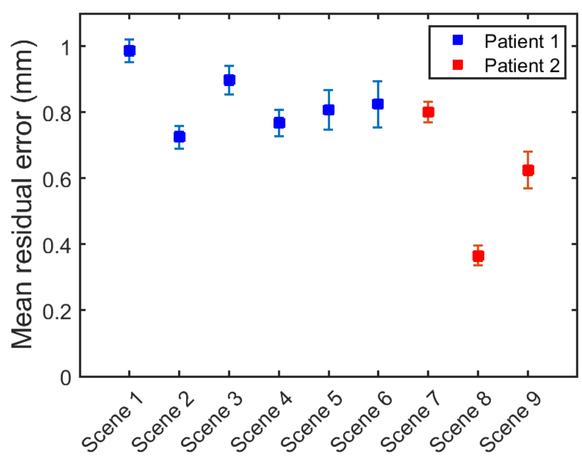


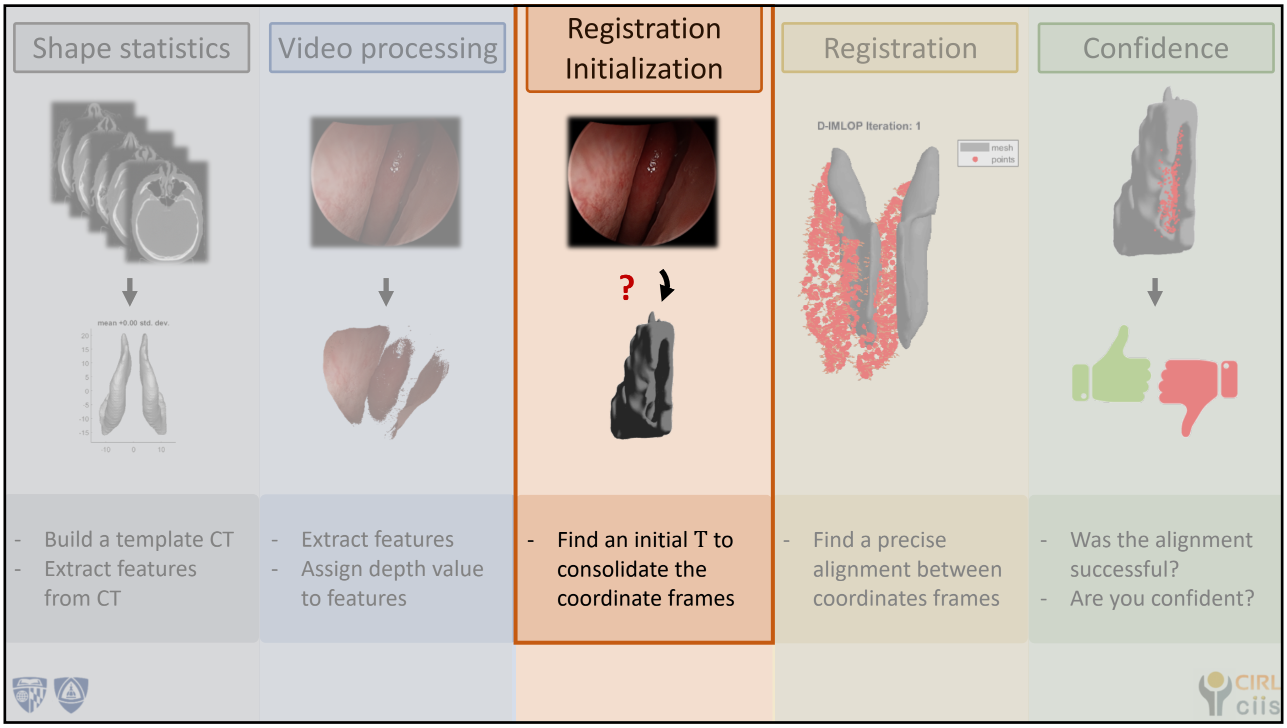
Application Phase



Dense point cloud

Feature extraction from video

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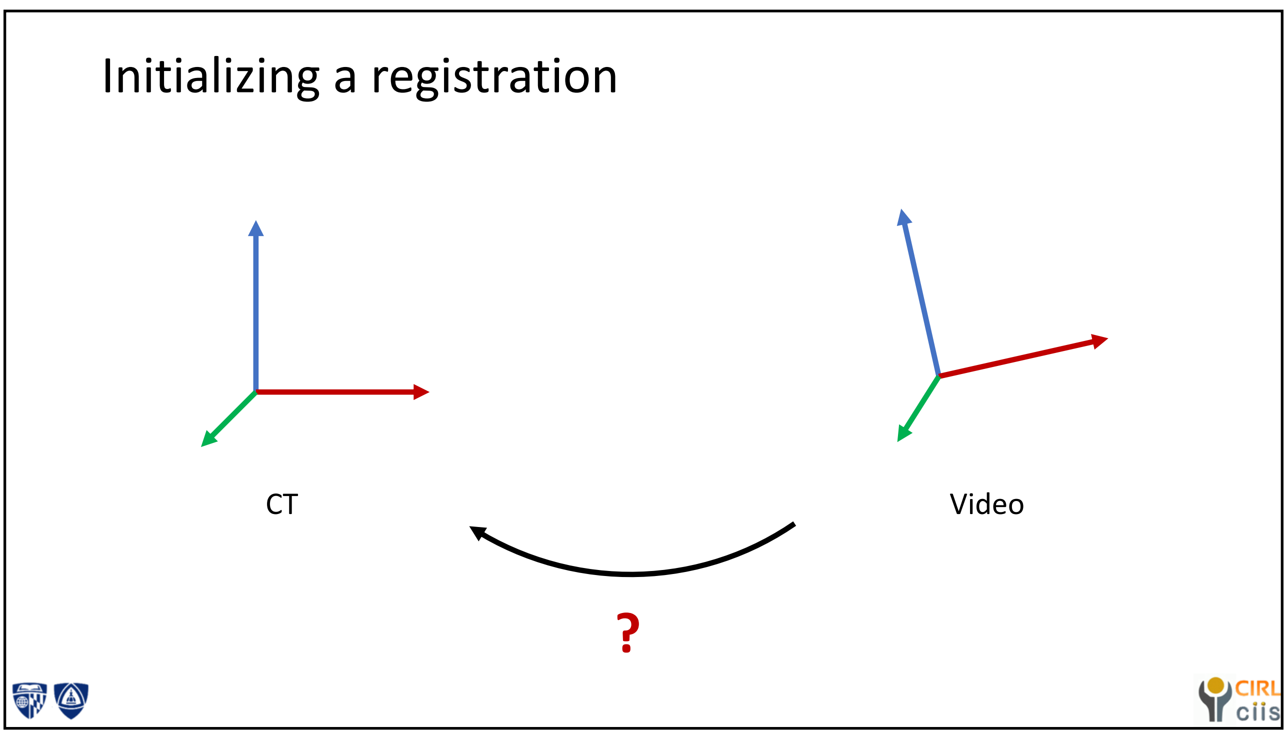
Initializing a registration
CT
Video
?
CIRL
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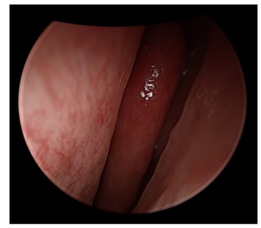
Initializing a registration

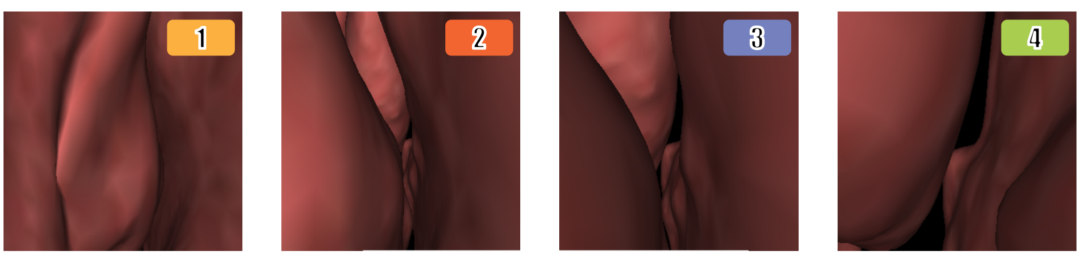
CT

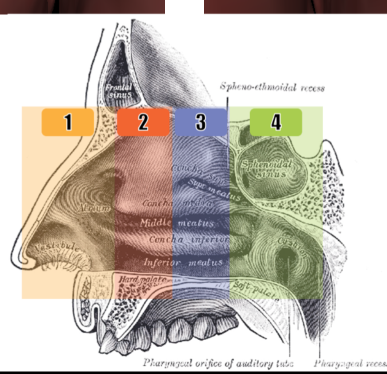


Video

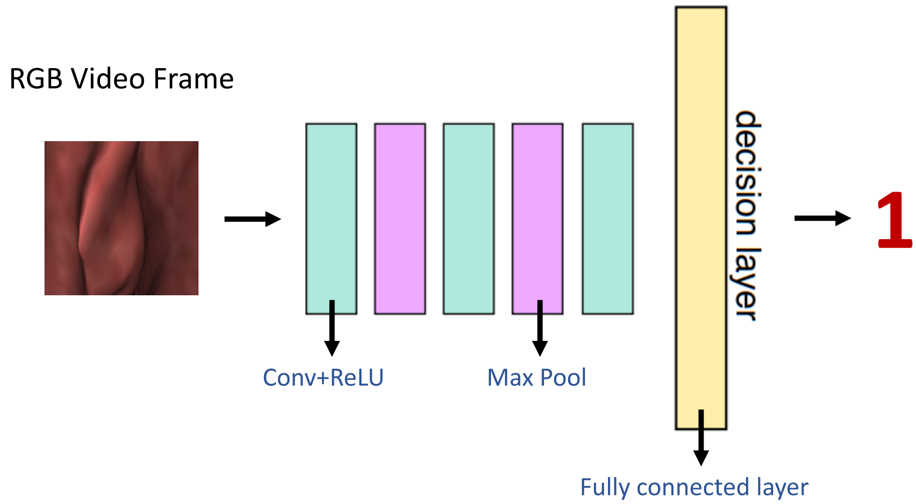
?

Coarse pose classification

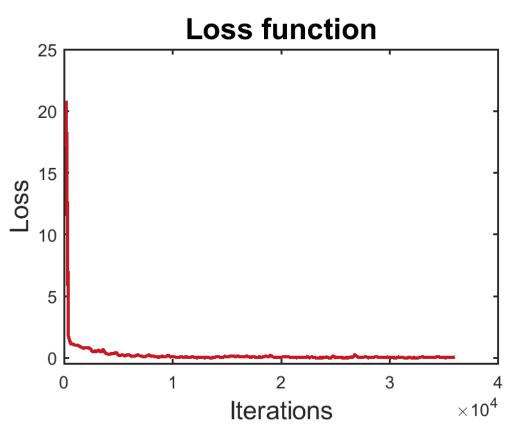


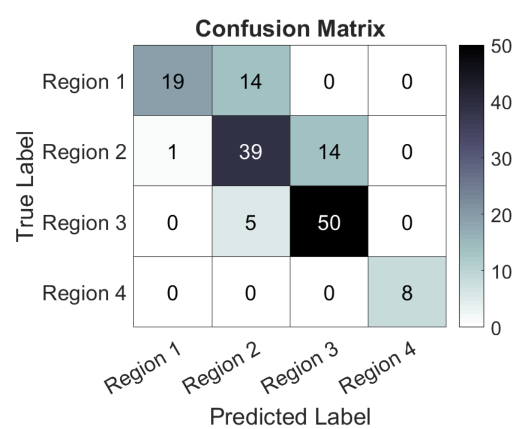


Coarse pose classification



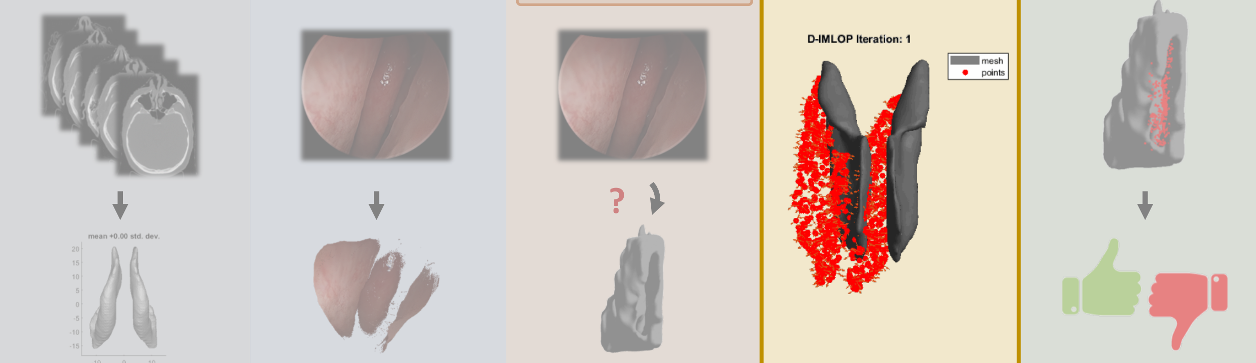
Coarse pose classification





Mean accuracy over 5 runs = 76.53 (± 1.19)%

Shape statistics	Video processing	Registration Initialization	Registration	Confidence



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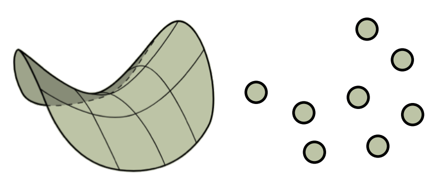
Iterative **closest** point (ICP) algorithm

Find closest point match on Ψ for all X

Compute transformation to align matches



$\mathrm{y}_i \in \Psi$ $\qquad$ $\mathrm{X} = \{\mathrm{x}_i\}$

$$\mathbf{T} = \underset{[\mathbf{R},\mathbf{t}]}{\operatorname{argmin}} \sum_{i=1}^{n} \|\mathbf{y}_i - \mathbf{R}\mathbf{x}_i - \mathbf{t}\|_2^2$$

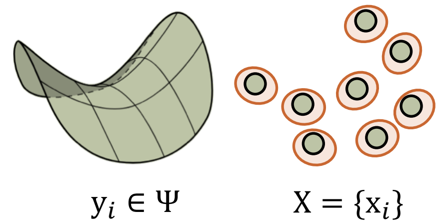
P. J. Besl, et al., *A method for registration of 3-d shapes*, Trans. PAMI, 1992

32

Iterative **most likely** point (IMLP) algorithm

Find most likely point match on Ψ for all X

Compute transformation to align matches



$$\mathbf{T} = \underset{[\mathbf{R},\mathbf{t}]}{\operatorname{argmin}} \sum_{i=1}^{n} (\mathbf{y}_i - \mathbf{R}\mathbf{x}_i - \mathbf{t})^{\mathsf{T}} (\mathbf{R}\Sigma_{\mathrm{x}i}\mathbf{R}^{\mathsf{T}})^{-1} (\mathbf{y}_i - \mathbf{R}\mathbf{x}_i - \mathbf{t})$$

S. D. Billings, et al., *Iterative most-likely point registration (IMLP): A robust algorithm for computing optimal shape alignment*, PLOS ONE, 2015

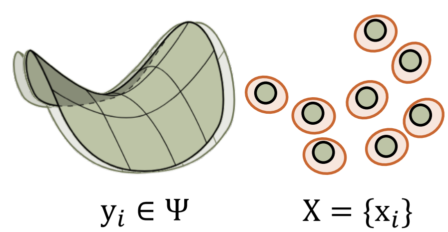
33

Deformable iterative most likely point (D-IMLP) algorithm

Find most likely point match on Ψ for all X

Compute transformation to align matches

and deform Ψ to fit to X

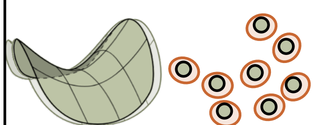


A Sinha, et al., *The deformable most-likely-point paradigm*, Medical Image Analysis, 2018 (*in submission*)

34

Deformable iterative most likely point (D-IMLP) algorithm

$$\mathrm{T} = \underset{[a,\mathbf{R},\mathbf{t}],\mathbf{s}}{\operatorname{argmin}} \left(\frac{1}{2} \sum_{i=1}^{n_{\text{data}}} \left((\mathrm{T}_{\text{ssm}}(\mathbf{y}_i) - a\mathbf{R}\mathbf{x}_i - \mathbf{t})^{\mathbf{T}} (\mathbf{R}\boldsymbol{\Sigma}_{\mathrm{x}_i}\mathbf{R}^{\mathbf{T}})^{-1} (\mathrm{T}_{\text{ssm}}(\mathbf{y}_i) - a\mathbf{R}\mathbf{x}_i - \mathbf{t}) \right) + \frac{1}{2} \sum_{j=1}^{n_{\mathrm{m}}} \|s_j\|_2^2 \right)$$



$\mathrm{y}_i \in \Psi$ $\quad$ $\mathrm{X} = \{\mathrm{x}_i\}$

$$\mathrm{T}_{\text{ssm}}(\mathbf{y}_i) = f(\mathrm{y_i}, \mathrm{s})$$

A Sinha, et al., *The deformable most-likely-point paradigm*, Medical Image Analysis, 2018 (*in submission*) 35

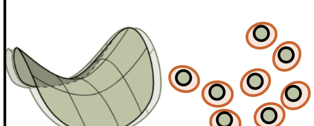
Deformable iterative most likely point (D-IMLP) algorithm

$$\mathrm{T} = \underset{[a,\mathbf{R},\mathbf{t}],\mathbf{s}}{\operatorname{argmin}} \left(\frac{1}{2} \sum_{i=1}^{n_{\text{data}}} \left((\mathrm{T}_{\text{ssm}}(\mathbf{y}_i) - a\mathbf{R}\mathbf{x}_i - \mathbf{t})^{\mathbf{T}} (\mathbf{R}\boldsymbol{\Sigma}_{\mathrm{x}_i}\mathbf{R}^{\mathbf{T}})^{-1} (\mathrm{T}_{\text{ssm}}(\mathbf{y}_i) - a\mathbf{R}\mathbf{x}_i - \mathbf{t}) \right)\right.$$

Find R, t and a such that x is best aligned with a deformed y

$$\left. + \frac{1}{2} \sum_{j=1}^{n_{\mathrm{m}}} \|s_j\|_2^2 \right)$$

Find s such that y deforms to fit x



$\mathrm{y}_i \in \Psi$ $\quad$ $\mathrm{X} = \{\mathrm{x}_i\}$

$$\mathrm{T}_{\text{ssm}}(\mathbf{y}_i) = f(\mathrm{y_i}, \mathrm{s})$$

A Sinha, et al., *The deformable most-likely-point paradigm*, Medical Image Analysis, 2018 (*in submission*) 36

Deformable iterative most likely **oriented** point (D-IMLOP) algorithm

$$\mathrm{T} = \underset{[a,\mathbf{R},\mathbf{t}],\mathbf{s}}{\operatorname{argmin}} \left(\frac{1}{2} \sum_{i=1}^{n_{\text{data}}} (\mathrm{T}_{\text{ssm}}(\mathbf{y}_{\mathbf{p}_i}) - a\mathbf{R}\mathbf{x}_{i\mathbf{p}} - \mathbf{t})^{\mathbf{T}} (\mathbf{R}\,\Sigma_{\text{x}}\mathbf{R}^{\mathbf{T}})^{-1} (\mathrm{T}_{\text{ssm}}(\mathbf{y}_{\mathbf{p}_i}) - a\mathbf{R}\mathbf{x}_{\mathbf{p}_i} - \mathbf{t}) \right.$$

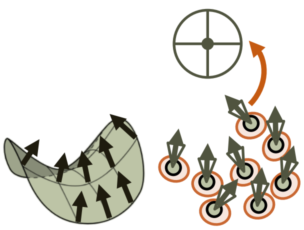
Find R, t and a such that x is best aligned with a deformed y…

$$+\kappa \sum_{i=1}^{n_{\text{data}}} (1 - \hat{\mathbf{y}}_{\mathbf{n}_i}\mathbf{R}\hat{\mathbf{x}}_{\mathbf{n}_i})$$

and such that the normal of y aligns with that of x

$$\left. + \frac{1}{2} \sum_{j=1}^{n_{\text{m}}} \|s_j\|_2^2 \right)$$

Find s such that y deforms to fit x



$y_i \in \Psi$ $\mathrm{X} = \{\mathrm{x}_i\}$

$$\mathrm{T}_{\text{ssm}}(\mathbf{y}_i) = f(\mathrm{y_i}, \mathrm{s}), \quad \kappa_0 = \frac{1}{\sigma^2_{\text{circ\_rad}}}$$

A Sinha, et al., *The deformable most-likely-point paradigm*, Medical Image Analysis, 2018 (*in submission*) 37

Generalized deformable iterative most likely oriented point (GD-IMLOP) algorithm

$$\mathrm{T} = \underset{[a,\mathbf{R},\mathbf{t}],\mathbf{s}}{\operatorname{argmin}} \left(\frac{1}{2} \sum_{i=1}^{n_{\text{data}}} (\mathrm{T}_{\text{ssm}}(\mathbf{y}_{\mathbf{p}_i}) - a\mathbf{R}\mathbf{x}_{i\mathbf{p}} - \mathbf{t})^{\mathbf{T}} (\mathbf{R}\,\Sigma_{\text{x}}\mathbf{R}^{\mathbf{T}})^{-1} (\mathrm{T}_{\text{ssm}}(\mathbf{y}_{\mathbf{p}_i}) - a\mathbf{R}\mathbf{x}_{\mathbf{p}_i} - \mathbf{t}) \right.$$

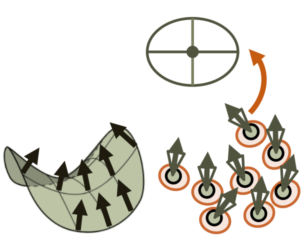
Find R, t and a such that x is best aligned with a deformed y…

$$- \sum_{i=1}^{n_{\text{data}}} \left(\kappa_i \hat{\mathbf{y}}_{\mathbf{n}_i}\mathbf{R}\hat{\mathbf{x}}_{\mathbf{n}_i} + \beta_i \left(\left(\hat{\gamma}_{1_i}{}^{\mathbf{T}}\mathbf{R}^{\mathbf{T}}\hat{\mathbf{y}}_{\mathbf{n}_i} \right)^2 - \left(\hat{\gamma}_{2_i}{}^{\mathbf{T}}\mathbf{R}^{\mathbf{T}}\hat{\mathbf{y}}_{\mathbf{n}_i} \right)^2 \right) \right)$$

and such that the normal of y aligns with that of x

$$\left. + \frac{1}{2} \sum_{j=1}^{n_{\text{m}}} \|s_j\|_2^2 \right)$$

Find s such that y deforms to fit x



$y_i \in \Psi$ $\mathrm{X} = \{\mathrm{x}_i\}$

$$\mathrm{T}_{\text{ssm}}(\mathbf{y}_i) = f(\mathrm{y_i}, \mathrm{s}), \quad \kappa_0 = \frac{1}{\sigma^2_{\text{circ\_rad}}}, \quad \beta = e\,\frac{\kappa}{2}$$

A Sinha, et al., *The deformable most-likely-point paradigm*, Medical Image Analysis, 2018 (*in submission*) 38

What is $T_{ssm}(y_i)$?

- Given shapes, $\mathbf{V} = [\mathbf{v}_1 \ \mathbf{v}_2 \ldots \mathbf{v}_{\mathbf{n}_v}]^{\mathbf{T}}$, with correspondences, we can compute the principal components:

- Mean:

$$\bar{\mathbf{V}} = \frac{1}{n_\mathbf{s}} \sum_{i=1}^{n_\mathbf{s}} \mathbf{V}_i$$

- Variance:

$$\boldsymbol{\Sigma} = \frac{1}{n_\mathbf{s}} \sum_{i=1}^{n_\mathbf{s}} (\mathbf{V}_i - \bar{\mathbf{V}})(\mathbf{V}_i - \bar{\mathbf{V}})^{\mathbf{T}}$$

$$\boldsymbol{\Sigma} = [\mathbf{m}_1 \ldots \mathbf{m}_{n_s}] \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_{n_\mathbf{s}} \end{bmatrix} [\mathbf{m}_1 \ldots \mathbf{m}_{n_s}]^{\mathbf{T}}$$

What is $T_{ssm}(y_i)$?

- Given a new shape, $\mathbf{V}^*$, we can compute:

- Mode weights:

$$s_i = \mathbf{w}_i^{\mathrm{T}} (\mathbf{V}^* - \bar{\mathbf{V}})$$

$$\mathbf{w}_i = \sqrt{\lambda_i} \mathbf{m}_i$$

- Estimated shape:

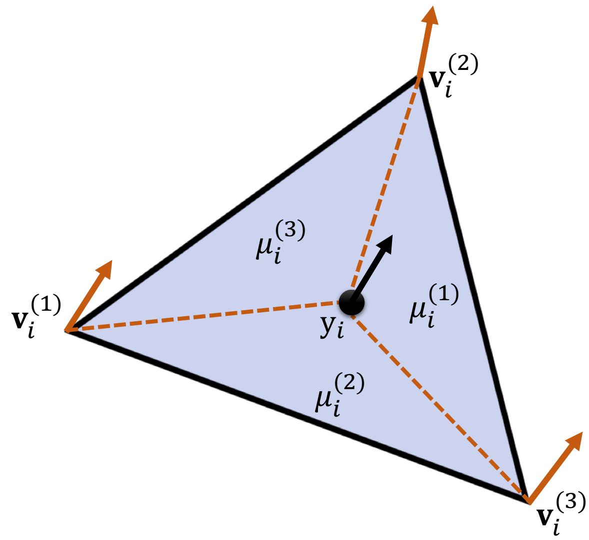
$$\tilde{\mathbf{V}}^* = \bar{\mathbf{V}} + \sum_{i=1}^{n_\mathbf{m}} s_i \mathbf{w}_i$$

What is $T_{ssm}(y_i)$?

$$\mathrm{T}_{\mathrm{ssm}}(\mathbf{v}_i) = \bar{\mathbf{v}}_i + \sum_{j=1}^{n_{\mathbf{m}}} s_j \mathbf{w}_j^{(i)}$$

$$\mathrm{T}_{\mathrm{ssm}}(\mathbf{y}_i) = \sum_{j=1}^{3} \mu_i^{(j)} \mathrm{T}_{\mathrm{ssm}}(\mathbf{v}_i^{(j)})$$

$$\sum_{j=1}^{3} \mu^{(j)} = 1$$



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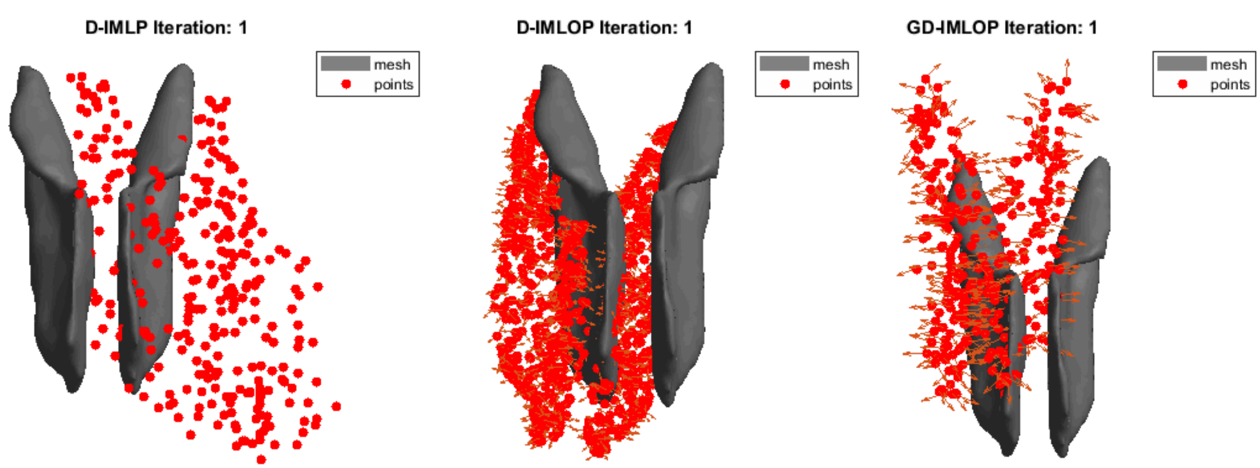
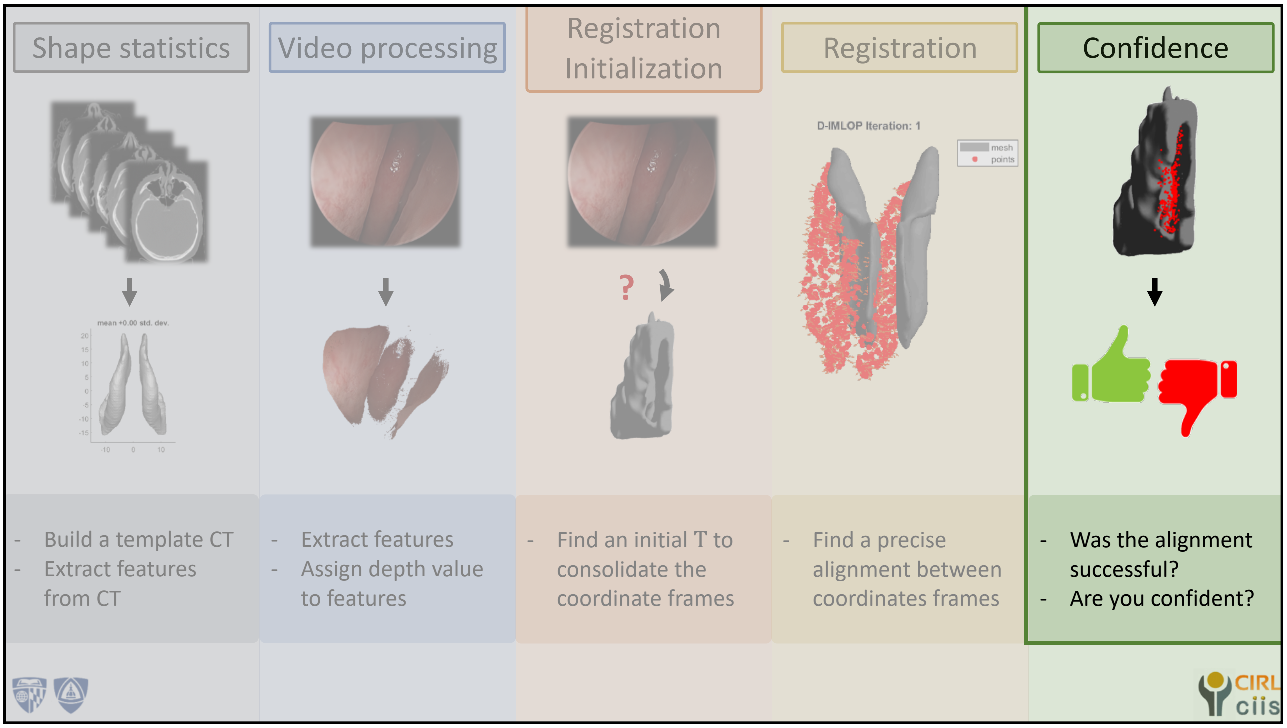
41

Deformable most likely point paradigm

- Deformable most likely point paradigm

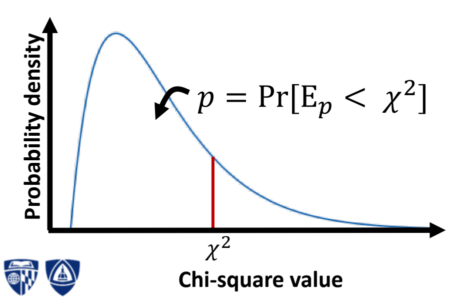




Again, did the registration work?

$$\mathrm{E}_p = \sum_{i=1}^{n_{\mathrm{data}}} \Big((\mathrm{T}_{\mathrm{ssm}}(\mathbf{y}_i) - a\mathbf{R}\mathbf{x}_i - \mathbf{t})^{\mathrm{T}} (\mathbf{R}\boldsymbol{\Sigma}_{\mathbf{x}_i}\mathbf{R}^{\mathrm{T}})^{-1} (\mathrm{T}_{\mathrm{ssm}}(\mathbf{y}_i) - a\mathbf{R}\mathbf{x}_i - \mathbf{t}) \Big) \approx \chi^2 \text{ distribution}$$

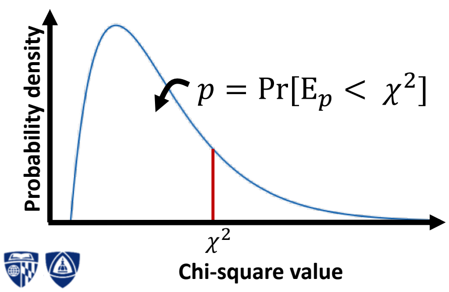
$$\mathrm{E}_o = \sum_{i=1}^{n_{\mathrm{data}}} \begin{bmatrix} \cos^{-1}(\hat{\mathbf{y}}_{\mathbf{n}_i}{}^{\mathrm{T}}\mathbf{R}\hat{\mathbf{x}}_{\mathbf{n}_i}) \\ \sin^{-1}(\hat{\gamma}_{1_i}{}^{\mathrm{T}}\mathbf{R}^{\mathrm{T}}\hat{\mathbf{y}}_{\mathbf{n}_i}) \\ \sin^{-1}(\hat{\gamma}_{2_i}{}^{\mathrm{T}}\mathbf{R}^{\mathrm{T}}\hat{\mathbf{y}}_{\mathbf{n}_i}) \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} \kappa_i & 0 & 0 \\ 0 & \kappa_i - 2\beta_i & 0 \\ 0 & 0 & \kappa_i + 2\beta_i \end{bmatrix} \begin{bmatrix} \cos^{-1}(\hat{\mathbf{y}}_{\mathbf{n}_i}{}^{\mathrm{T}}\mathbf{R}\hat{\mathbf{x}}_{\mathbf{n}_i}) \\ \sin^{-1}(\hat{\gamma}_{1_i}{}^{\mathrm{T}}\mathbf{R}^{\mathrm{T}}\hat{\mathbf{y}}_{\mathbf{n}_i}) \\ \sin^{-1}(\hat{\gamma}_{2_i}{}^{\mathrm{T}}\mathbf{R}^{\mathrm{T}}\hat{\mathbf{y}}_{\mathbf{n}_i}) \end{bmatrix} \approx \chi^2 \text{ distribution}$$



Again, did the registration work?

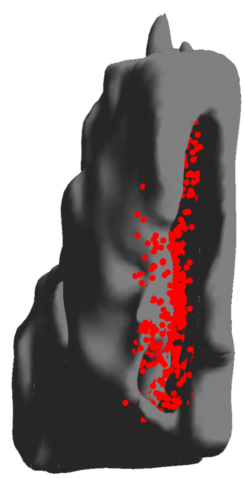
$$\mathrm{E}_p = \sum_{i=1}^{n_{\mathrm{data}}} \left((\mathrm{T}_{\mathrm{ssm}}(\mathbf{y}_i) - a\mathbf{R}\mathbf{x}_i - \mathbf{t})^{\mathrm{T}} (\mathbf{R}\boldsymbol{\Sigma}_{\mathrm{x}_i}\mathbf{R}^{\mathrm{T}})^{-1} (\mathrm{T}_{\mathrm{ssm}}(\mathbf{y}_i) - a\mathbf{R}\mathbf{x}_i - \mathbf{t}) \right) \leq \mathrm{chi2inv}(p, 3n_{\mathrm{data}})$$

$$\mathrm{E}_o = \sum_{i=1}^{n_{\mathrm{data}}} \begin{bmatrix} \cos^{-1}\left(\hat{\mathbf{y}}_{\mathbf{n}_i}{}^{\mathrm{T}}\mathbf{R}\hat{\mathbf{x}}_{\mathbf{n}_i}\right) \\ \sin^{-1}\left(\hat{\gamma}_{1_i}{}^{\mathrm{T}}\mathbf{R}^{\mathrm{T}}\hat{\mathbf{y}}_{\mathbf{n}_i}\right) \\ \sin^{-1}\left(\hat{\gamma}_{2_i}{}^{\mathrm{T}}\mathbf{R}^{\mathrm{T}}\hat{\mathbf{y}}_{\mathbf{n}_i}\right) \end{bmatrix}^{\mathrm{T}} \begin{bmatrix} \kappa_i & 0 & 0 \\ 0 & \kappa_i - 2\beta_i & 0 \\ 0 & 0 & \kappa_i + 2\beta_i \end{bmatrix} \begin{bmatrix} \cos^{-1}\left(\hat{\mathbf{y}}_{\mathbf{n}_i}{}^{\mathrm{T}}\mathbf{R}\hat{\mathbf{x}}_{\mathbf{n}_i}\right) \\ \sin^{-1}\left(\hat{\gamma}_{1_i}{}^{\mathrm{T}}\mathbf{R}^{\mathrm{T}}\hat{\mathbf{y}}_{\mathbf{n}_i}\right) \\ \sin^{-1}\left(\hat{\gamma}_{2_i}{}^{\mathrm{T}}\mathbf{R}^{\mathrm{T}}\hat{\mathbf{y}}_{\mathbf{n}_i}\right) \end{bmatrix} \leq \mathrm{chi2inv}(p, 2n_{\mathrm{data}})$$



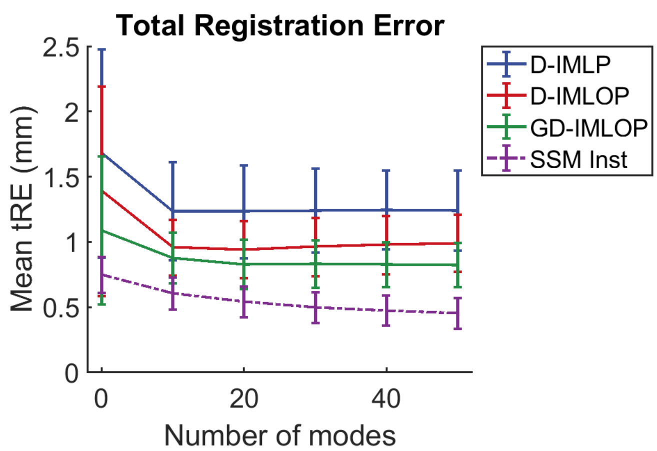
Leave-one-out analysis

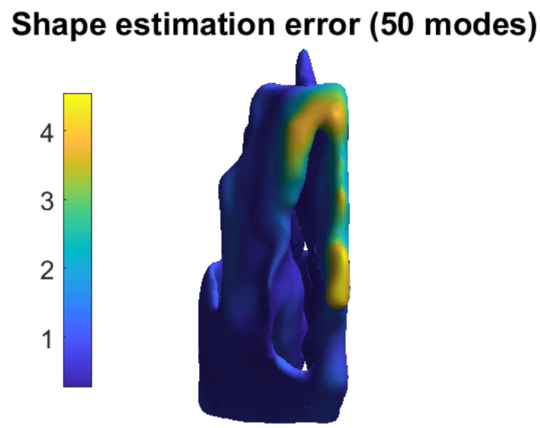
- # sample point: 3000
- Translational offset: [0, 10] mm
- Rotational offset: [0, 10] degrees
- Noise:
  - $0.5 \times 0.5 \times 0.75 \mathrm{mm}^3$
  - $10° \ (e = 0.5)$
- Noise assumed:
  - $1 \times 1 \times 2 \mathrm{mm}^3$
  - $30° \ (e = 0.5)$
- $n_{\mathbf{m}} \in \{0, 10, 20, 30, 40, 50\}$



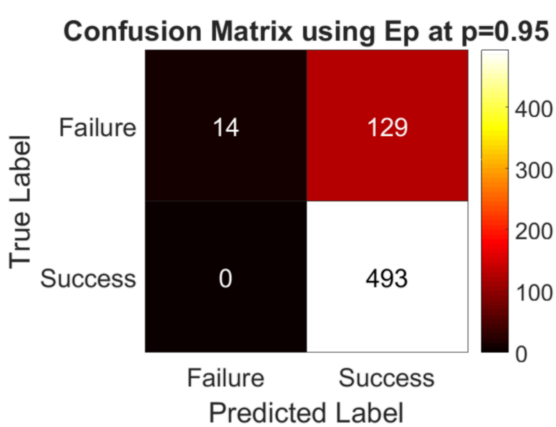
Right nasal airway

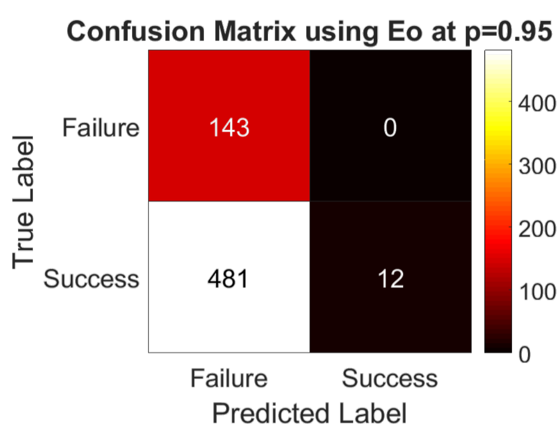
Leave-one-out analysis



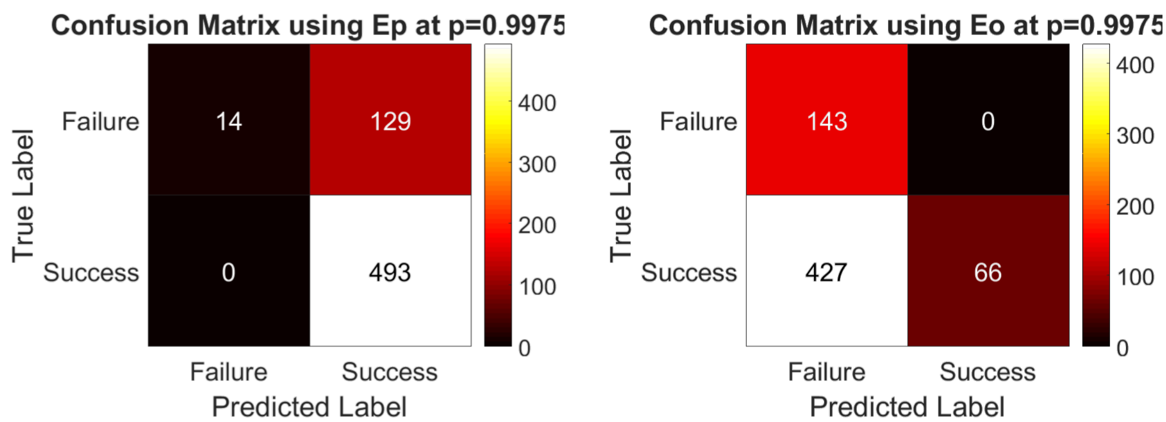


Leave-one-out analysis

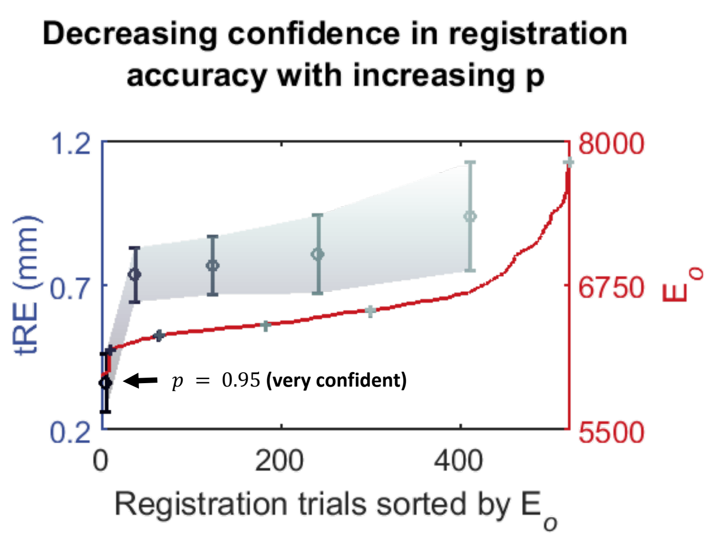




Leave-one-out analysis

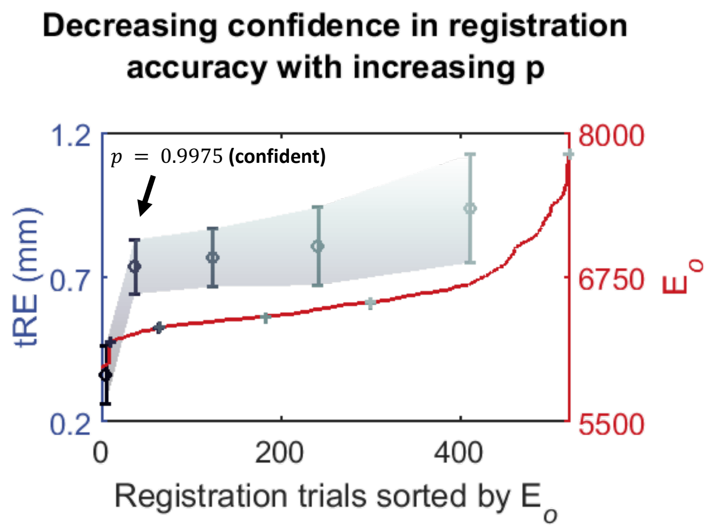


Leave-one-out analysis



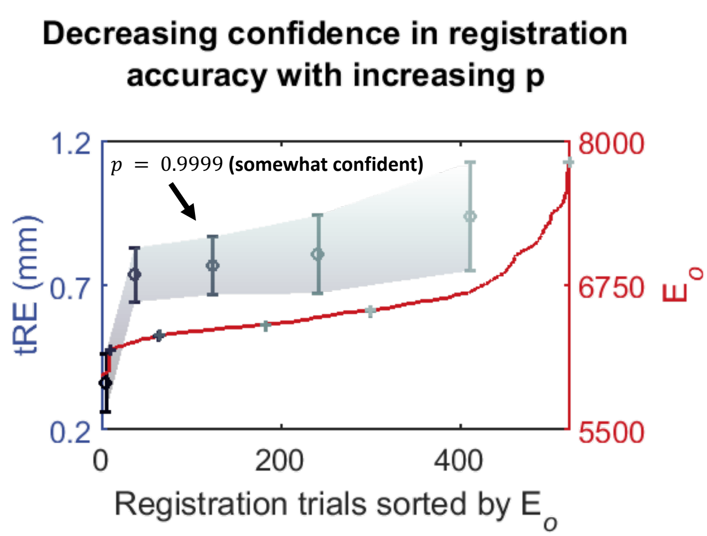
TRE $= 0.34\ (\pm\ 0.03)$**mm**

Leave-one-out analysis



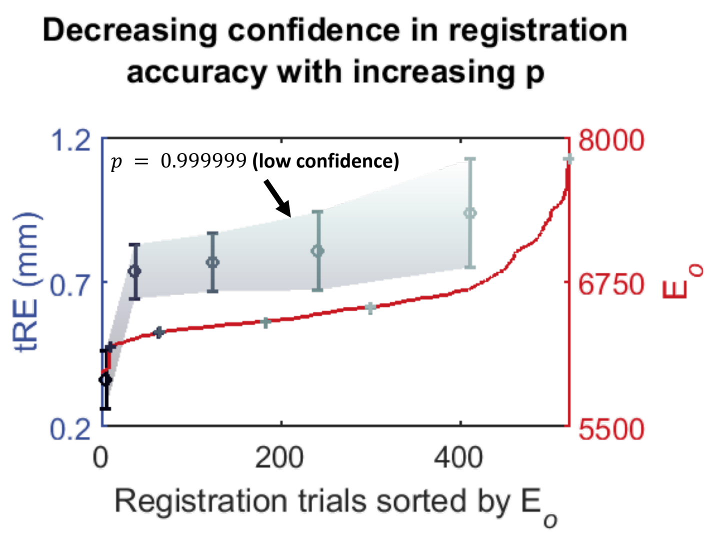
TRE $= 0.62\ (\pm\ 0.03)$**mm**

Leave-one-out analysis



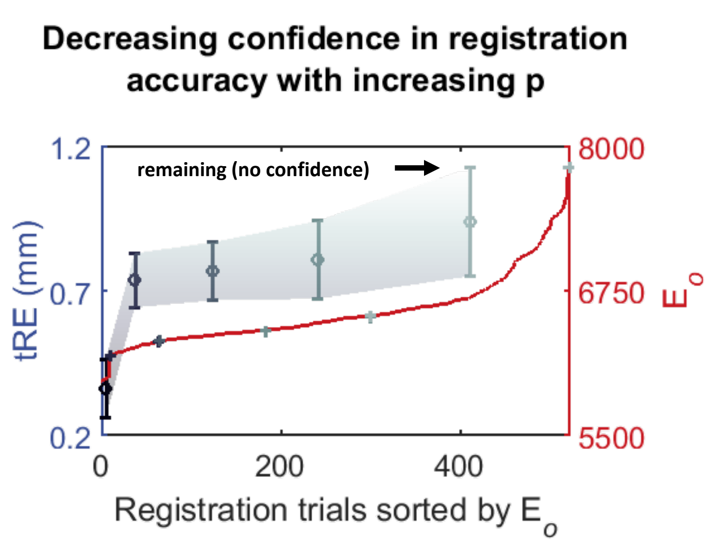
TRE $= 0.78\ (\pm\ 0.04)$**mm**

Leave-one-out analysis



TRE $= 0.80\ (\pm\ 0.05)$mm

Leave-one-out analysis



TRE $>$ 1 mm

In vivo experiment

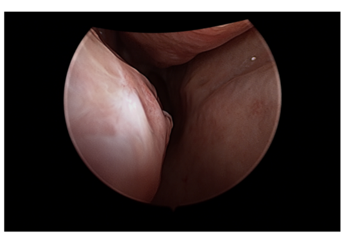
- 5 clinical sequences
- 3000 sample points
- Noise assumed:
  - $1 \times 1 \times 2\mathrm{mm}^3$
  - $30°\ (e = 0.5)$
- $n_{\mathbf{m}} \in \{0, 10, 20, 30, 40, 50\}$

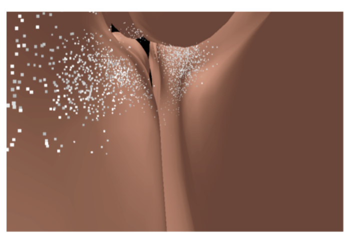
Right nasal airway

Dense reconstruction from video

In vivo experiment

	# registrations	Residual error (mm)	Max error (mm)	Min error (mm)
All registrations	30/30	1.09 (±1.03)	4.74	0.50
Registrations that pass E_p test	27/30	0.76 (±0.14)	0.99	0.50
Registrations that pass E_p and E_o tests	12/30	0.78 (±0.07)	0.94	0.72





Conclusion

- Steps towards fully automated navigation during clinical exploration and surgery
- In the process of building a comprehensive atlas of the nasal cavity and sinuses
- Confidence measures to allow clinicians to modulate trust in navigation system

Thank you!

Questions?