MICCAI 2018 Granada SPAIN

Endoscopic navigation in the absence of CT imaging

Ayushi Sinha[1,✉], Xingtong Liu[1], Austin Reiter[1], Masaru Ishii[2], Greg Hager[1], Russ Taylor[1]

[1]The Johns Hopkins University, Baltimore, USA
[2]Johns Hopkins Medical Institutes, Baltimore, USA

Code: https://github.com/AyushiSinha/cisstICP

✉ sinha@jhu.edu

JOHNS HOPKINS WHITING SCHOOL of ENGINEERING

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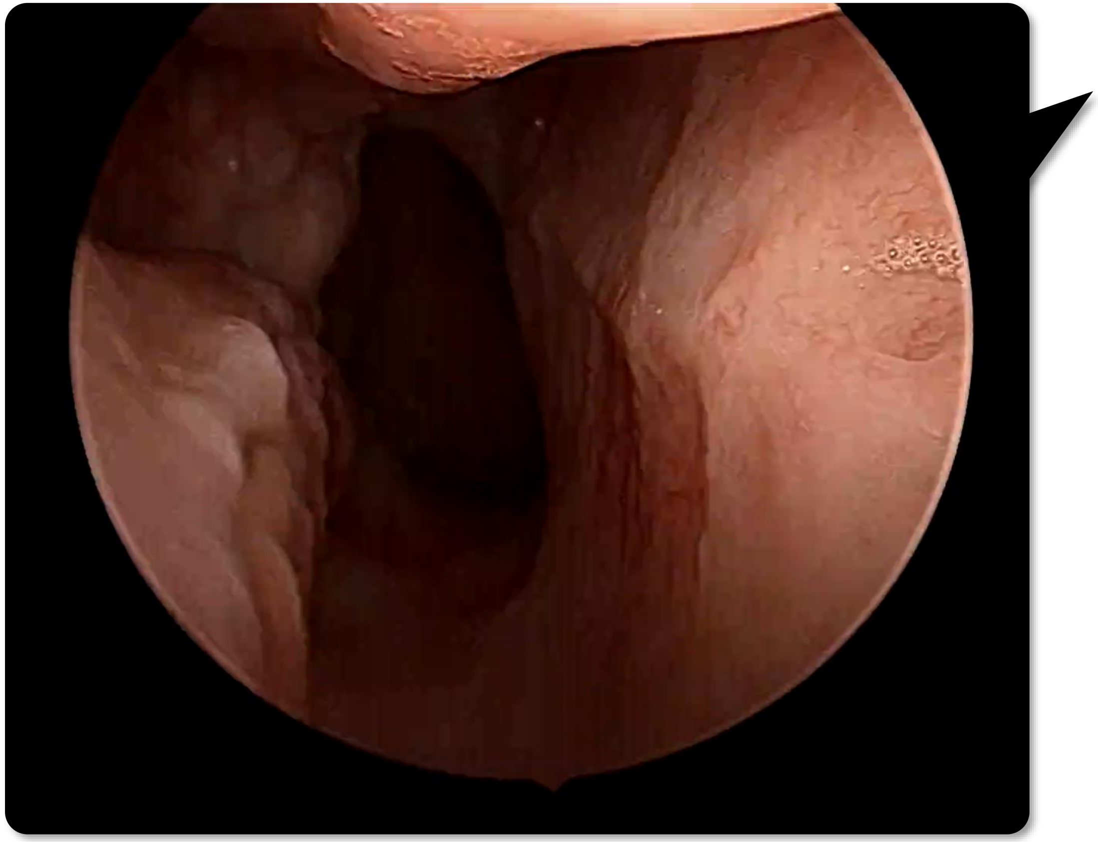
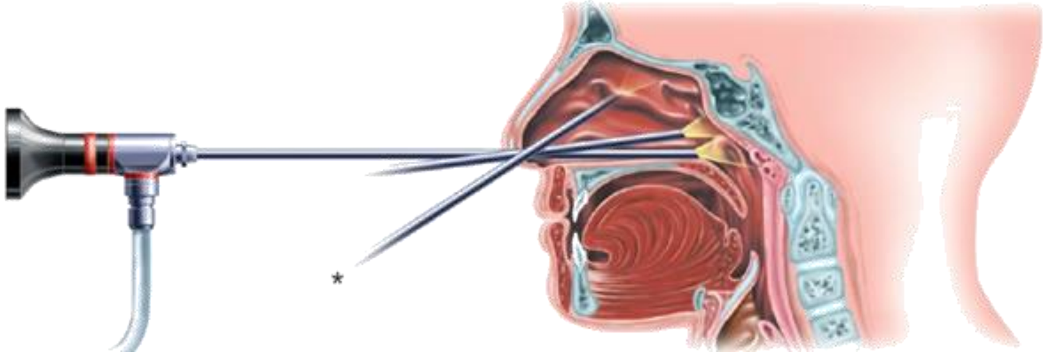
Nasal endoscopy in the clinic





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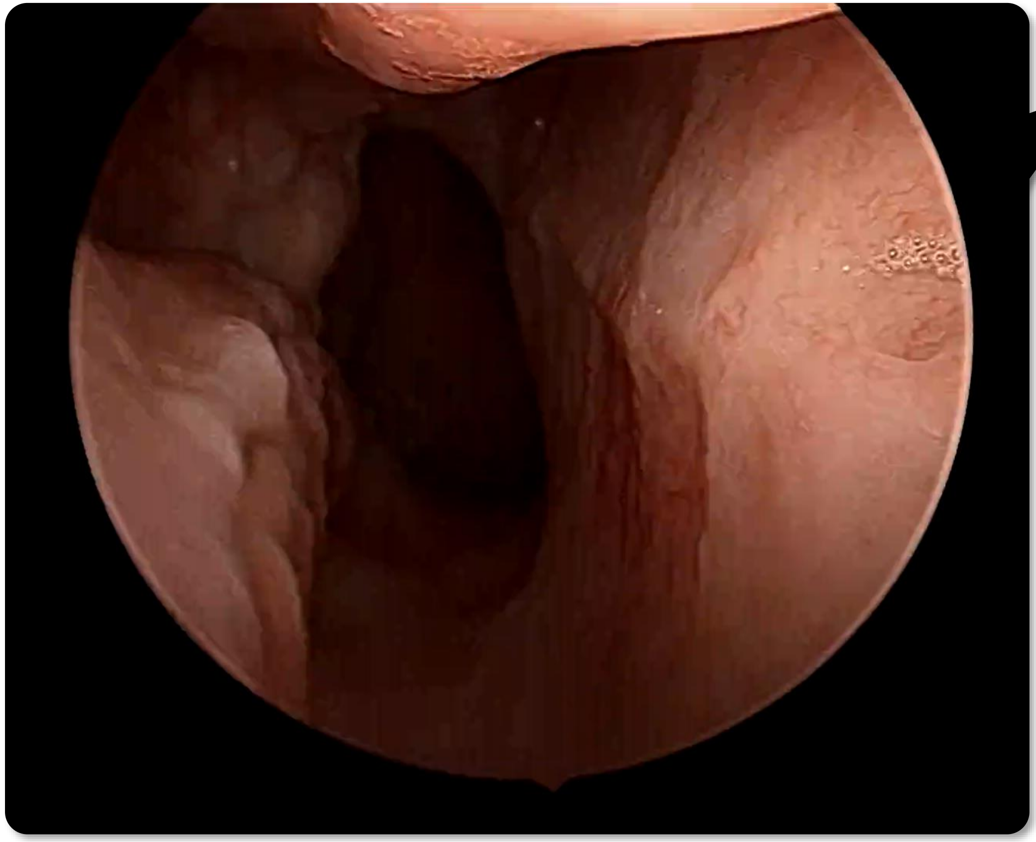

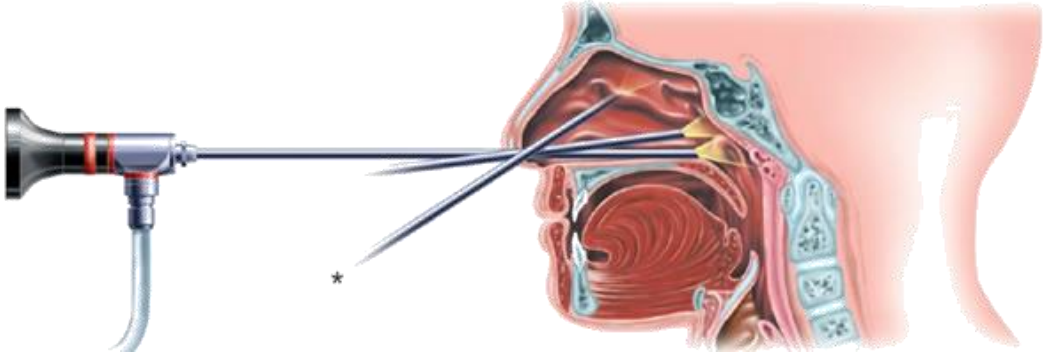

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Navigation without additional tools

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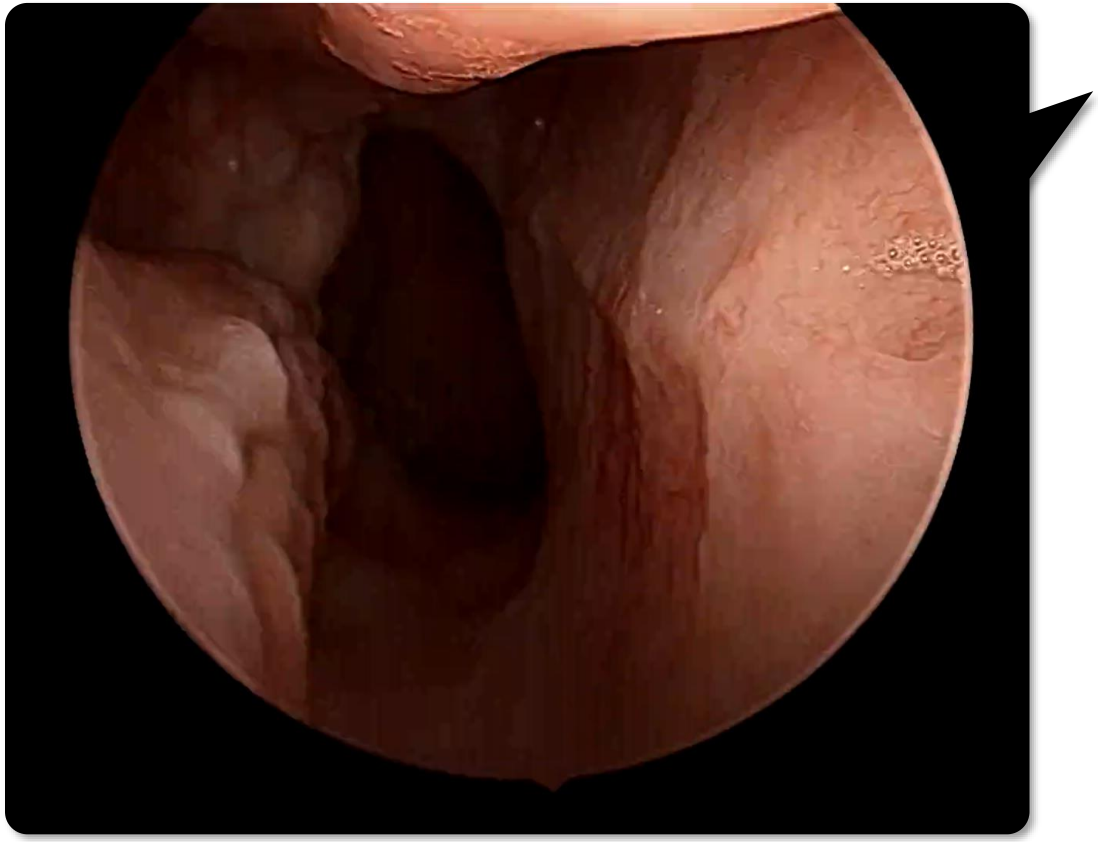

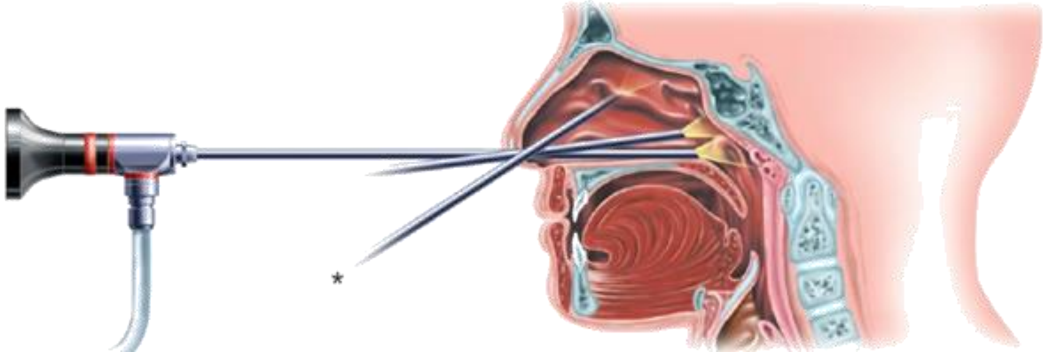

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Navigation without additional tools

Estimate anatomy without CT scan

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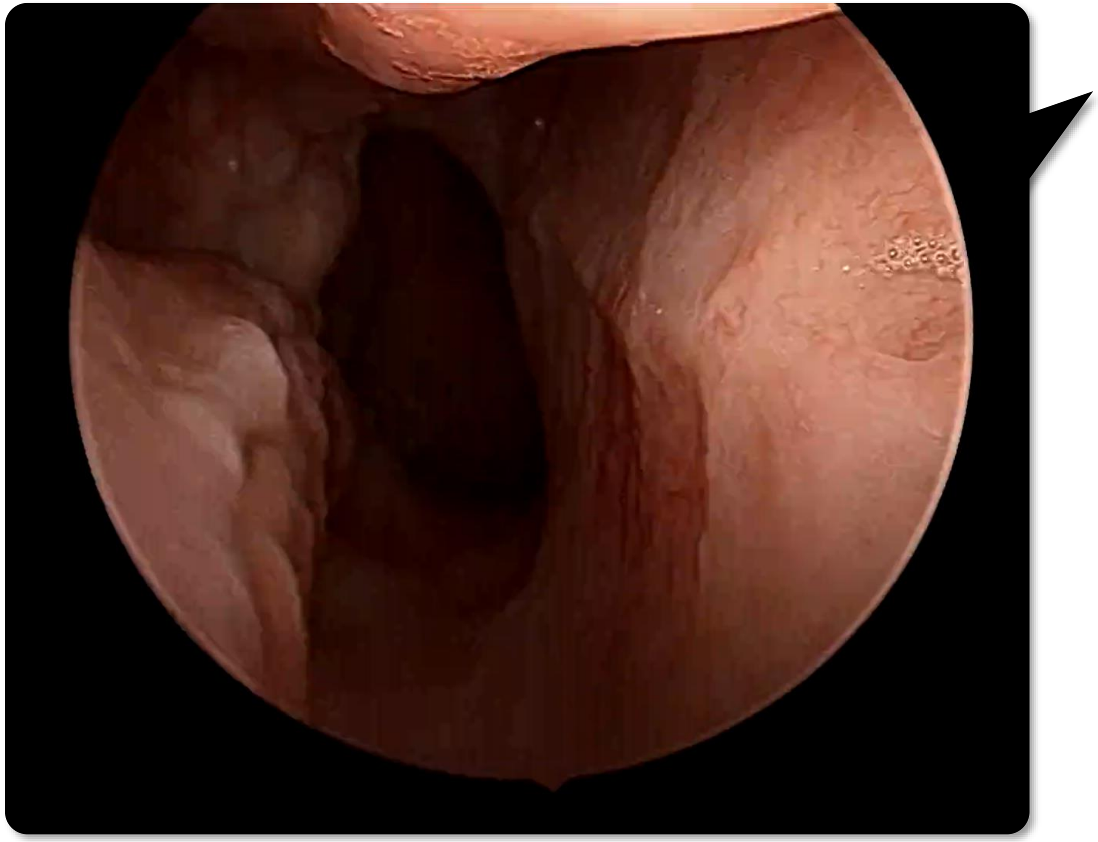

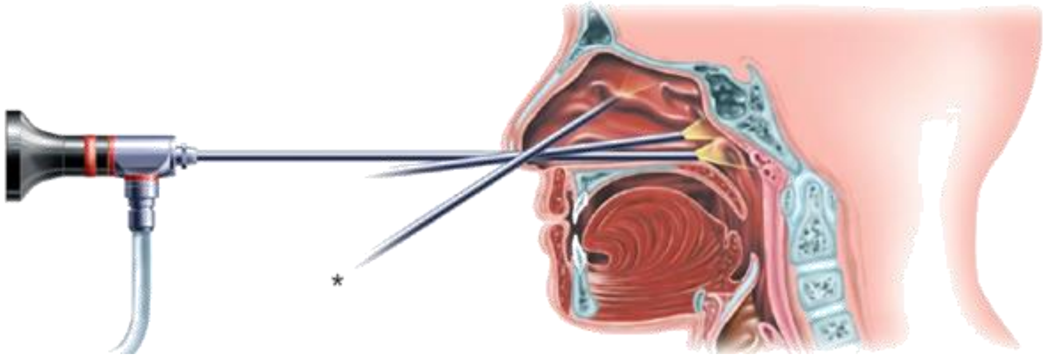

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Navigation without additional tools

Estimate anatomy without CT scan

Assign confidence to registration

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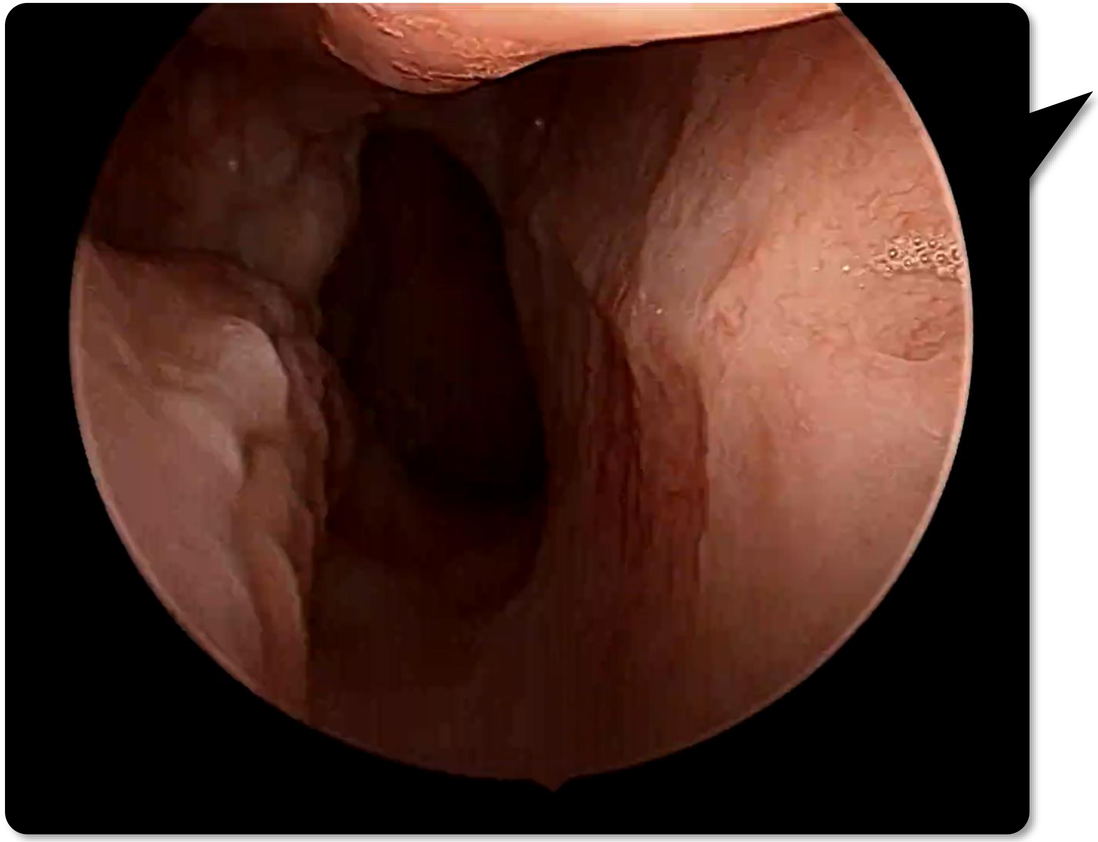

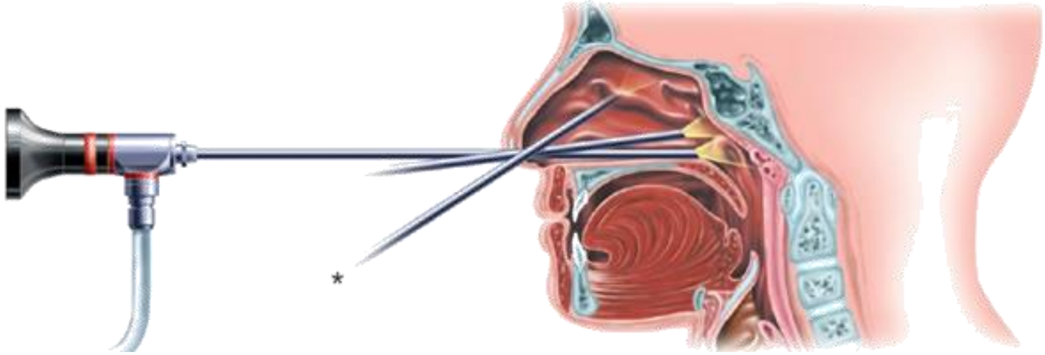

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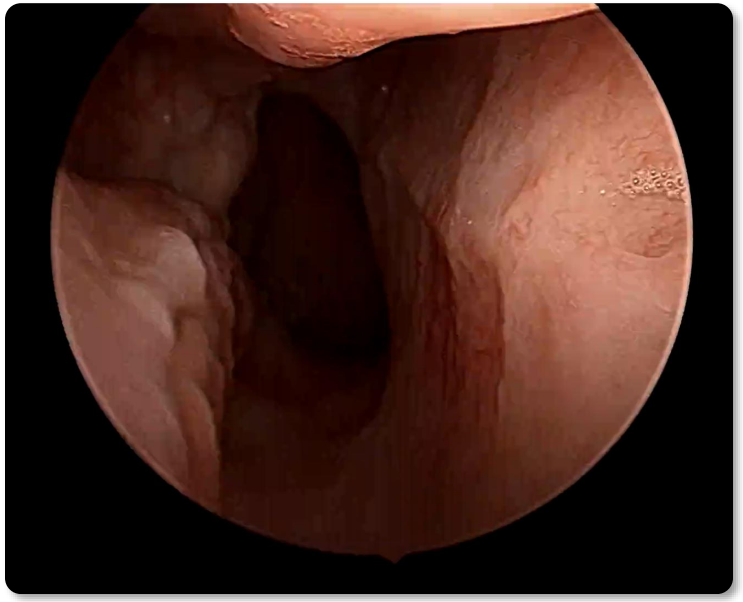
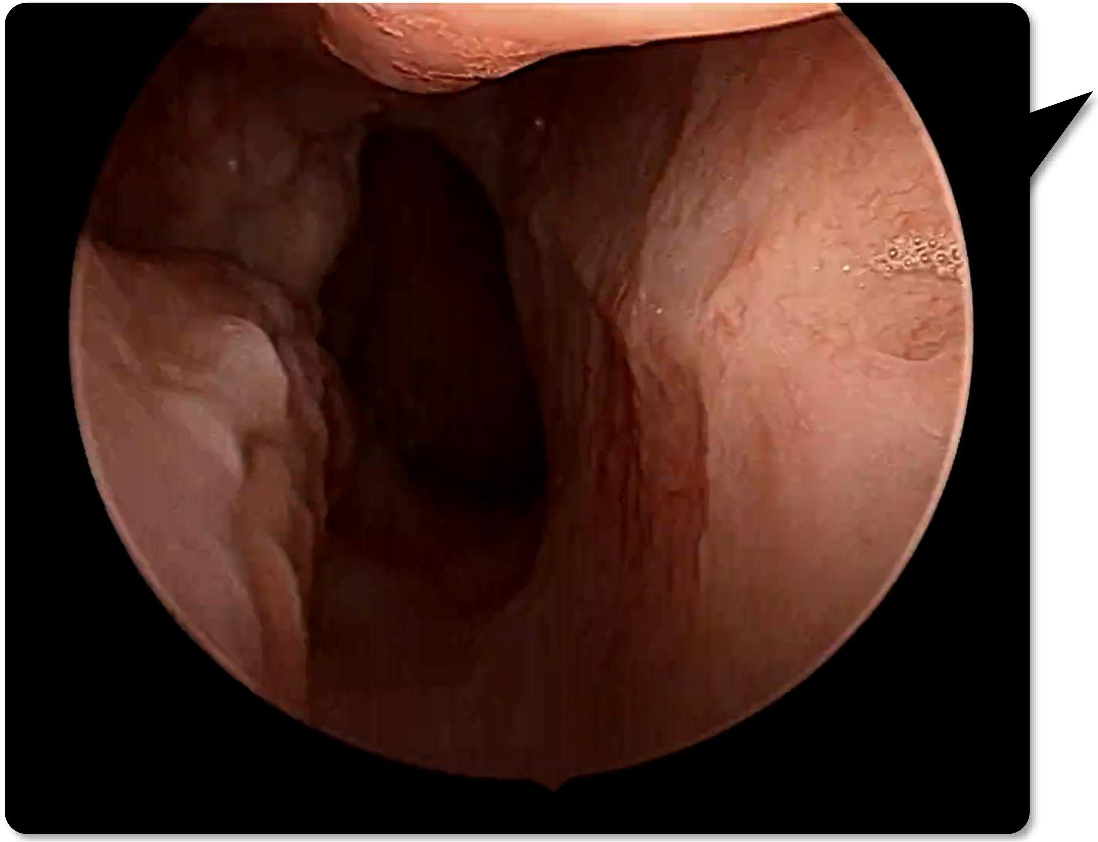
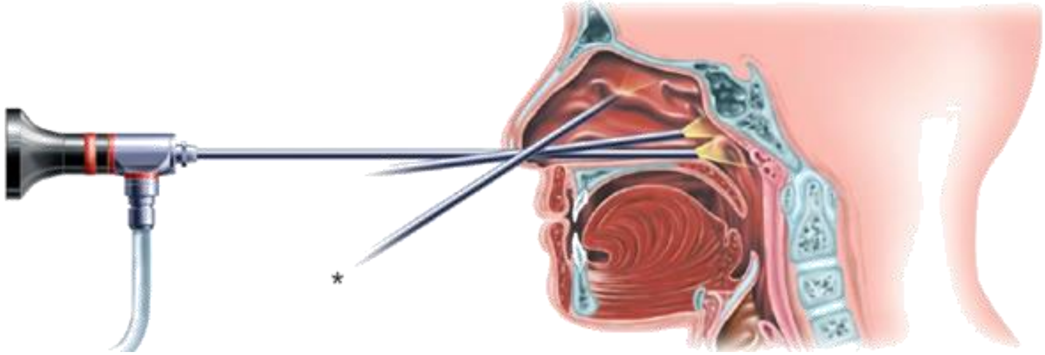


Learning-based method

Liu, X. et al., "Self-supervised Learning for Dense Depth Estimation in Monocular Endoscopy", CARE Workshop 2018

Nasal endoscopy in the clinic





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Navigation without additional tools

Estimate anatomy without CT scan

Assign confidence to registration

Estimate anatomy without CT scan

- Build statistical shape models
  - Principal component analysis
  - Capture anatomical variation
- Deformable registration
  - Optimize PCA model parameters
  - Produce registration score

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Statistical shape models

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

- Mean:

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

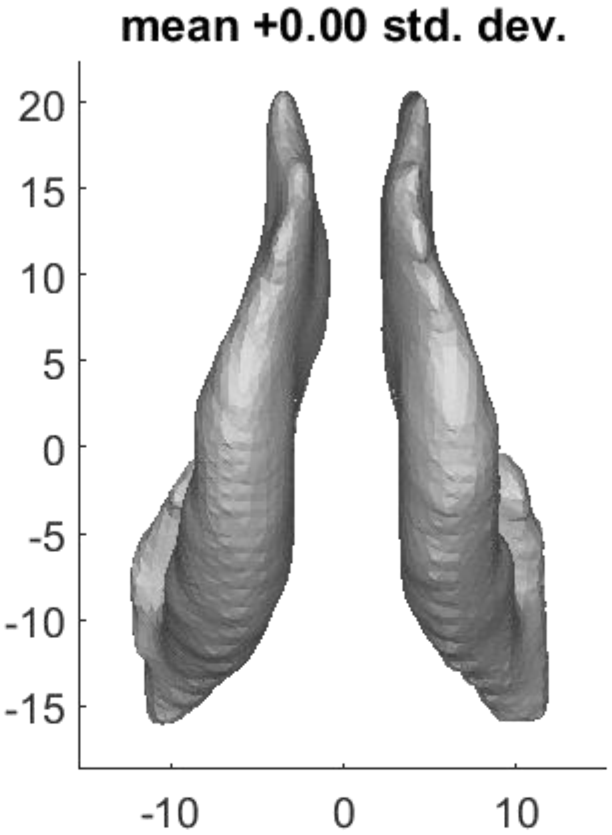
- Variance:

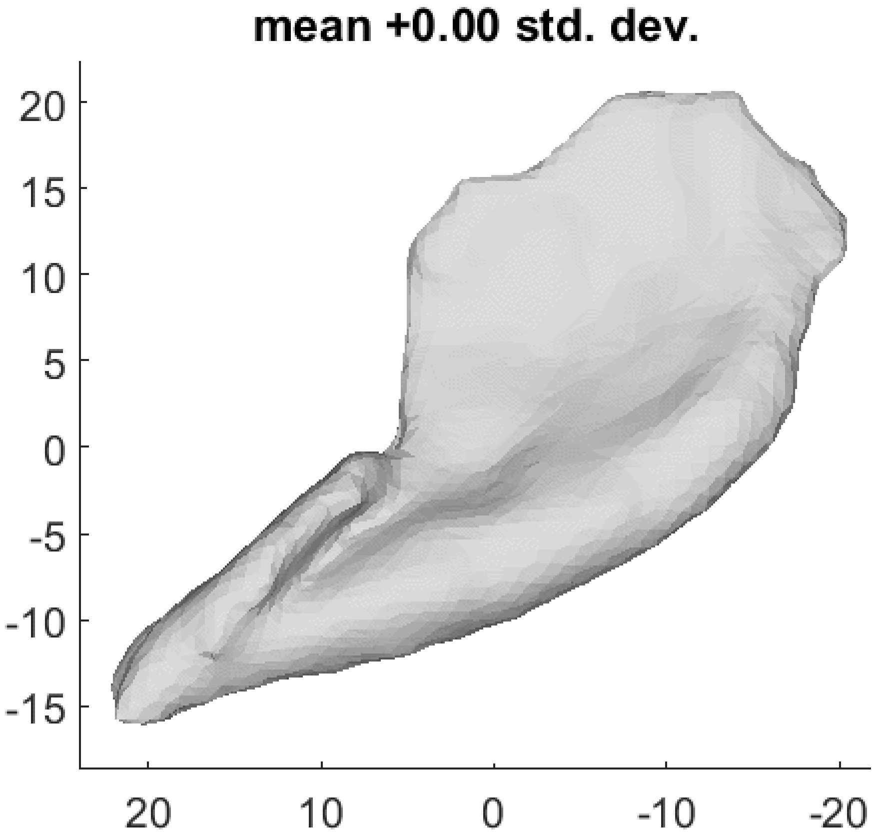
$$\boldsymbol{\Sigma} = \frac{1}{n_{\mathbf{s}}} \sum_{i=1}^{n_{\mathbf{s}}} (\mathbf{V}_i - \bar{\mathbf{V}})(\mathbf{V}_i - \bar{\mathbf{V}})^{\mathbf{T}}$$

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

Statistical shape models

- Variance along the principal mode for middle turbinates





Statistical shape models

- 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:

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

Estimate anatomy without CT scan

- Build statistical shape models
  - Principal component analysis
  - Capture anatomical variation
- Deformable registration
  - Optimize PCA model parameters
  - Produce registration score

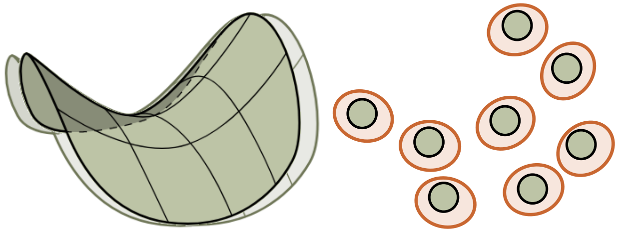
Deformable most likely point (D-IMLP)

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

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



$y_i \in \Psi$ $\quad$ $X = \{x_i\}$

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

Generalized deformable most likely oriented point (GD-IMLOP)

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

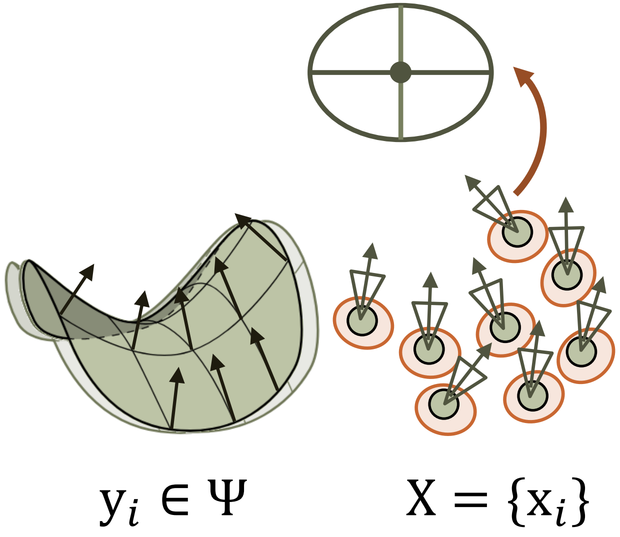
Find R, t and a such that x is best aligned with a deformed y…

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

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

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

Find s such that y deforms to fit x



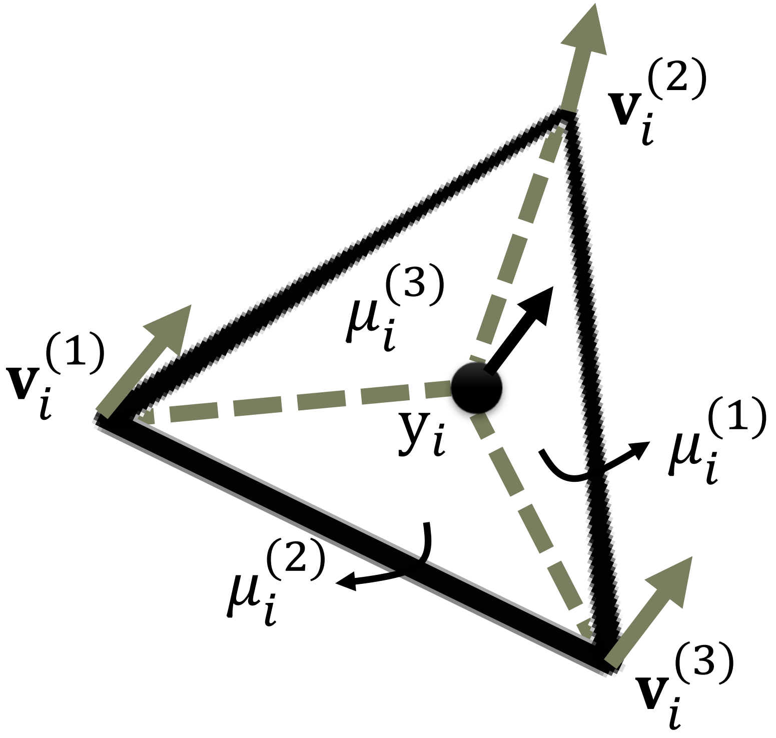
$$\mathrm{T}_{\text{ssm}}(\mathbf{y}_i) = f(\mathrm{y_i}, \mathrm{s}), \quad \kappa_0 = \frac{1}{\sigma^2_{\text{circ\_rad}}}, \quad \beta = e\,\frac{\kappa}{2}$$

What is $\mathrm{T}_{\mathrm{ssm}}(\mathbf{y}_i)$?

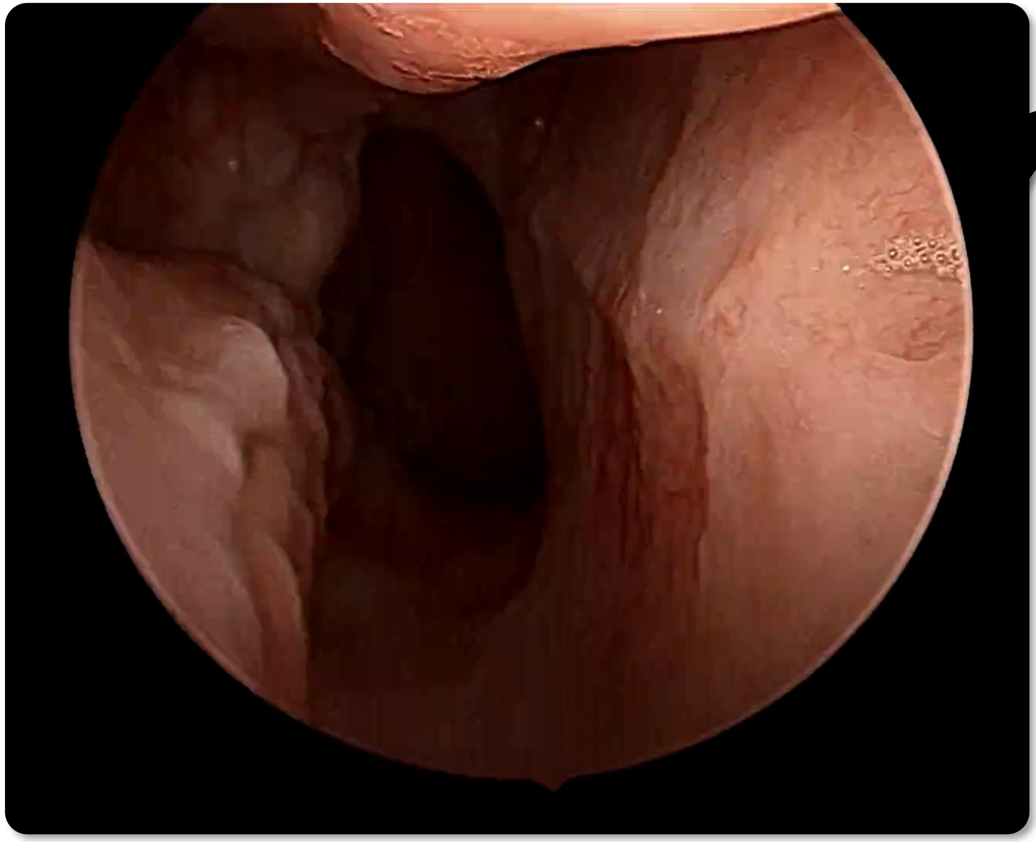
$$\mathrm{T}_{\mathrm{ssm}}(\mathbf{v}_i) = \bar{\mathbf{v}}_i + \sum_{j=1}^{n_{\mathbf{m}}} s_j \mathbf{w}_j^{(i)}$$

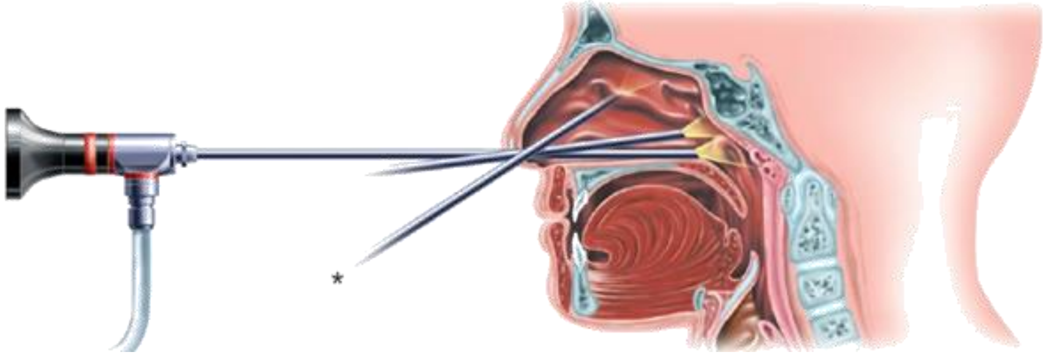
$$\mathrm{T}_{\mathrm{ssm}}(\mathbf{y}_i) = \sum_{j=1}^{3} \mu_i^{(j)} \mathrm{T}_{\mathrm{ssm}}(\mathbf{v}_i^{(j)})$$

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



Nasal endoscopy in the clinic





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Navigation without additional tools

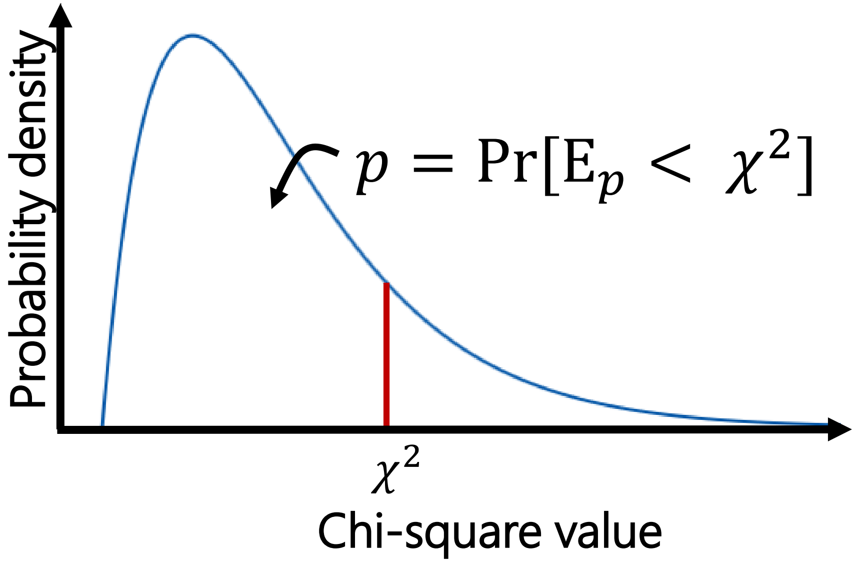
Estimate anatomy without CT scan

Assign confidence to registration

Did it work?

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

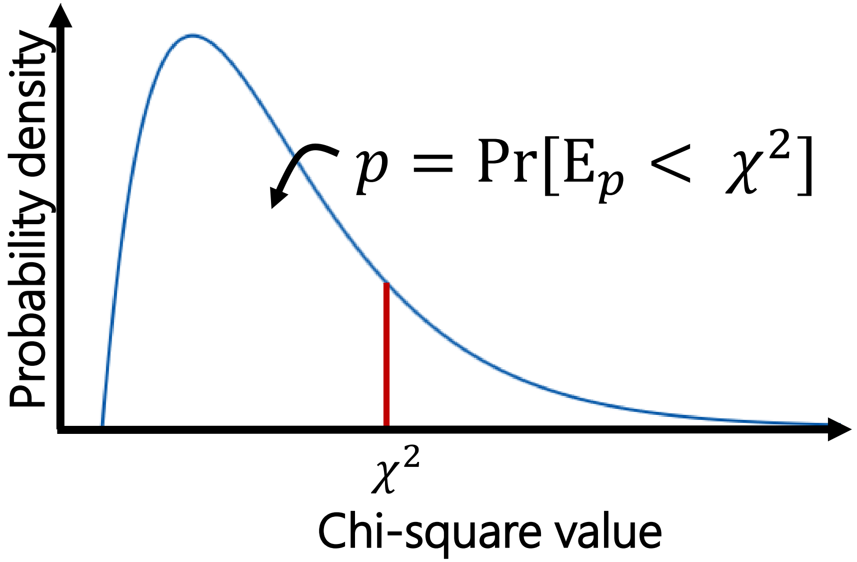
$$\mathrm{E}_o = \sum_{i=1}^{n_{\text{data}}} \begin{bmatrix} \cos^{-1}\left(\hat{\mathbf{y}}_{\mathbf{n}_i}{}^{\mathbf{T}}\mathbf{R}\hat{\mathbf{x}}_{\mathbf{n}_i}\right) \\ \sin^{-1}\left(\hat{\gamma}_{1_i}{}^{\mathbf{T}}\mathbf{R}^{\mathbf{T}}\hat{\mathbf{y}}_{\mathbf{n}_i}\right) \\ \sin^{-1}\left(\hat{\gamma}_{2_i}{}^{\mathbf{T}}\mathbf{R}^{\mathbf{T}}\hat{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



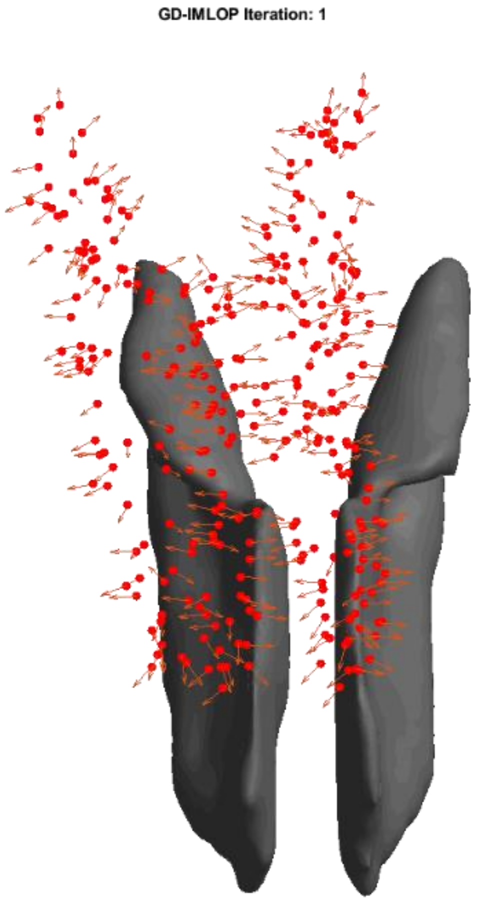
Did it work?

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

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

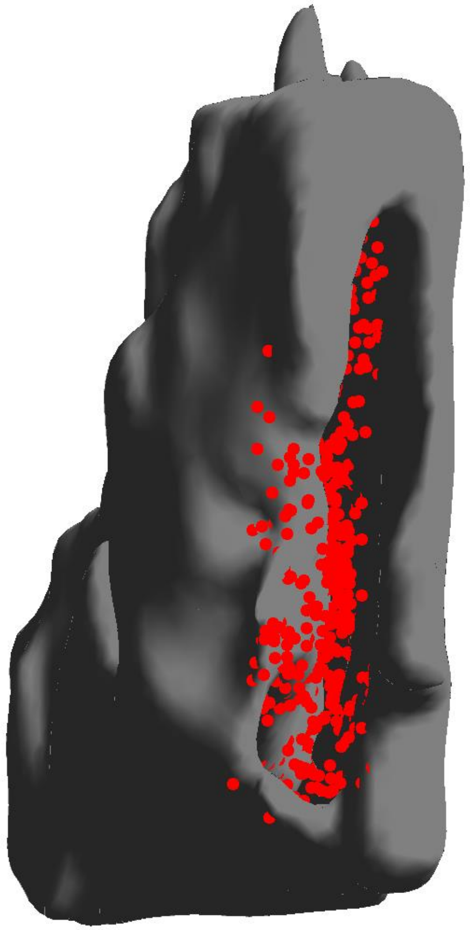


Experiments



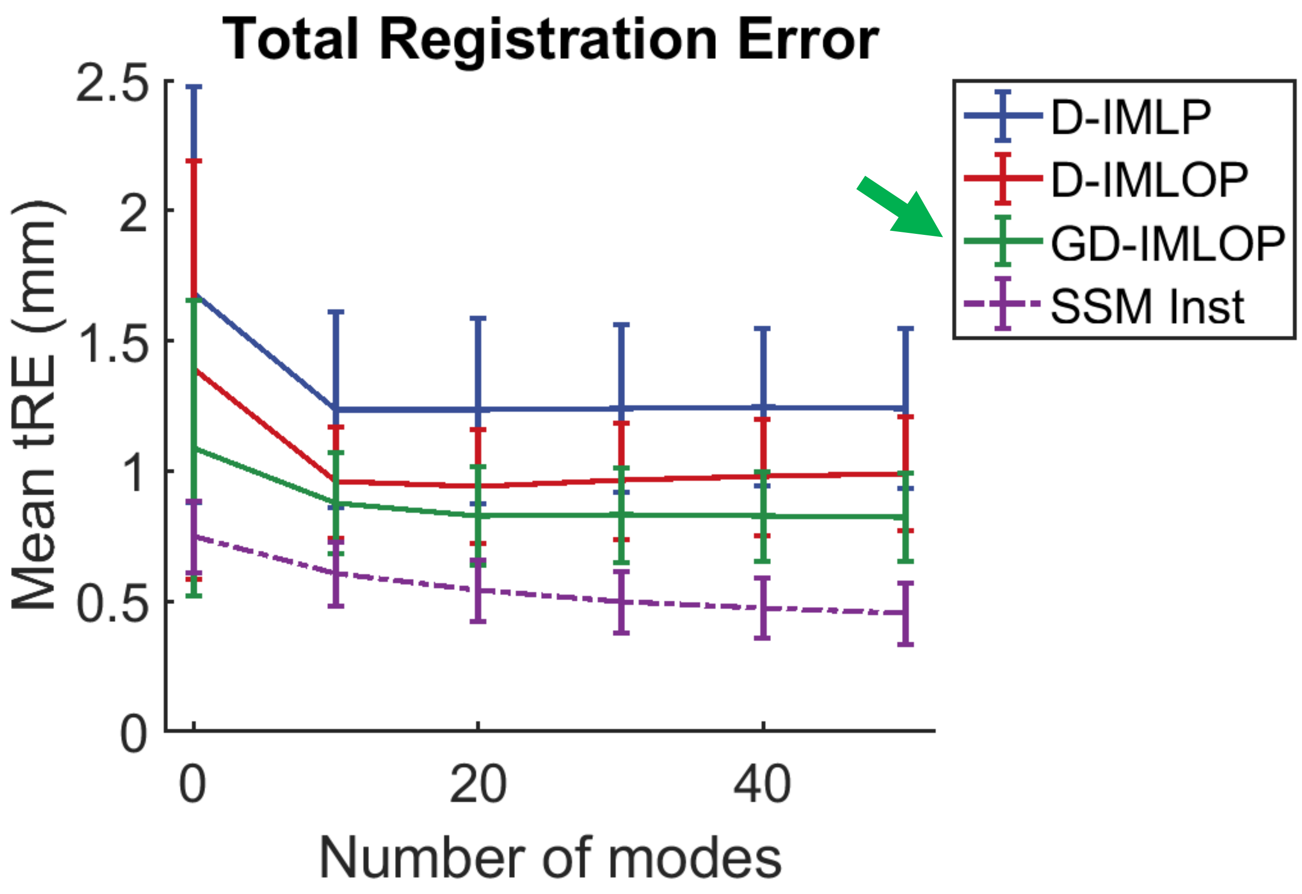
Leave-one-out

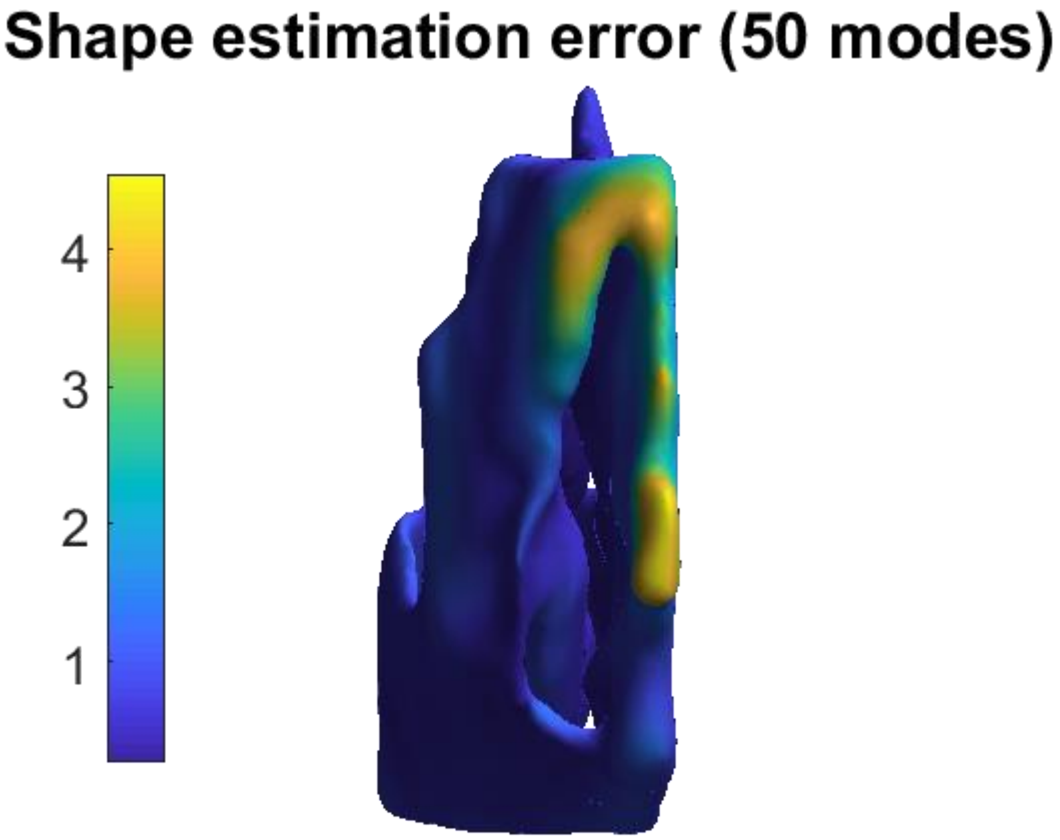
- # sample point: 3000
- Translational offset: [0, 10] mm
- Rotational offset: [0, 10] degrees
- Noise:
  - $0.5 \times 0.5 \times 0.75\text{mm}^3$
  - $10° \ (e = 0.5)$
- Noise assumed:
  - $1 \times 1 \times 2\text{mm}^3$
  - $30° \ (e = 0.5)$
- $n_{\mathbf{m}} \in \{0, 10, 20, 30, 40, 50\}$



Right nasal airway

Leave-one-out





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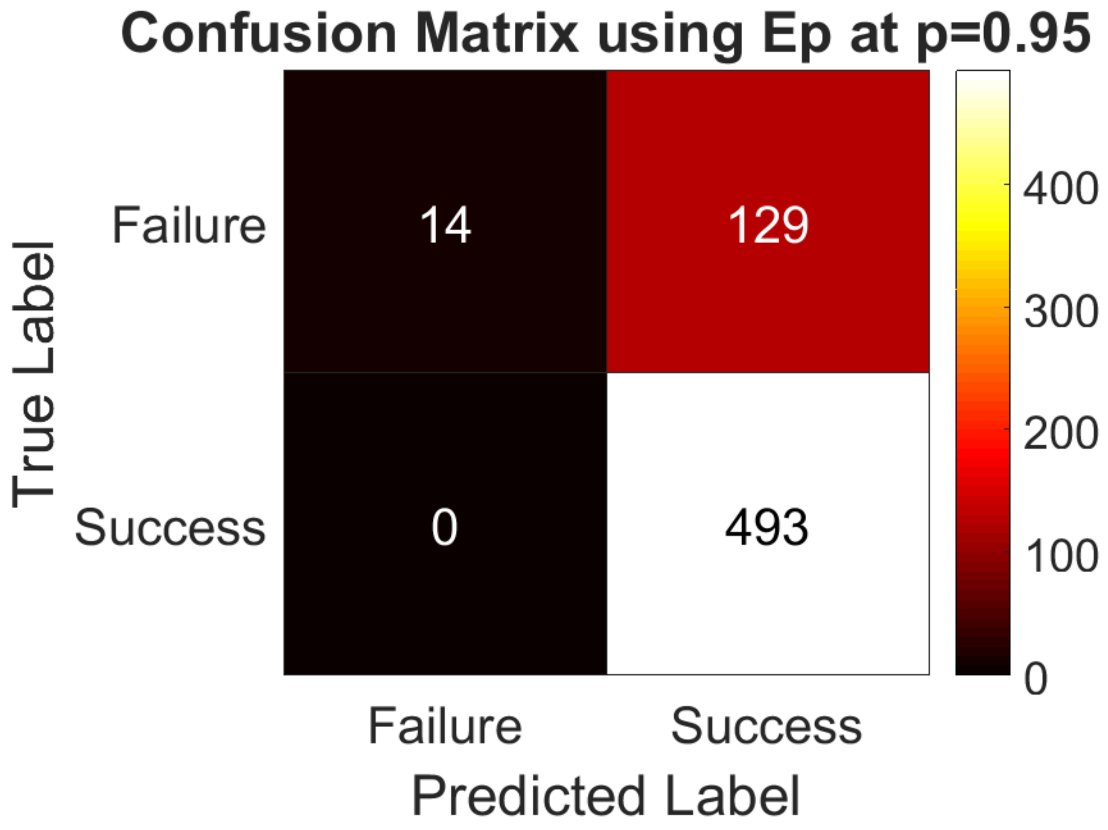

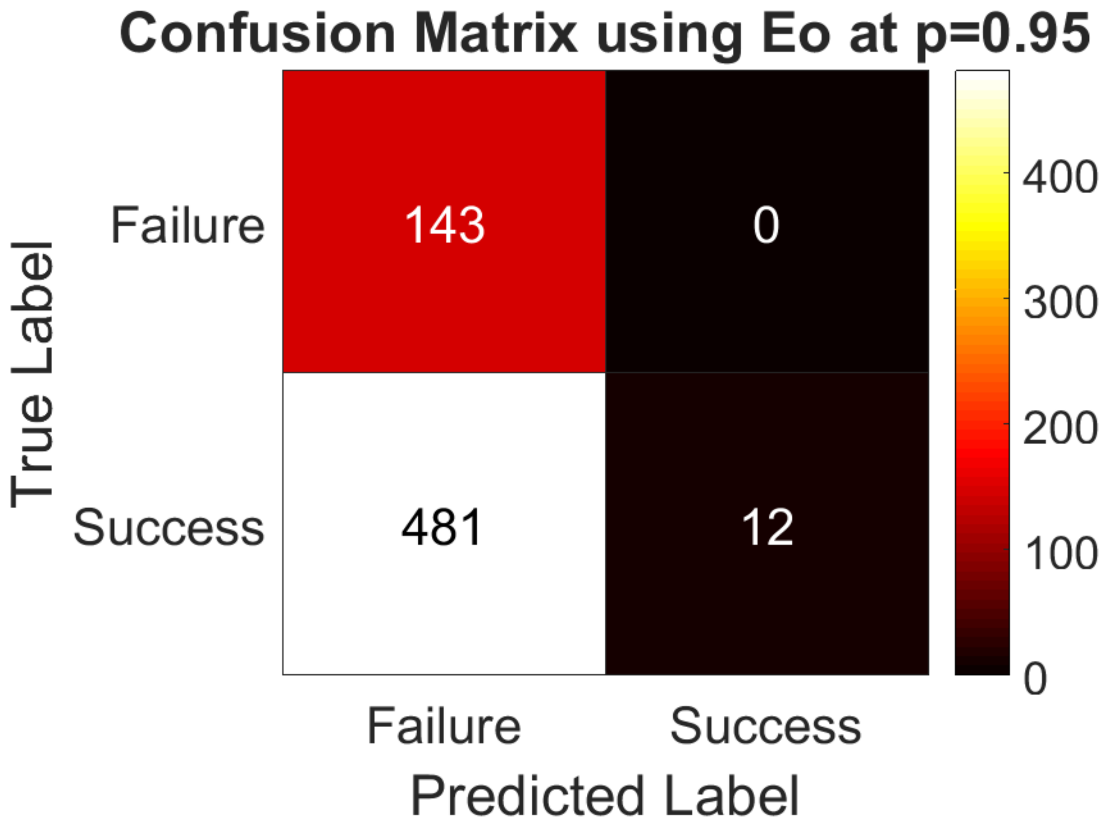

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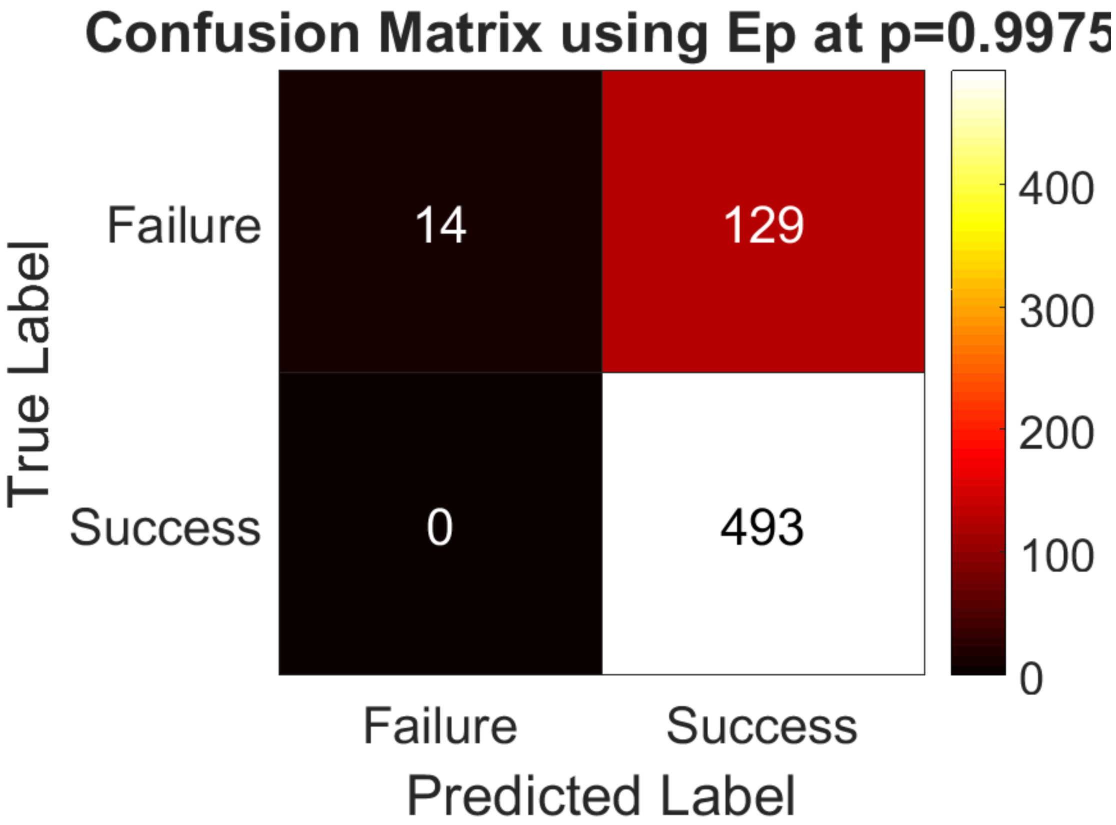

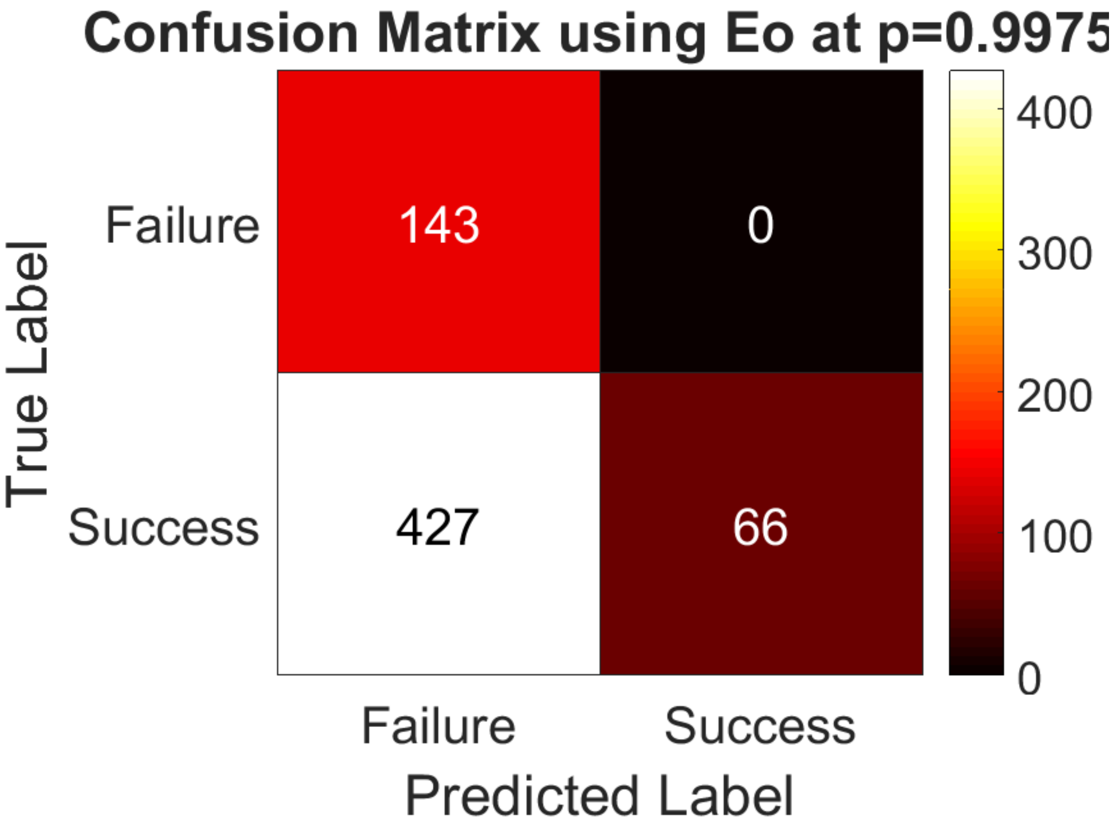

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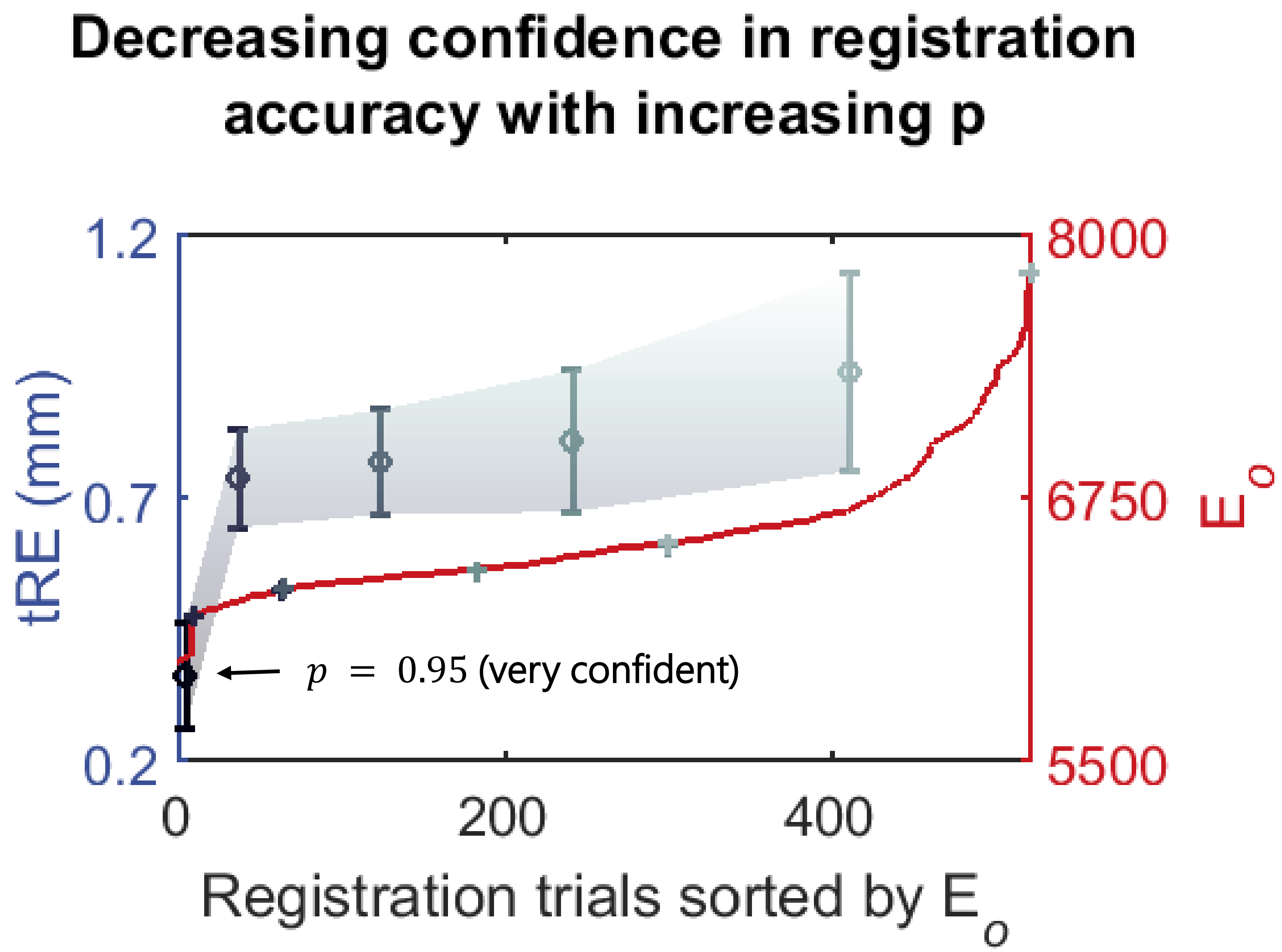
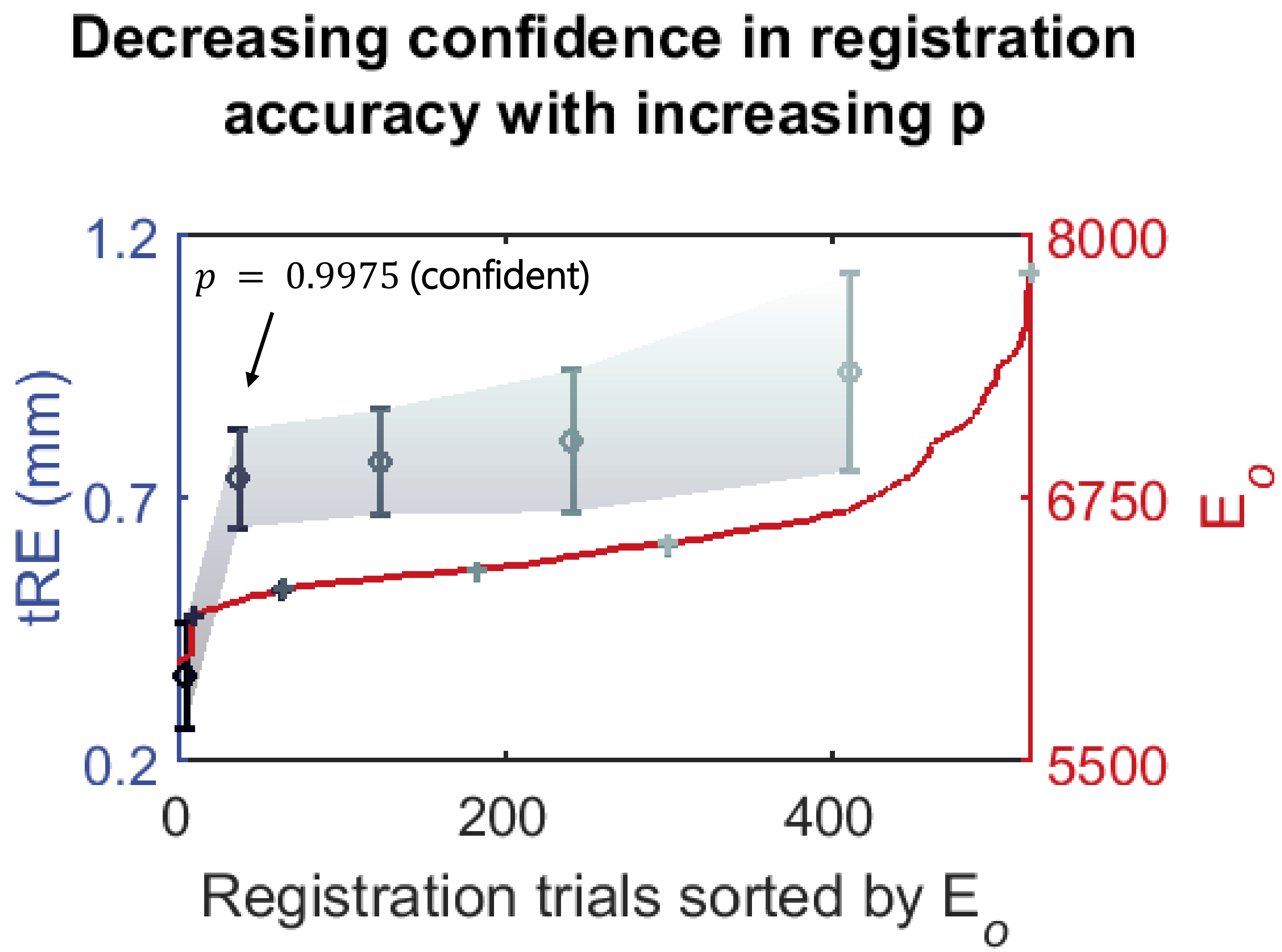


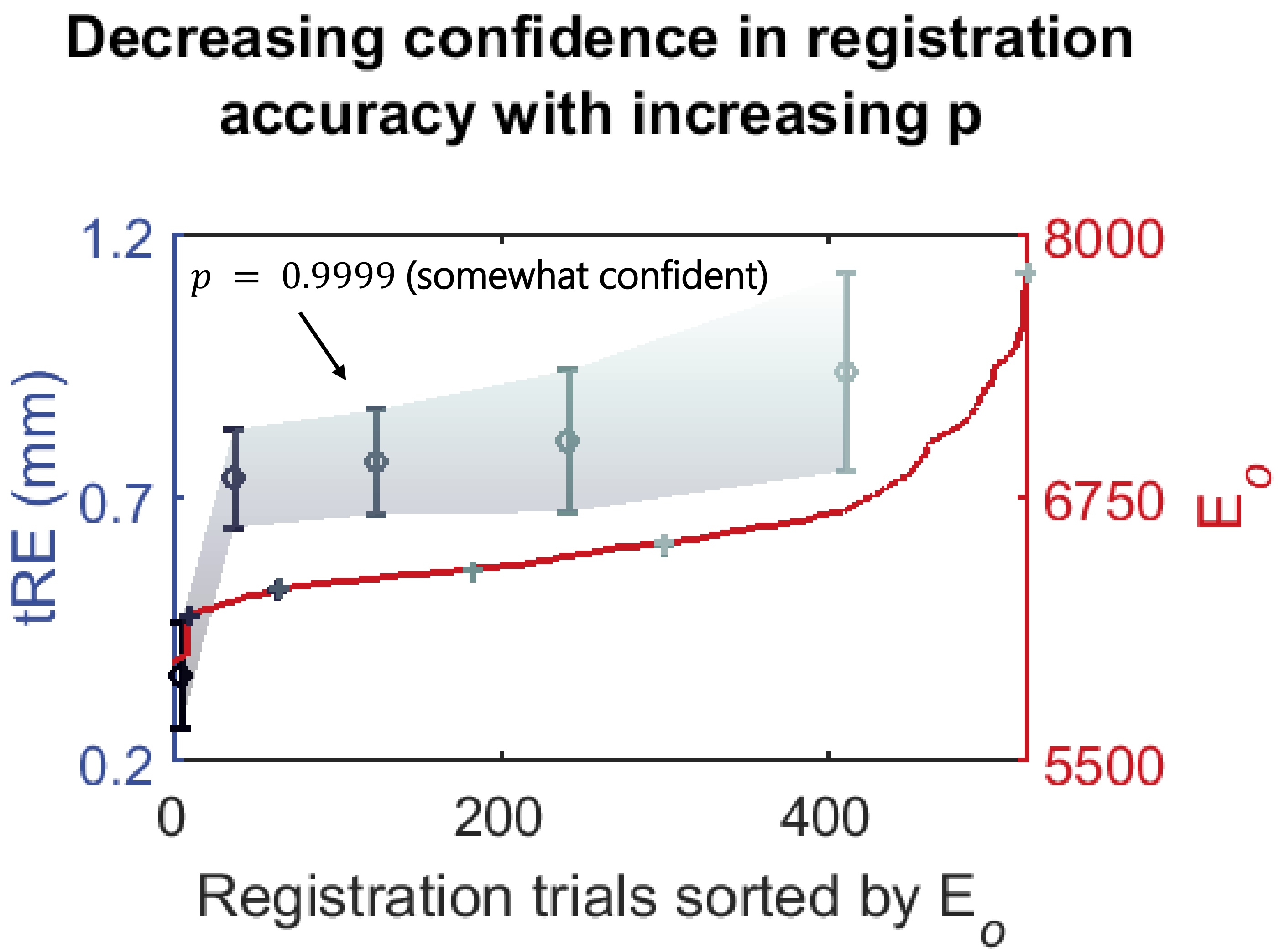
TRE $= 0.34\ (\pm\ 0.03)$mm

Leave-one-out



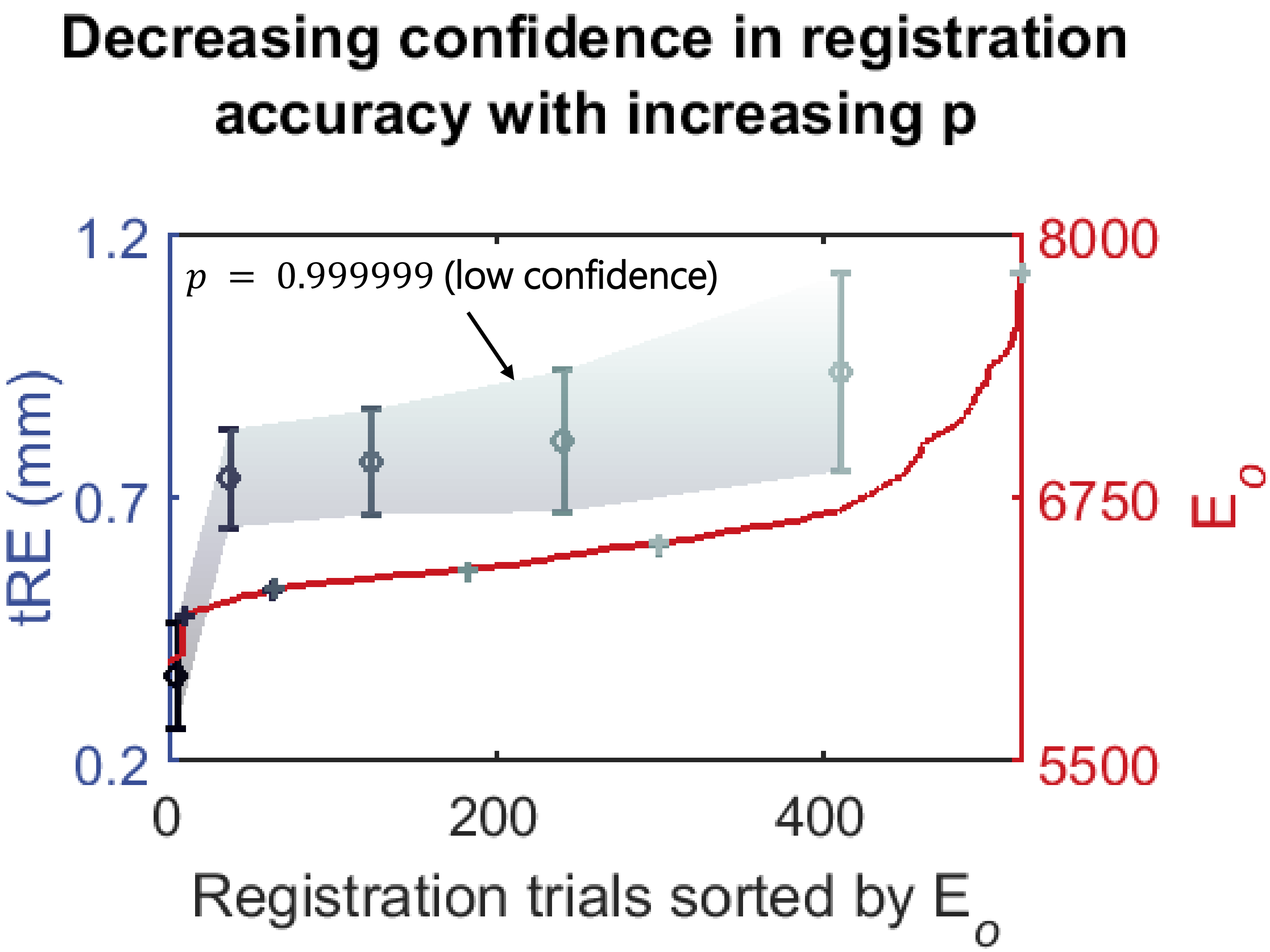
TRE $= 0.62\ (\pm\ 0.03)$mm

Leave-one-out



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

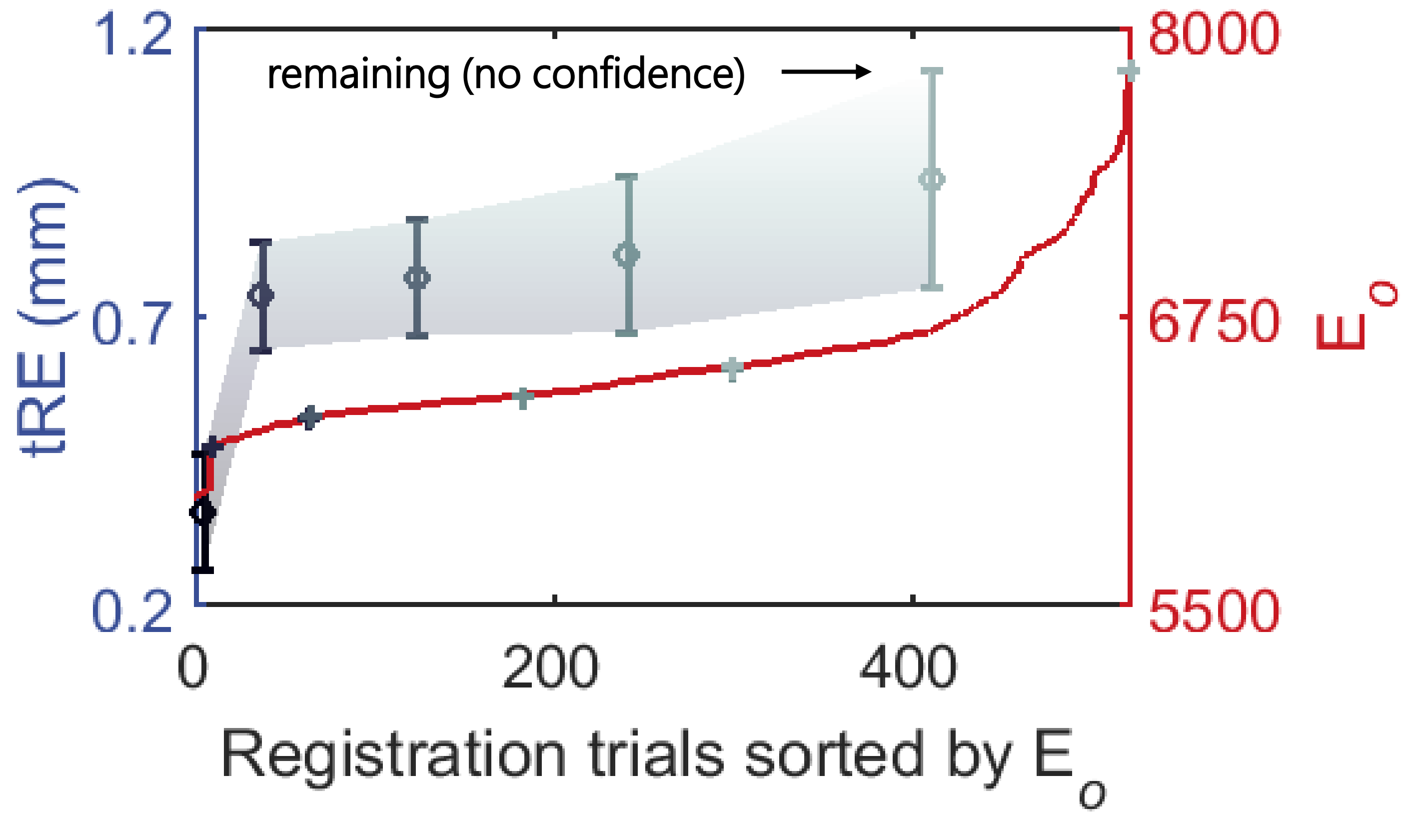
Leave-one-out



TRE = 0.80 (± 0.05)mm

Leave-one-out

Decreasing confidence in registration accuracy with increasing p



TRE > 1 mm

In vivo

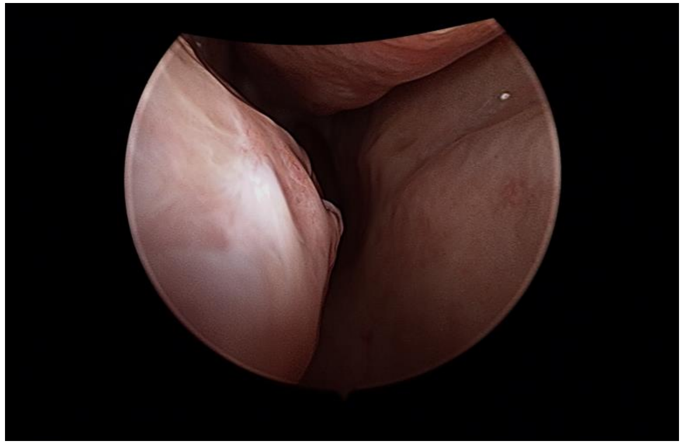
- 5 clinical sequences
- 3000 sample points
- Noise assumed:
  - $1 \times 1 \times 2\mathrm{mm}^3$
  - $30°\ (e = 0.5)$
- $n_{\mathbf{m}} \in \{0, 10, 20, 30, 40, 50\}$

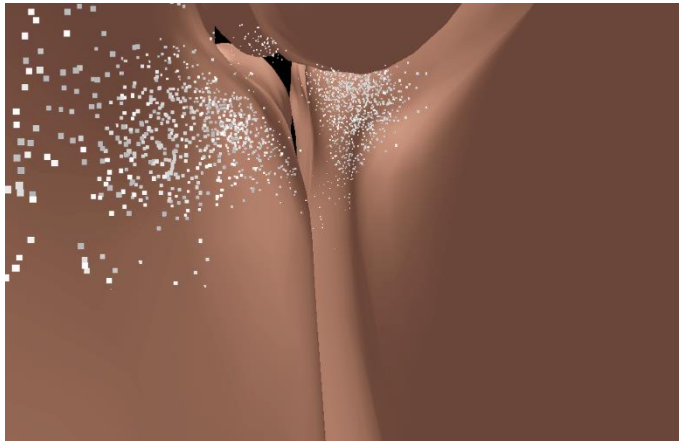
Right nasal airway

Dense reconstruction from video

In vivo

	# 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





Conclusions and future work

- Navigation without additional tools ✓
- Estimate anatomy without CT scan ✓
- Assign confidence to registration ✓

- Learn statistics from 1000s of CTs
- Use additional features
- Evaluate further on in vivo data

Thank you!

Code: https://github.com/AyushiSinha/cisstICP

Poster: W-2

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🖂: sinha@jhu.edu

: @ItsAyushiSinha