Classification of nasal pathologies: enhancing machine learning with CFD

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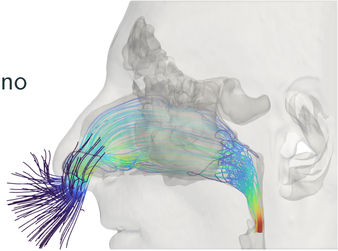
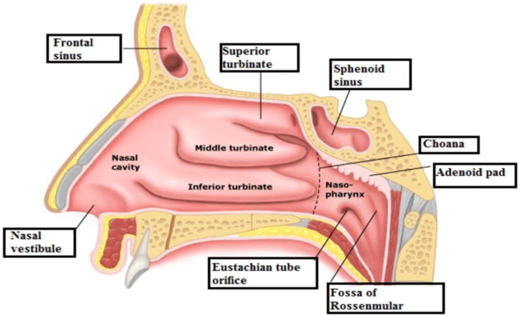
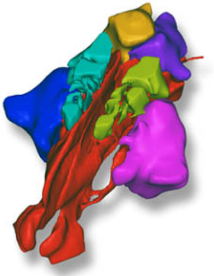
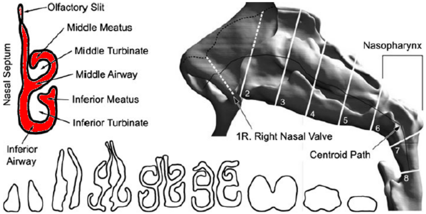


The human nose: functions and anatomy







Is the nose flow important?

- At least 1/3 of the adult world population is troubled with nasal breathing difficulties[1]
- In 2014, the one-year (only!) cost of cronic rhinosinusits (alone!) in US (only!) was $22bn[2]
- Certain nose surgeries have 50% failure rate[3]

Huge room for improvement!

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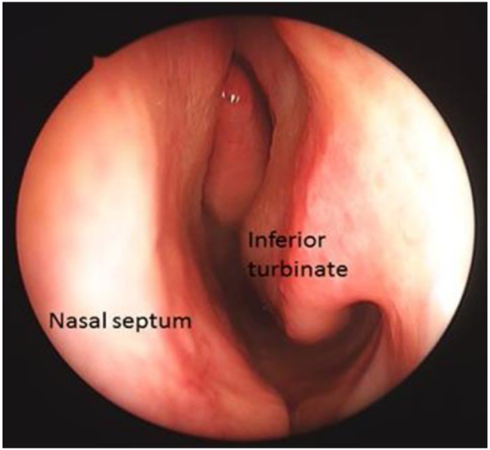
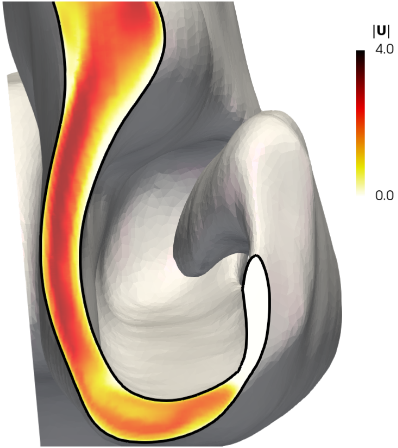
[1] Stewart *et al.* Int J Gen Med 2010

[2] Smith *et al.* The Laryngoscope 2015

[3] Sundh & Sonnergreen, Eur Arch Otholaringol 2015

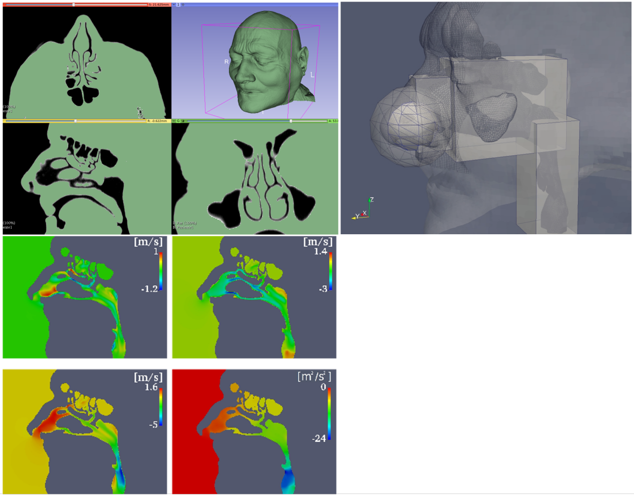
The contribution from fluid mechanics: form and function





The workflow: from CT scan to...

1. Segment the CT scan
2. Build a volume mesh
3. Compute a CFD solution (DNS, LES, RANS, ...)



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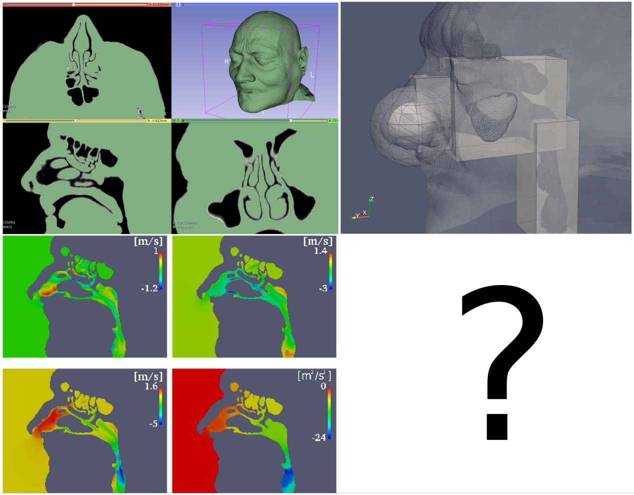


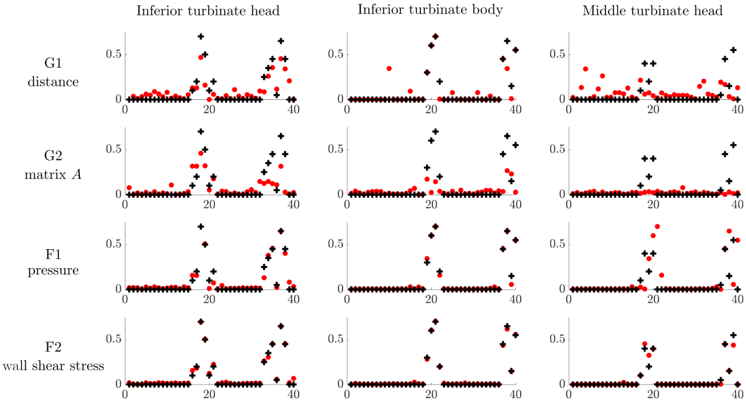
The lack of the functionally normal nose

CFD solution alone does not help surgeons to find the "best" surgery

- Reason: lack of functionally normal nose
- Shape optimization problem, but an objective function is lacking
- Strong inter-subject anatomical variations with different functional significance

Today's talk

- Augment ML with CFD
- Hypothesis: the flow field amplifies anatomic information

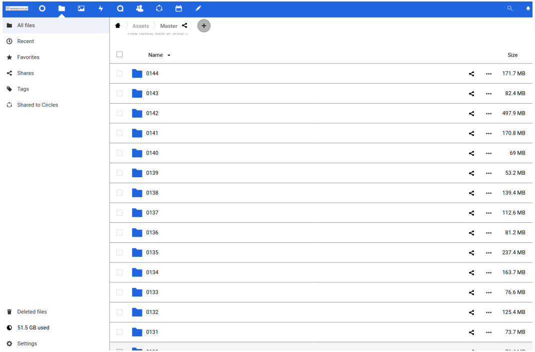


Big Data and Machine Learning

Database of:

- CT scans
- rhinomanometry data
- ENT evaluation sheet

Open and labeled data: huge value!

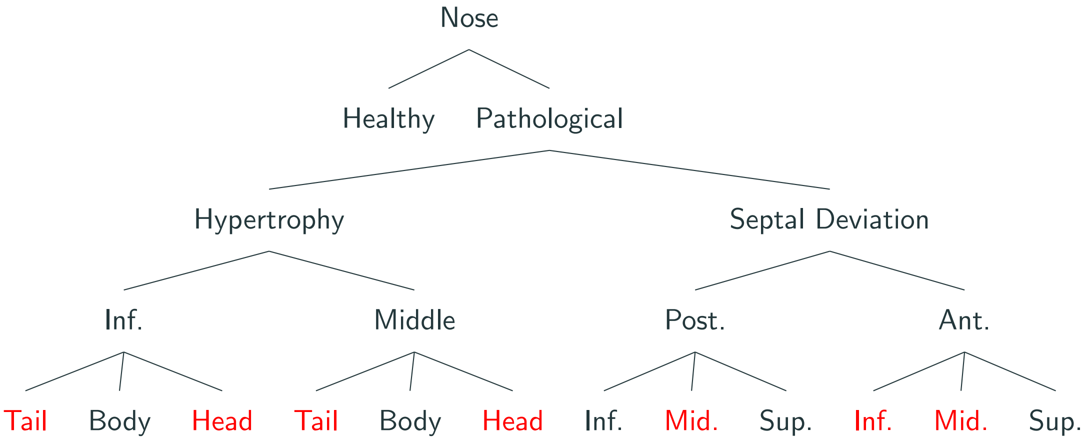


CFD-augmented ML is new

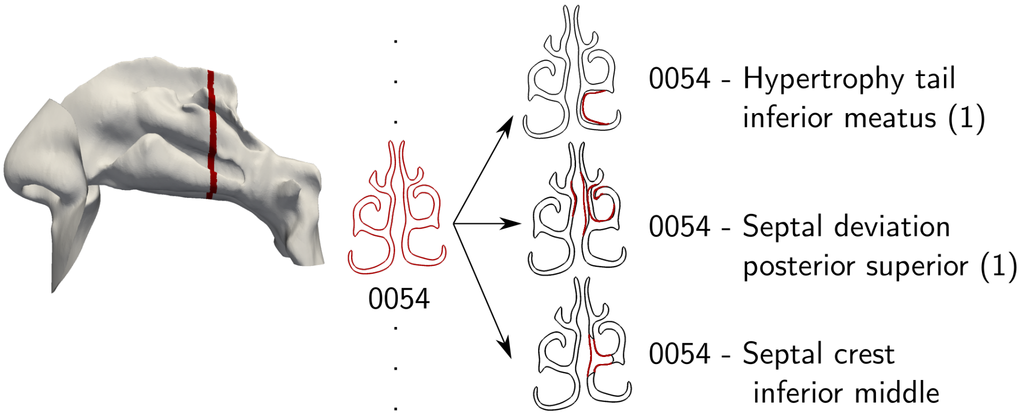
Issues:

1. Univocal training data are needed
2. The dimensionality of the CFD output is much larger than the allowed ML input

Step 1. Define a tree of elementary defects

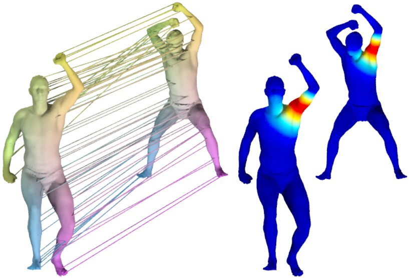


Step 2. Design defects as virtual anti-surgeries



Step 3. Use functional maps to transfer defects

- On a first healthy patient, realistic deformations are created by hand (time: weeks)
- Deformations are applied to other healthy patients via functional maps[a] (time: minutes)



[a] M.Ovsjanikov *et al.* ACM Trans. Graph. 2012

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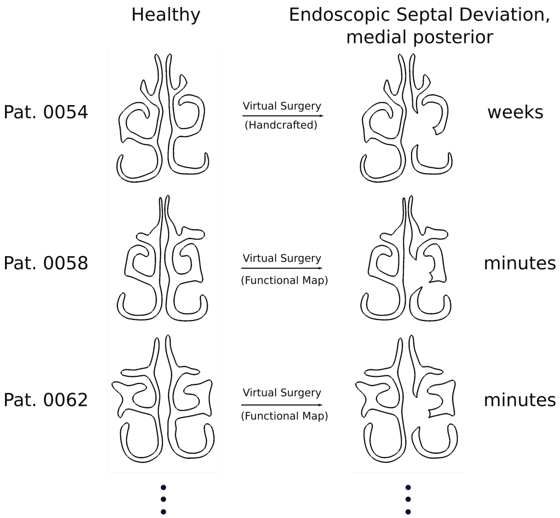

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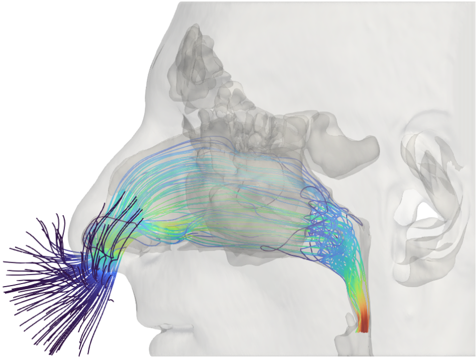
Step 4. Run CFD to create the database

- 277 distinct anatomies are generated from 7 healthy patients
- Defects are isolated or in combination, various severities
- Classes are relatively balanced (but for the healthy class)
- OpenFOAM is used to compute the flow field

The OF setup

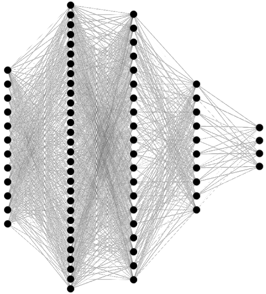
- Steady inspiration at 280 ml/s (mild breathing)
- Well resolved (incompressible) LES
- All terms at second-order accuracy
- Statistics computed over 0.6 s
- Mesh with 15M cells, no layers, $\nu_t/\nu < 4.4$
- 5000 core hours for each case



A neural network to classify pathologies

- A standard neural network is trained to classify pathologies
- Three fully-connected hidden layers (30, 20, 10 neurons each)
- Hyperbolic tangent as activation function (sigmoid for output); cross-entropy as loss function; scaled conjugate gradient as backpropagation algorithm to update weights and biases
- LOO (preferred to k-CV) as partition method to carry out validation and testing

Our classifier (12 inputs, 4 outputs):

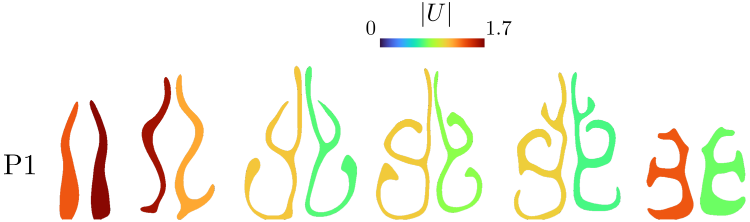


Converting CFD to a small feature set

The number of inputs to the NN (related to the number of observations) must be small

We opt for manual feature extraction

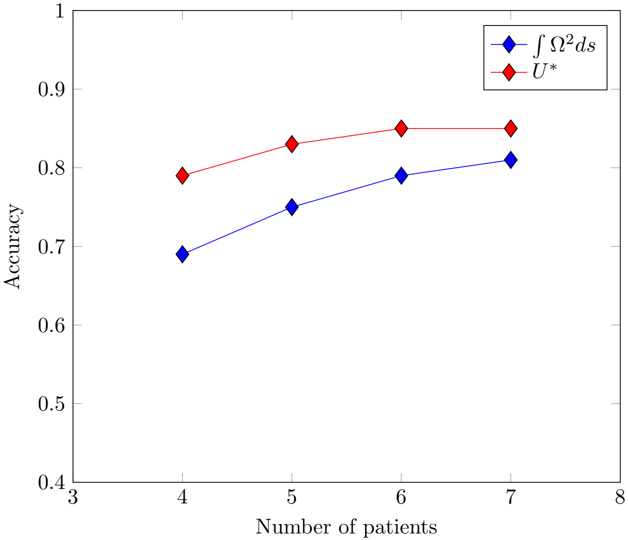
Two strategies: regional averages (of velocity, vorticity, TKE, strain, pressure, pressure gradient, etc), and integral over streamlines



Results: classification experiment (four classes, LOO)

Class	accuracy	precision	recall	F1
Anterior septal deviation, SD-A	0.91	0.82	0.91	0.86
Posterior septal deviation, SD-P	0.90	0.30	0.11	0.16
Middle turbinate hypertrophy, TH-M	0.67	0.47	0.51	0.49
Inferior turbinate hypertrophy, TH-I	0.71	0.51	0.51	0.51

Results: on the size of the dataset



Concluding remarks

- Data-driven techniques have a bright future in medicine and rhinology
- CFD-augmented ML techniques are promising
- A reasonably-sized dataset with CFD input features is expected to be accurate enough for clinical needs

Acknowledgment to the OpenNOSE group!