



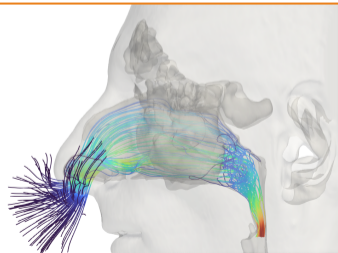
POLITECNICO
MILANO 1863

DIPARTIMENTO DI SCIENZE
E TECNOLOGIE AEROSPAZIALI

Fluid dynamics of the human nose: modeling and clinical perspectives

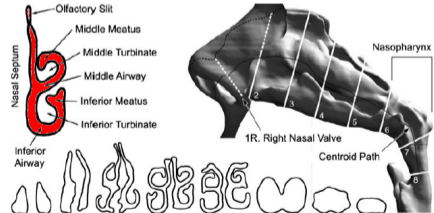
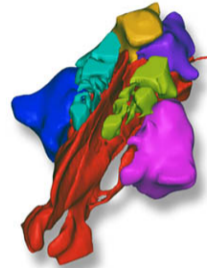
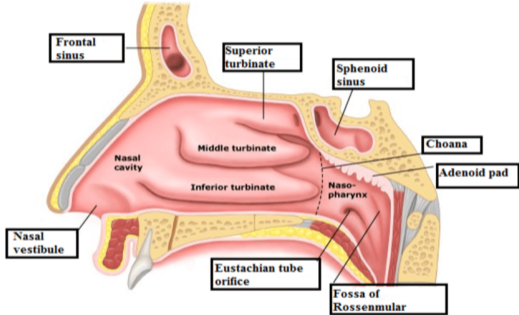
Maurizio Quadrio

CFD parschool, L'Aquila, July 16, 2023



Part I: The nose flow
(overview and clinical implications)

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 difficulties¹
- ▶ In 2014, the one-year (only!) cost of cronic rhinosinusits (alone!) in US (only!) was \$22bn²
- ▶ Certain nose surgeries have 50% failure rate³

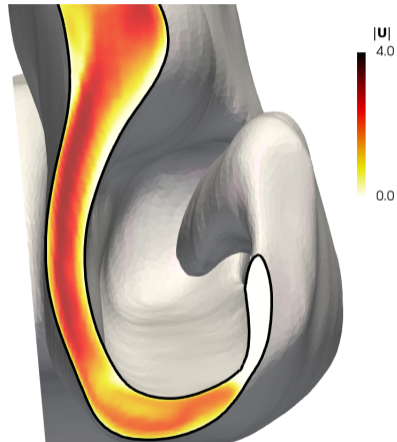
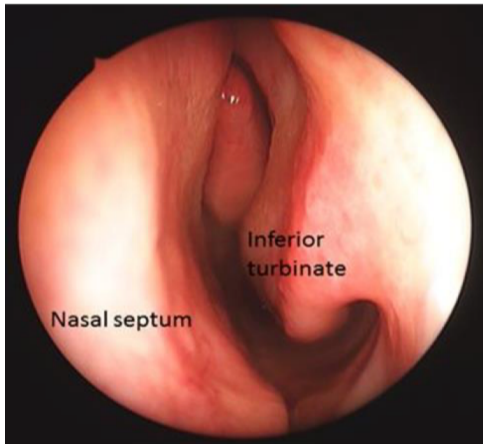
Huge **room for improvement!**

¹Stewart *et al.* Int J Gen Med 2010

²Smith *et al.* The Laryngoscope 2015

³Sundh & Sonnergreen, Eur Arch Otholaringol 2015

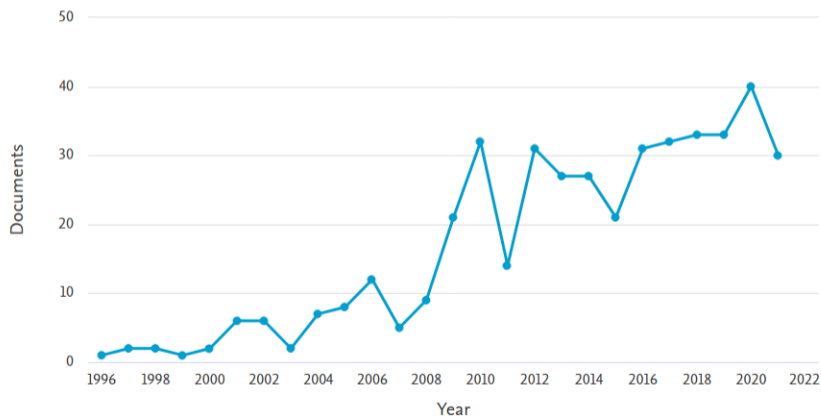
The contribution from fluid mechanics: adding function to form



The contribution of fluid mechanics

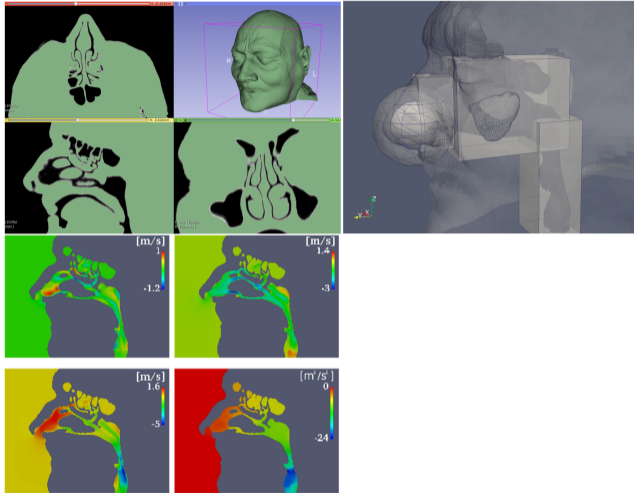
Scopus query: "CFD" + "nasal"

Documents by year



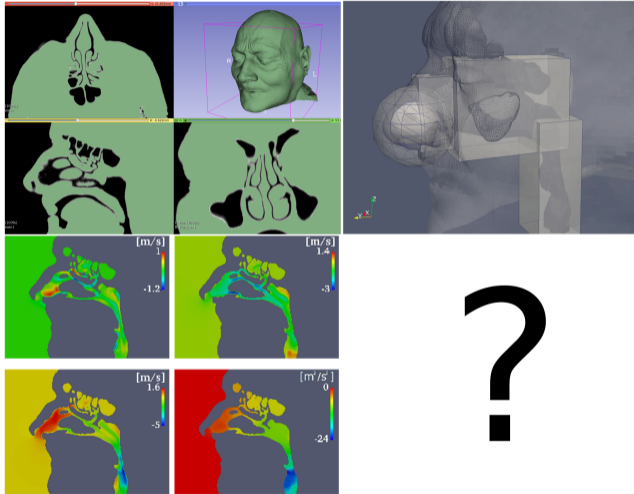
The workflow: from CT scan to...

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



The workflow: from CT scan to...

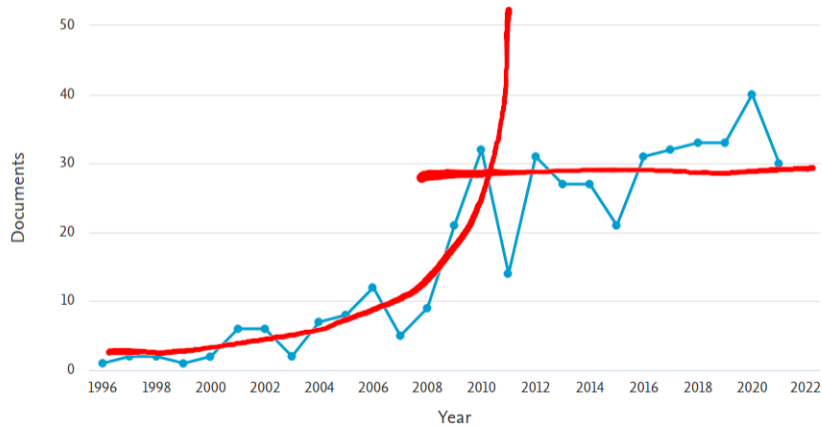
1. Segment the CT scan
2. Build a volume mesh
3. Compute a CFD solution (DNS, LES, RANS, ...)



Only academic?

Scopus query: "CFD" + "nasal"

Documents by year



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 **objective function** is unknown
- ▶ Strong inter-subject anatomical variations with different functional significance

How to proceed?

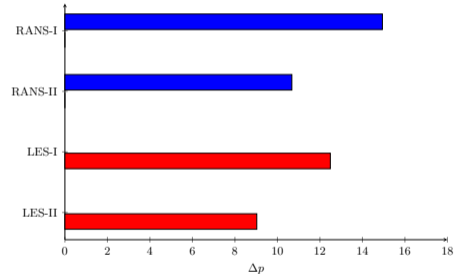
Bringing CFD into the **clinical** setting requires:

- ▶ Assess reliability through a solid benchmark
- ▶ Distill CFD results into something useful (Part II)

Trusting CFD results

- ▶ An unique Reynolds number does not exist
- ▶ Most authors use RANS, but the flow is low- Re and **not** turbulent
- ▶ Most authors use steady RANS, but vortex shedding is crucial
- ▶ Accuracy of discretization is critical (more than one would expect)

Pressure drop for a given flow rate
(Nasal Resistance, NR)

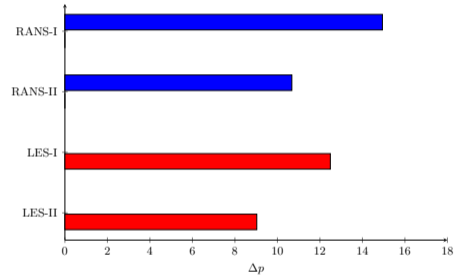


Trusting CFD results

- ▶ An unique Reynolds number does not exist
- ▶ Most authors use RANS, but the flow is low- Re and **not** turbulent
- ▶ Most authors use steady RANS, but vortex shedding is crucial
- ▶ Accuracy of discretization is critical (more than one would expect)

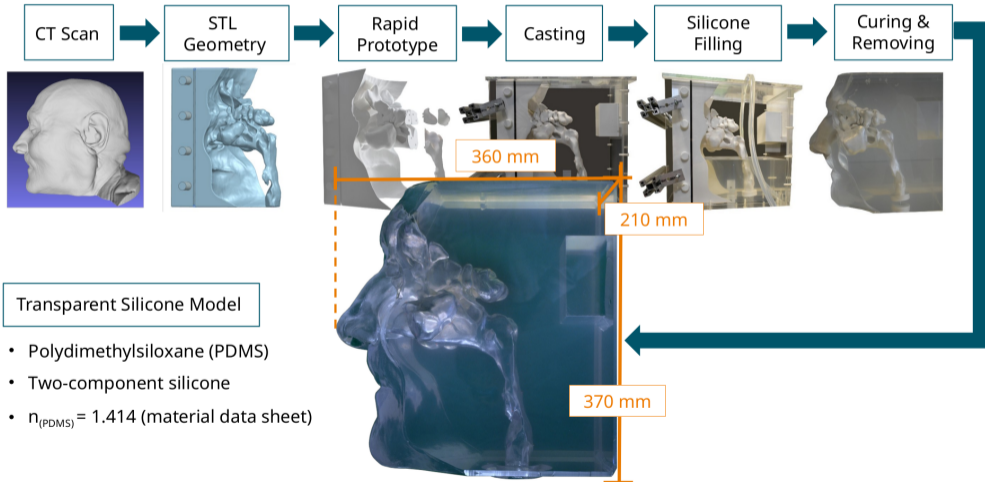
The major limiting factor is **lack of reproducibility**: anatomies are sensible information!

Pressure drop for a given flow rate
(Nasal Resistance, NR)



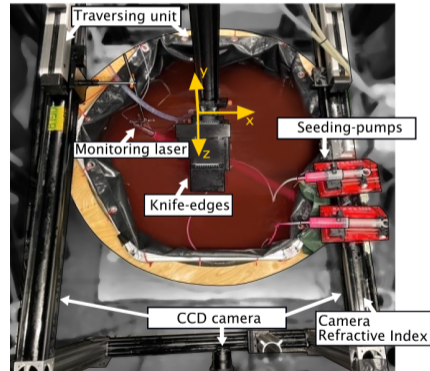
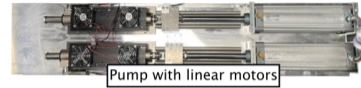
Creating a benchmark: a tomo-PIV experiment

Transparent Silicone Model

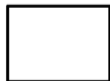
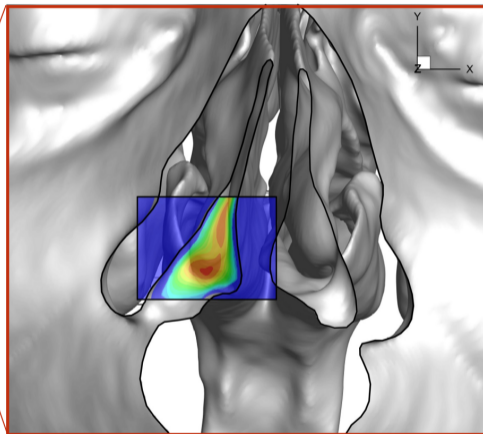
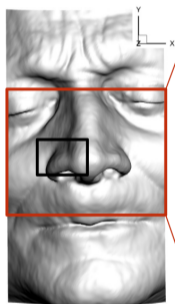
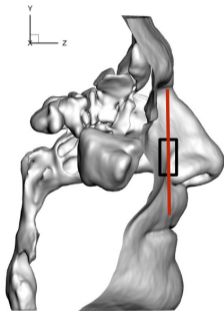


The experimental setup

- ▶ 800L fish tank with 3 portholes
- ▶ 3-axis traversing unit
- ▶ CCD cameras (1600×1200 px) and Nd:Yag laser, 15Hz
- ▶ 2 pumps driven by linear motors
- ▶ fluorescent particles with two seeding pumps
- ▶ laser and camera for RI monitoring



Preliminary results



FoV = 49.5 mm x 36.5 mm
RoI = 49.5 mm x 36.5 mm x 4.5 mm
Scale factor = 29.1 pix/mm
VSC error < 0.1 pix

- ▶ Domain `opennose.org` registered since 2015
- ▶ Fostering the new community of *computational rhinology*
- ▶ Simultaneous availability of i) DNS data; ii) experimental data; iii) anatomy information (industrial CT scan of the phantom)

Acknowledgment to the OpenNOSE group!

EXPERIMENTS



MACHINE LEARNING



SURGEONS



CFD



Part II: The role of CFD

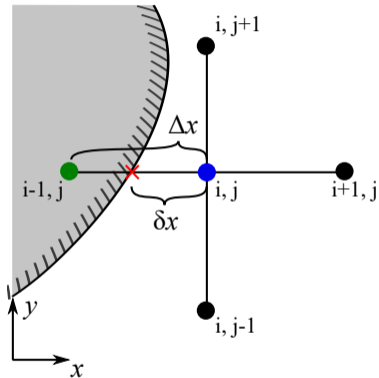
Our suggested avenues to make CFD clinically viable

Currently, classic CFD (90% RANS, 9% LES) is **too expensive** for surgery planning:

- ▶ Time
- ▶ Skills
- ▶ Money

1. An *ad-hoc* DNS solver (in CPL)

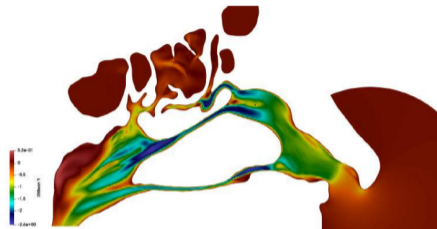
- ▶ 2nd-order in space, staggered grid, linear extrapolation
- ▶ 2nd-order in time but **implicit** (no issues when grid point approaches boundary)
- ▶ Computing and storing solution at ghost nodes is not required
- ▶ Simple and efficient: it modifies the central weight of the Laplacian only
- ▶ Extrapolations in the 3 directions are independent and additive



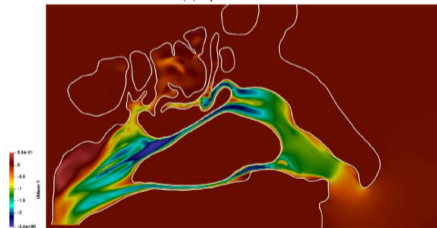
CPL: Compiler and Programming language, <https://cplcode.net>

Testing against OpenFOAM

- ▶ STL of the nose as input
- ▶ Verified II-order convergence
- ▶ 10-100x faster than OpenFOAM
- ▶ Speed **compatible with a clinical setting**
- ▶ (General interest?)



(a) OpenFOAM

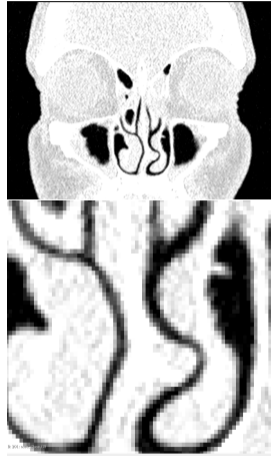


(b) STLIMB

2. An *ad-hoc* physical model (in CPL)

Geometric information is the major limiting factor

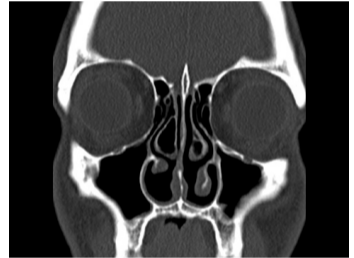
- ▶ Thickness of the **nasal fossae** is often 1-2 voxels (even less for pathologies)
- ▶ No less than the **CT grid** must be used (typically 512^3)



Nasal resistance is not telling the whole story

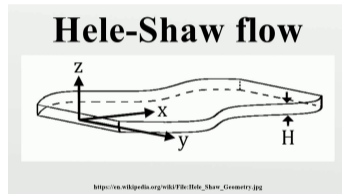
- ▶ Restoring a good Nasal Resistance is not enough
- ▶ Cfr. the "Empty Nose Syndrome"
- ▶ **Heat transfer** characteristics must be also considered!

Scan of an Empty Nose



The reduced model

- ▶ The nasal fossae are thin, non-planar channels
- ▶ Less than Navier–Stokes suffices to compute nasal resistance
- ▶ A **quasi-1d** approximation in the "narrow" direction: **Hele–Shaw** for a non-planar channel (with temperature)
- ▶ **Local** porosity computed for each voxel as a function of the wall distance
- ▶ Explicit reconstruction, segmentation, meshing are avoided



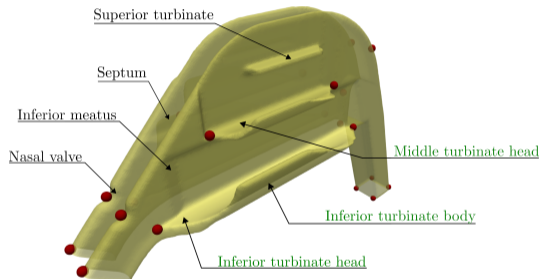
An optimization problem (at last!)

Hypothesis: The functionally normal nose provides **balanced** heat transfer and hydraulic characteristics

- ▶ Analogy with heat exchangers
- ▶ An **optimization problem** is formulated and solved with adjoint techniques
- ▶ Lighting-fast code: 1 second on 1 core, all inclusive

3. Using Machine Learning?

- ▶ Augment ML with CFD
- ▶ Hypothesis: the flow field amplifies anatomic information
- ▶ A simple regression problem is set up to test the hypothesis
- ▶ Parametric, CAD-based model nose with 4 pathological parameters
- ▶ Regression performance is compared for **geometric**- vs **flow**-based features



The way we derive features

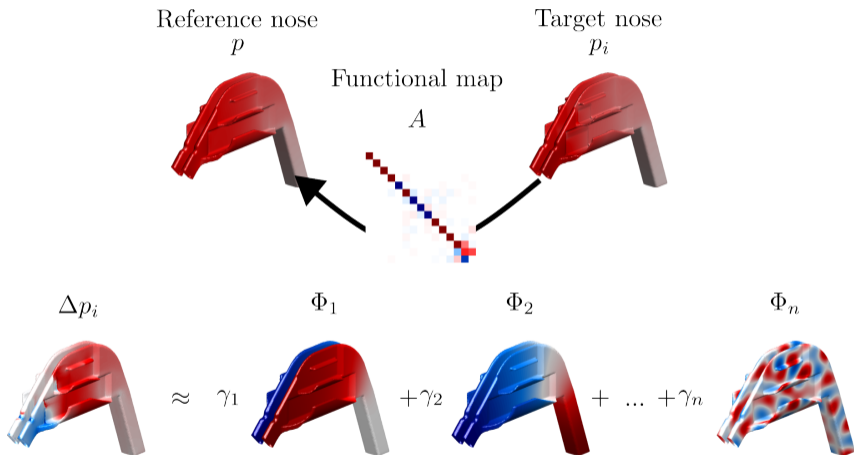
Features are computed with **functional mappings^a** (FM)

- ▶ FM are a tool from computational geometry
- ▶ FM express bidirectional mapping between two shapes (and functions defined over them)

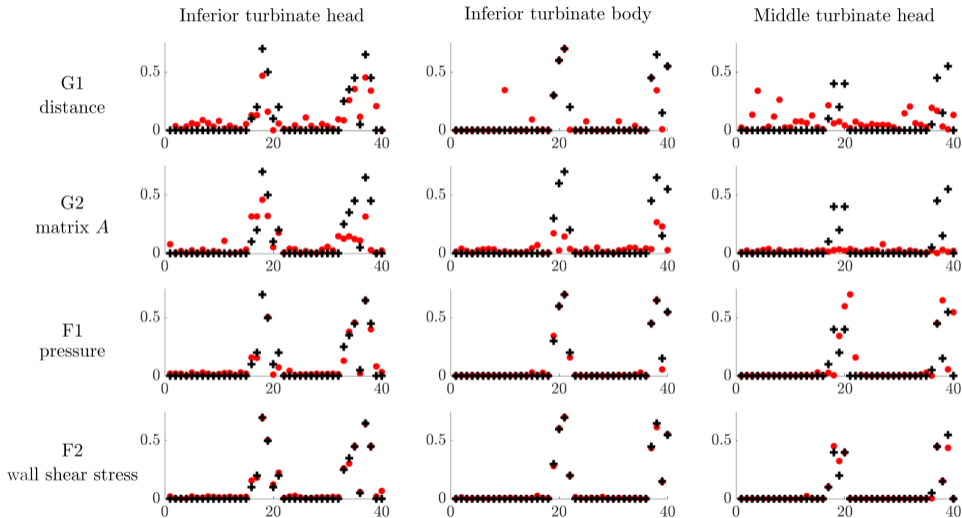


^aM.Ovsjanikov et al. ACM Trans. Graph. 2012

An example of flow-based feature



F-features are superior to G-features

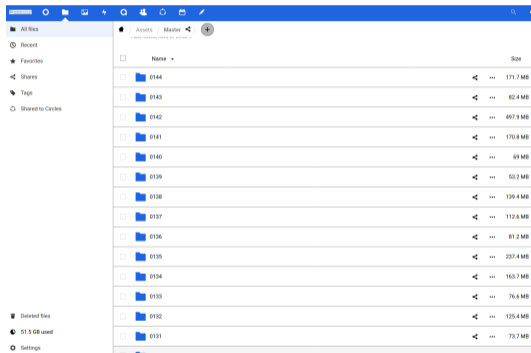


4. Using Machine Learning!

Database of:

- ▶ CT scans
- ▶ rhinomanometry data
- ▶ ENT evaluation sheet

Open and labeled data: huge value!

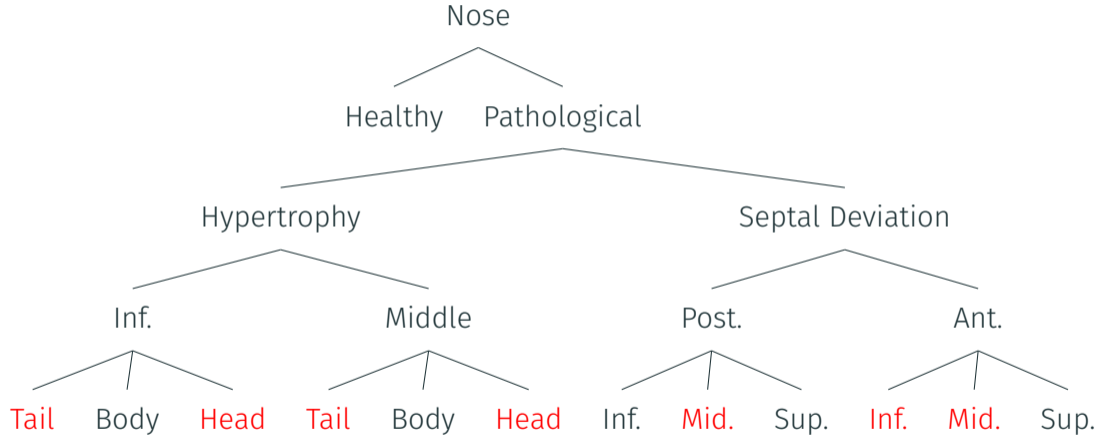


Name	Size
0144	171.7 MB
0143	82.4 MB
0142	497.9 MB
0141	170.8 MB
0140	69 MB
0139	53.2 MB
0138	130.4 MB
0137	112.6 MB
0136	81.2 MB
0135	237.4 MB
0134	168.7 MB
0133	76.6 MB
0132	126.4 MB
0131	78.7 MB

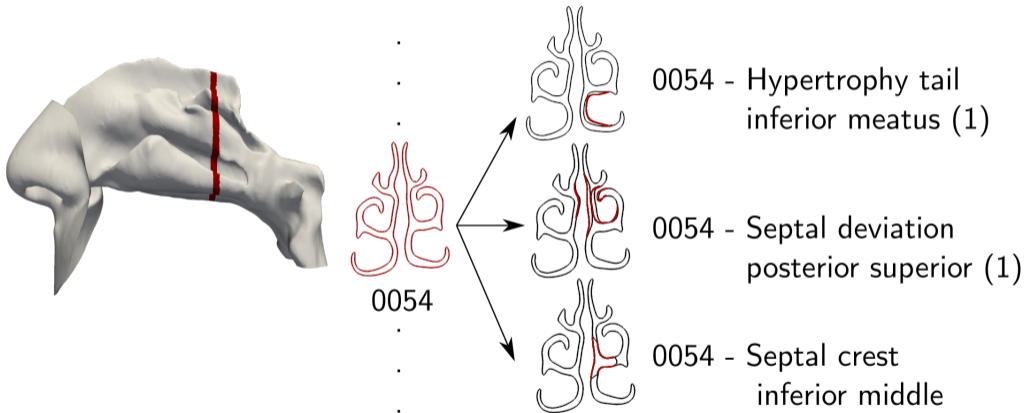
Augmenting ML with CFD (not the other way around) is new and poses new problems

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**

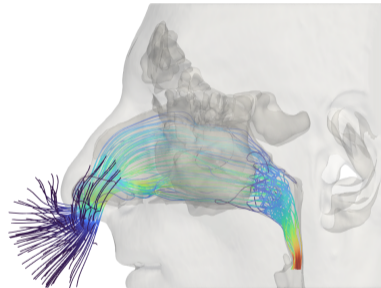
	Healthy		Endoscopic Septal Deviation, medial posterior	
Pat. 0054		<u>Virtual Surgery</u> (Handcrafted)		weeks
Pat. 0058		<u>Virtual Surgery</u> (Functional Map)		minutes
Pat. 0062		<u>Virtual Surgery</u> (Functional Map)		minutes
	⋮		⋮	

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 OpenFOAM setup

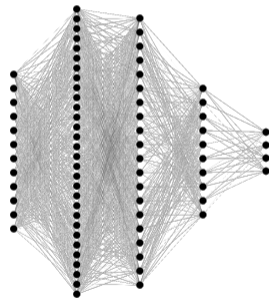
- ▶ Steady inspiration at 280 *ml/s* (mild breathing)
- ▶ Well resolved (incompressible) LES
- ▶ Mesh with 15M cells, no layers,
 $\nu_t/\nu < 4.4$
- ▶ All terms at second-order accuracy
- ▶ Statistics computed over 0.6 s
- ▶ 7000 core hours for each case



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-CV (preferred to k -CV) as **partition method** to carry out validation and testing

Our classifier (12 inputs, 4 outputs):

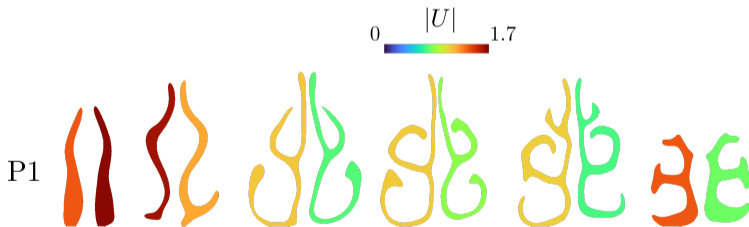


Converting CFD to a small feature set

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 line integral over **streamlines**

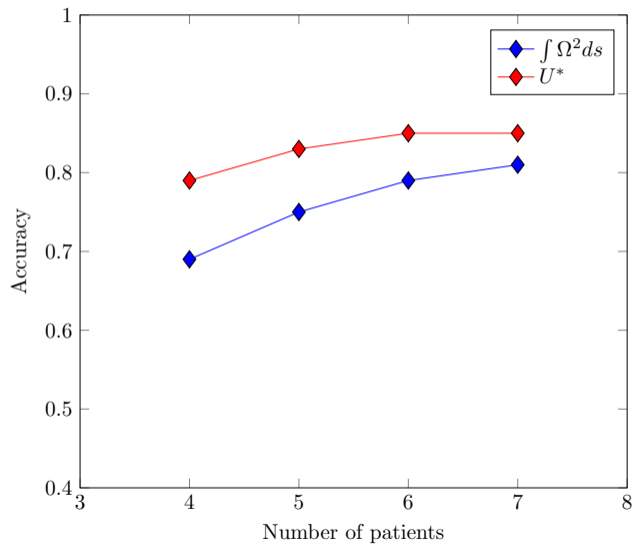


Results: classification experiment (four classes, LOO)

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

- ▶ With k -CV accuracy approaches 100%
- ▶ Adding simple features improves accuracy further

The dataset needs to grow



Concluding remarks

- ▶ The nose flow is an interesting, high-potential interdisciplinary topic
- ▶ CFD-augmented ML techniques are promising
- ▶ CFD (and HPC to some extent) has a bright future in medicine

Acknowledgment to the OpenNOSE group!

EXPERIMENTS



MACHINE LEARNING



SURGEONS



CFD

