Machine learning and fluid mechanics in biological applications

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Karlsruhe, Sept 17, 2019

POLITECNICO
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DIPARTIMENTO DI SCIENZE
E TECNOLOGIE AEROSPAZIALI

Outline

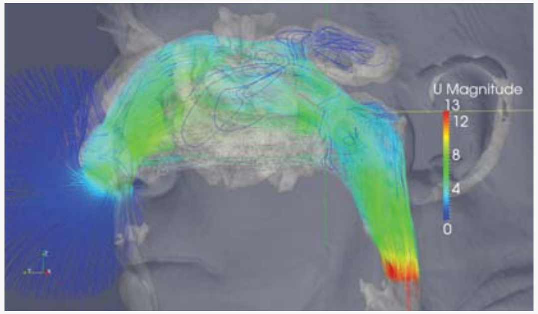
Background

The human nose

Machine learning

Conclusions

We are all familiar with the nose, aren't we?



Several functions:

- Air conditioning (humidification, heating or cooling)
- Filtering
- Preventing infections
- Olfaction (+ taste!)
- Voice

Nose is key to an healthy life

Nasal disorders may induce:

- lung problems
- disturbed sleep (e.g. snoring)
- allergen-driven inflammation of the mucosa
- reduced smelling
- middle-ear aeration problem
- aesthetic surgery (often disrupted functionality)

Why studying the nose?

Nasal pathologies are widespread

- Large incidence
- Lack of (reliable) diagnostic and therapeutic tools
- Large failure rate of surgical corrections
- Huge societal cost

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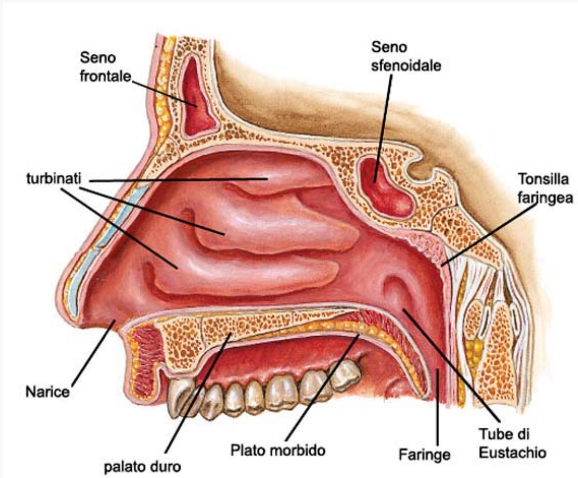
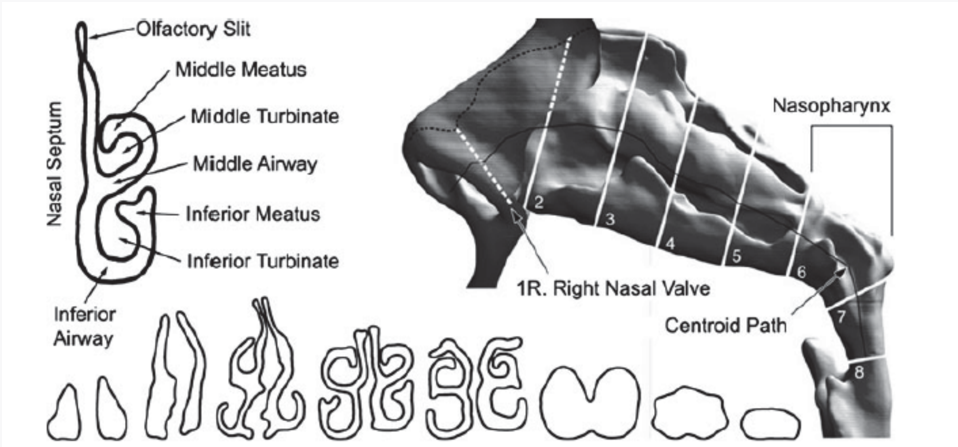
Anatomy

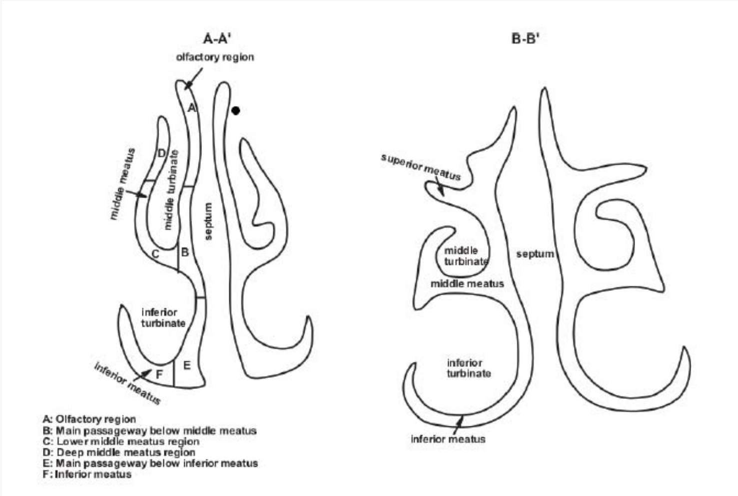


Seno
frontale
Seno
sfenoidale
turbinati
Tonsilla
faringea
Narice
palato duro
Plato morbido
Faringe
Tube di
Eustachio

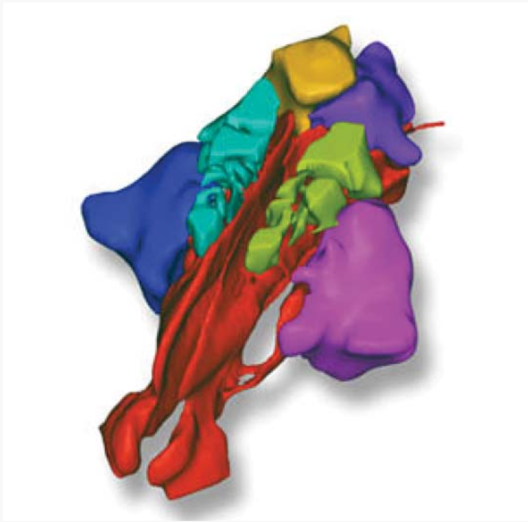
A simple duct?



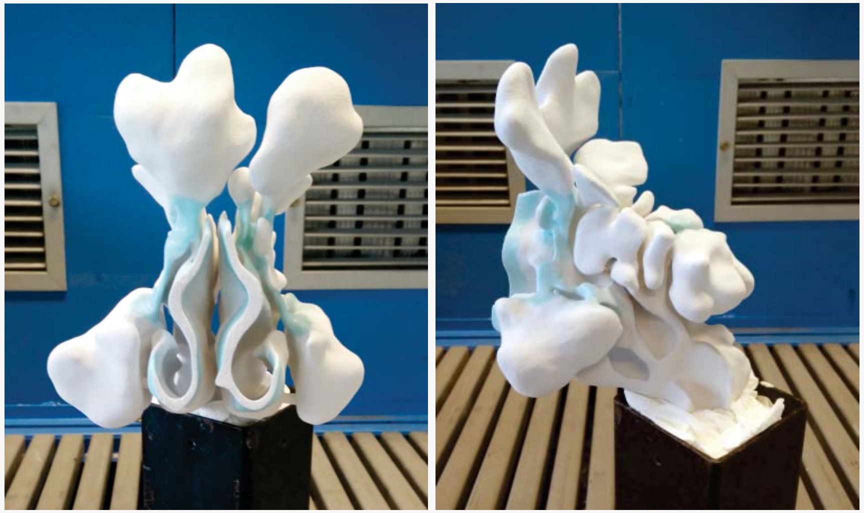
Turbinates and meata



A 3D view of the naval cavities



Sinuses and turbinates



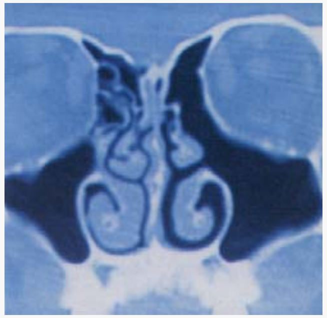
The state of the art

Nowadays functional endoscopic sinus surgery (FESS) is the gold standard for chronic NBD treatment. The operation generally involves inferior/middle turbinoplasty and uncinate and ethmoid excision, sometimes followed by opening of the maxillary, sphenoid and frontal sinuses. A correction of a nasal septal deviation can also be necessary.

...

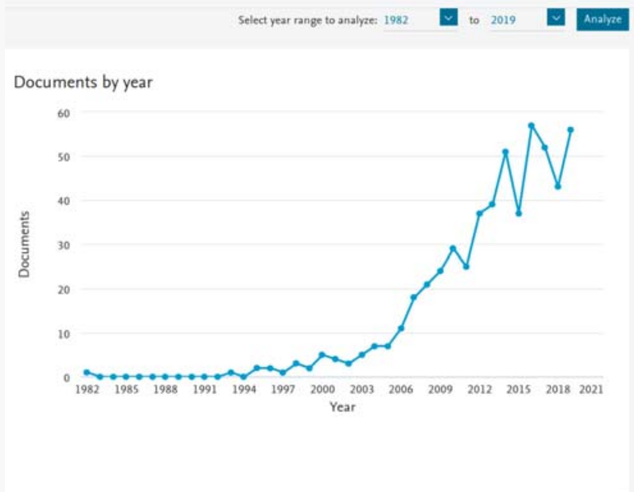
However, we are currently unable to assess the relevance of every single anatomic anomaly and its surgical modification on the overall nasal flow quality and nasal obstruction.

A typical FESS with radical turbinectomy or turbinoplasy



Can CFD help?

- *In-vivo* approach: difficult, not useful
- *In-vitro* approach: rarely used
- CFD: first "good" study in 2004 (Zhao et al, Chem. Senses)

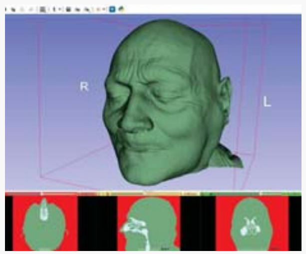


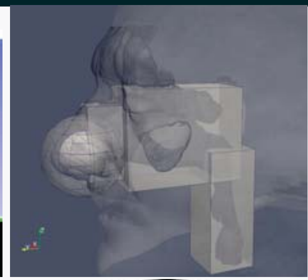
CFD of the nose: still a young field

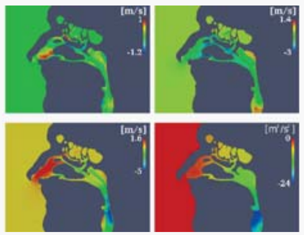
- Producing a decent mesh is long and complicated
- Questionable (but never questioned) modellistic approaches
- 3d, unsteady, chaotic, mostly laminar flow (often computed with RANS and turbulence models)
- Results are never validated!

The patient-specific procedure in a nutshell

1. CT
2. meshing
3. CFD
4. analysis







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The role of machine learning

CT	CFD	ML
Form	Form	Form
	+Function	Function
		+Inference

The OpenNOSE group

The long-term workplan

CFD :	RANS	LES	DNS
ANATOMY :	 CAD 200	 SYNTHETIC 200	 REAL CT 5000
ML :	HAND-CRAFTED FEATURES		DEEP LEARNING

The Titanic dataset

- 891 passenger data or observations
- 11 known features: Passenger's ID, Class, Name, Sex, Age, Siblings/spouses aboard, Parents/children aboard, Ticket number, Fare, Cabin, Embarked from
- one target variable to predict: Survived Y/N

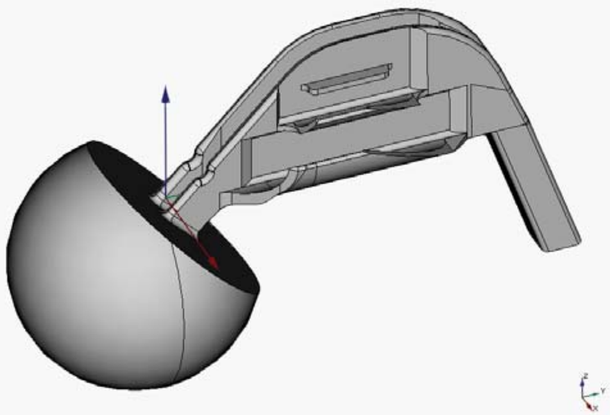
Our first simplified ML experiment

Goal: predict the (known) degree of severity for turbinate hypertrophy

- Simplified anatomy
- Simplified computational approach
- Supervised Learning: regression
- Need for feature selection (worst than Titanic)

The simplified anatomy

A simple parametric CAD model to reproduce the main features of the real nose

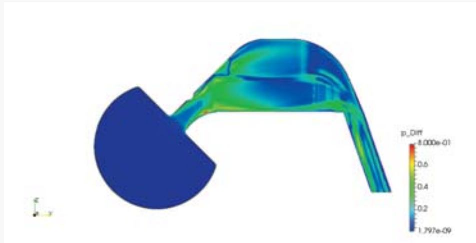


The simplified anatomy

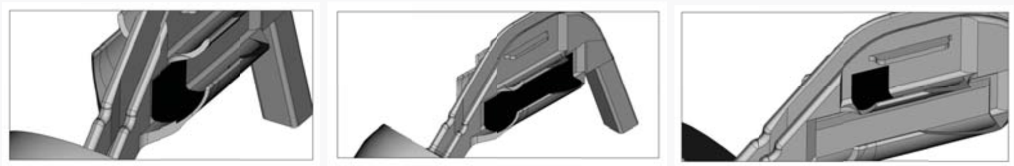
The real nose vs a CAD model (RANS solutions)

The simplified computational approach

Difference between RANS and LES of the model



Introducing anatomical anomalies



- Eight independent variations (5 harmless, 3 pathological) closely supervised by MDs
- 3 types of monolateral turbinate hypertrophy
- 200 geometries, 50% with non-pathological variations only
- Different ”amplitudes” of the anomalies

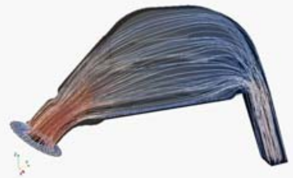
Need for reduction of data size!

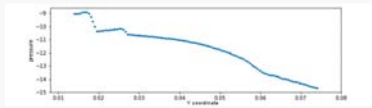
- Switch from 3D fields (210 MB) to smaller data structures
- Extract handcrafted features
- Feature selection (by standard techniques)

1. Expert dimensionality reduction (from 210 MB to 3 MB)

Examples:

- Cut planes following selected landmarks
- Streamlines (interesting for unsteady CFD)
- Area-averaged pressure along the airways

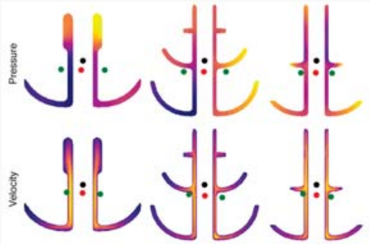




2. Feature Engineering

Define and extract handcrafted features (with no morphological information)

- ”Center of gravity” in coronal planes
- Flow rate distribution on low-res grids
- Average field values on low-res grids
- Polynomial fitting of the mean pressure evolution
- Arrival-time histograms (not used)
- Average streamline (not used)



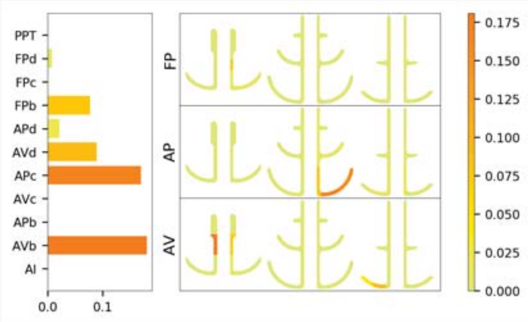
3. Feature Selection

Identify the most relevant features

- Three separate regressions (to learn more)
- 20% of cases set aside for test, 80% used as training set
- Main algorithms: Lasso (linear) and Extra-Trees (non-linear)
- Feature Selecion Strategies: RFE-CV (embedded), FFS (wrapper)

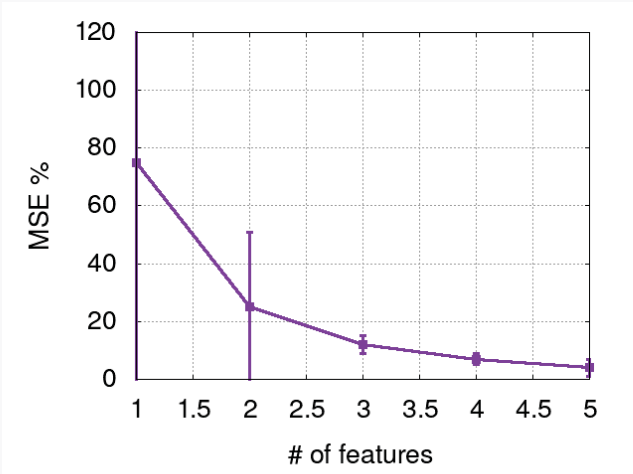
Feature importance: example (inferior turbinate, anterior hyp.)

- Pressure in the inferior meatus of section c (just downstream the alteration)
- Velocity magnitude ahead of the hypertrophy in both fossae
- Predictive value is not associated to pressure in each region, but to its difference



Prediction

Gaussian process (easier to interpret, also provides variance and confidence interval)



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Final remarks

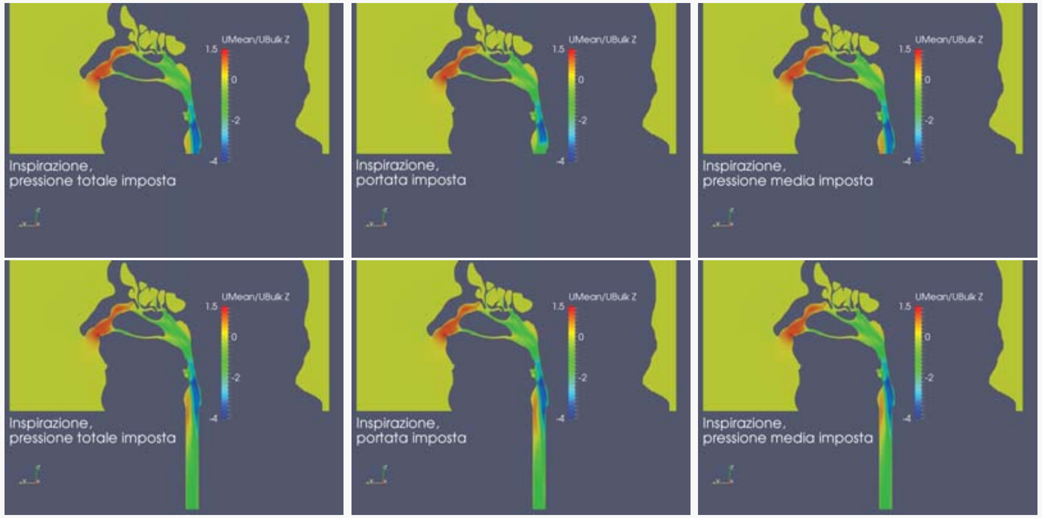
- Very preliminary study
- Yes, one learns something from CFD
- Successful detection of anomalies from anatomy + CFD

Outlook

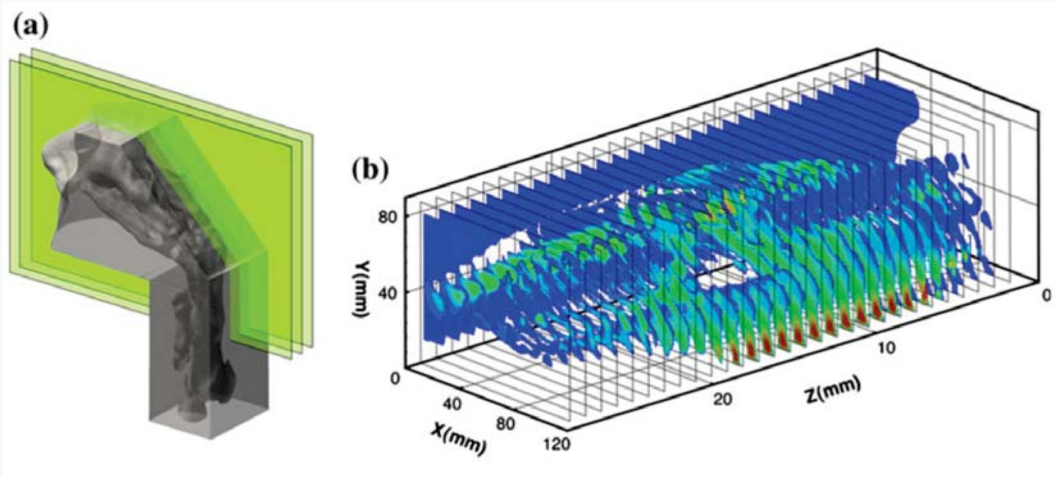
- Black-box tools should be used with care in medicine
- Real CT, LES/DNS data, realistic patient variations
- Need for Big Data (large number of CT scans)

Final goal: understanding what is the right goal (i.e. define the ”good” nasal airflow)

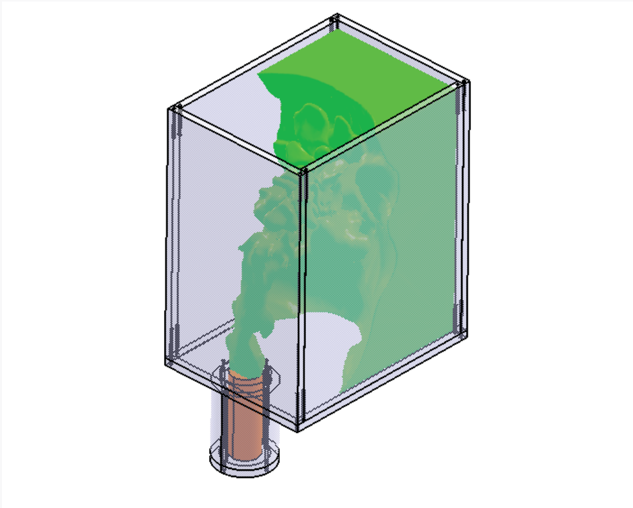
Which boundary condition(s)?



PIV velocity measurements

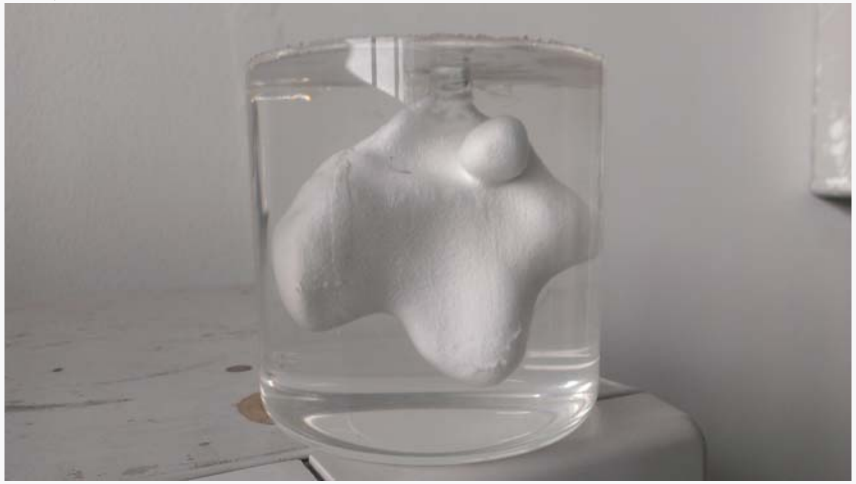


Building the model



The phantom model

1) Dissoluble material coated and embedded in silicone resin



The phantom model

2) Removal of the dissoluble material by water

The phantom model

3) Filled with water + glycerine: the model is... phantom!