SURGERY PLANNING FOR THE HUMAN NOSE: TACKLING ANATOMIC VARIABILITY WITH MACHINE LEARNING AND CFD

Maurizio Quadrio[1*], Giacomo Boracchi[2], Riccardo Margheritti[2], Carlotta Pipolo[3], Andrea Schillaci[1]
[1]*Department of Aerospace Science and Technologies, Politecnico di Milano, Italy*
[2]*Department of Electronics and Bioengineering, Politecnico di Milano, Italy*
[3]*Otolaryngology Unit, Asst Santi Paolo e Carlo, Department of Health Sciences, University of Milan*

Summary In the surgical treatment of nasal breathing difficulties, the underlying huge anatomical variability poses a significant challenge to ENT surgeons, who are often unable to take proper surgical decisions based on functional information. In this contribution, we describe a procedure that uses machine learning to identify pathologies and related surgical corrections. An important novelty is that here the (standard) neural network is driven by functional information related to the fluid mechanics of the nose, derived from CT scan of the patients after large-scale CFD simulations.

BACKGROUND AND MOTIVATION

The motivation of this work is supporting the surgical decisions of the Ear, Nose and Throat (ENT) doctors regarding the frequently occurring corrections of the nasal breathing difficulties which affect so many of us, because of pathologies or malformations of the upper respiratory airways. The many functions of the human nose are primarily driven by fluid mechanics, but the convoluted shape of the nasal cavities, which determines such functions, is highly variable among subjects. Hence, a clear link between shape and function is not assessed yet [2]. hence, ENT surgeons must take surgical decisions mostly relying on the visual analysis of the patient's anatomy, acquired by a CT scan. Since extreme anatomies sometimes happen to be asymptomatic, while other apparently "normal" anatomies lead to severe symptoms, the notion of a functionally average nose is not available [1]. The clinical path leading to surgical decisions is thus often quite subjective, and many surgical maneuvers simply do not achieve the expected goal: an impressive example is the surgical correction of septal deviations, where more than 50% of the patients report dissatisfaction after surgery [3, 7].

In this work, we exploit the recent suggestion [5] that a machine-learning approach based on flow features, available after a Computational Fluid Dynamics (CFD) analysis, might be more effective than purely geometric features at determining the proper surgical treatment. Therefore, we describe the construction of a properly annotated dataset, to be processed by CFD, designed to train a standard machine-learning model capable to identify the most appropriate surgical action for a specific patient, starting from his/her Computed Tomography (CT) scan.

METHOD

The database needed for training must be reasonably sized, and equipped with robust and non-equivocal labels. Further, it needs both healthy and pathological patients.

By perusing our own internal database of nasal CT scans, we select 7 patients that by consensus have a normal sinonasal anatomy. In tight collaboration with ENT surgeons, we then develop a tree of elementary defects, to be injected onto the healthy anatomies. These defects are defined as the typical deformations that would be corrected by the smallest conceivable, *atomic* surgical action, and are created by a sort of *virtual anti-surgery*. A complete view of all the considered geometrical defects is provided in the tree of pathologies schematically shown in figure 1: they include the two large families of septal deviations and hypertrophies of the turbinates. These defects can be present either one at a time or in combination, and are given a severity parameter.

Creating a properly defined, anatomically representative defect like one of those described in fig.1 is extremely time-consuming. Therefore, an automated procedure to carry out such inverse surgeries automatically is devised. Once deformations have been satisfactorily created manually for the first patient, they are replicated for the other patients by taking advantage of functional mapping [4]. Functional mapping is a computational geometry technique which allows the seamless transfer of the deformation function over the anatomy of one patient to that of any other patients. An example of corresponding defects is shown in figure 2.

The 7 healthy patients and various combinations of defects applied to them leads to the creation of a dataset with 277 distinct anatomies. These are processed via CFD, and the computed flow solution is further processed to extract a small set of significant features. The three-dimensional CFD simulations employ well-resolved Large Eddy Simulation (LES) with approx. 15 millions cells, computed using the finite-volume library OpenFOAM. Each anatomy is simulated for a steady inspiration at a rate of 280 ml/s, corresponding to a restful breathing.

Since the size of the CFD output is much larger than the number of available observations, the direct use of the full CFD-computed flow field is not conceivable, and one has to resort to compact features to shrink the number of inputs to the classifier, while preserving as much as possible of the information content of the CFD solution. The extraction

* Corresponding author. E-mail: maurizio.quadrio@polimi.it

of meaningful features is a crucial step of the procedure, preliminarily discussed in [6] and not reported in this Abstract owing to lack of space. Results discussed below are obtained by distilling the entire CFD output into 12 real numbers, the average of the mean velocity is six cross-sections of the nasal cavities, separated in left and right.

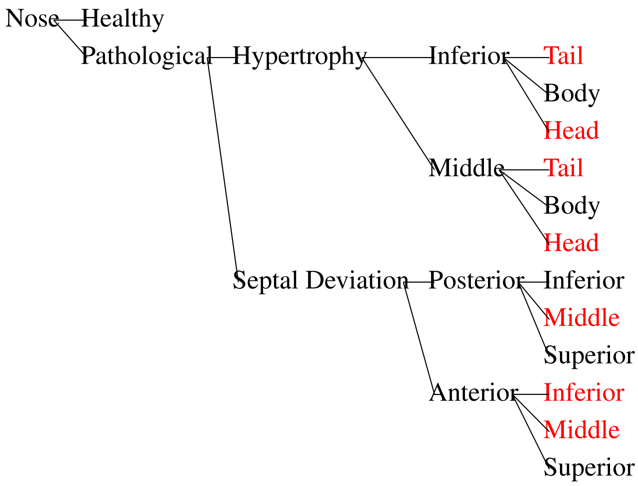

Figure 1. Tree of deformations/pathologies. Every pathology is accompanied by a grade of severity. Red leaves at the rightmost level indicates pathologies considered in the present work.

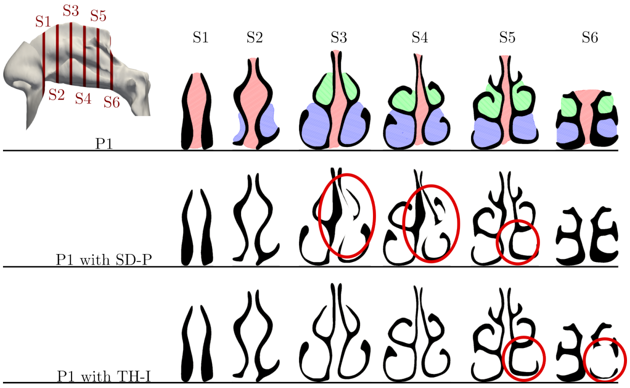

Figure 2. Healthy anatomy of patient P1 (top) versus two pathological modifications: severe septal deviation located posteriorly (middle), and severe hypertrophy of the inferior turbinate (bottom). Colours indicate the main anatomical areas: the airways (black), the inferior turbinates (blue), the middle turbinates (green), the septum (red). Red circles highlight regions altered by the pathology.

RESULTS

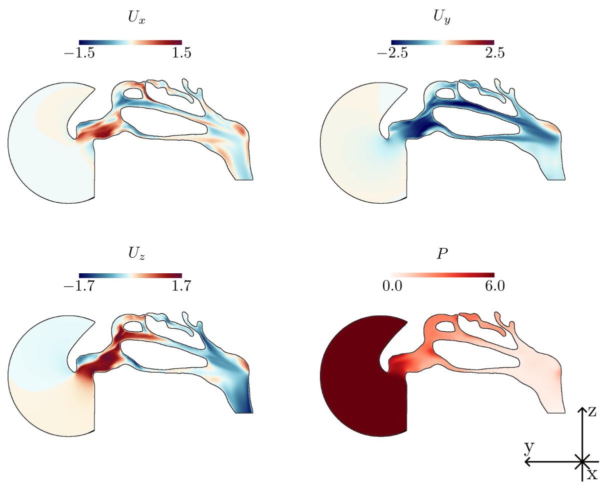

Figure 3. The mean velocity and pressure field for the healthy patient P1.

The CFD analysis (a sample result is shown in figure 3) and the ensuing small set of features are used to train a neural network, made by four layers and with less than 100 neurons overall, whose goal is to classify the case. The network is tested on never-seen-before patients, both artificially derived as above from healthy cases, and real CT scans. Results, to be shown in detail at the presentation, indicate that the current dataset, consisting of less than 300 samples, already enables high classification accuracies on never-seen-before patients when processed via a standard, shallow neural network. We stress again that solving a classification problem here is tantamount to suggesting a surgical decision, thanks to the way deformations have been designed. Work is underway to verify the level of accuracy required by the underlying CFD engine; after that, the database will be redesigned and expanded by a factor 3-5: once the cardinality of the dataset will be large enough to allow for approximately 40 features, the deployment of the method in clinical practice becomes realistically conceivable.

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