The human nasal cavity: towards the optimal surgery with CFD and Machine Learning

Andrea Schillaci*[1], Luca Butera[2], Gianluca Romani[1], Carlotta Pipolo[3], Giovanni Felisati[3], Marcello Restelli[2], Giacomo Boracchi[2], and Maurizio Quadrio[1]

[1]*Dipartimento di Scienze e Tecnologie Aerospaziali, Politecnico di Milano, Milano, Italy*

[2]*Dipartimento di Elettronica, Informazione e Bioingegneria, Politecnico di Milano, Milano, Italy*

[3]*Unità di Otorinolaringoiatria, ASST Santi Paolo e Carlo, Dip. Scienze della Salute, Milano, Italy*

Summary Nasal breathing difficulties are a common condition, and their treatment often requires surgery. Unfortunately, procedures are designed and carried out mostly based on the surgeon's experience; data supporting surgical choices are lacking. Computational Fluid Dynamics (CFD), by naturally accessesing functional properties of the human nose, improves the understanding of its flow field. However, a detailed flow prediction alone does not immediately lead to identifying the best surgical maneuver. We intend to leverage Machine Learning (ML) to bridge this gap and infer functional information from CFD data. The present study is preliminary and uses rather crude anatomical and computational models; however, its results demonstrate the potential of a ML model trained on CFD data.

INTRODUCTION

Nasal breathing difficulties (NBD) are a commonly encountered condition in the clinical practice of the Ear, Nose and Throat (ENT) doctors, causing huge societal cost. For example, the overall annual economic burden of chronic rhinosinusitis in the U.S. alone is estimated at 22 billion USD per year [1]. Though a variety of techniques is available to ENT surgeons, consensus is lacking on the surgical approach for a specific patient. As a consequence, up to 50% of the patients undergoing common surgical procedures, as for example septoplasty, report that symptoms did not improve [2].

During the last years, Computational Fluid Dynamics (CFD) has successfully tackled increasingly complex geometries; the anatomy of the human nasal cavity has become affordable, and CFD is nowadays a further item in the toolbox of the ENT surgeons (Fig.1a). We have designed a computational procedure, described e.g. in [3], that starts from a CT-scan of the patient, and reliably computes the (mean and instantaneous) flow field in the nose via Direct Numerical Simulation. Our ambitious long-term goal is the development of a robust tool to support ENT surgeons in discriminating pathologies from the normal, often large anatomical variations, and in selecting the best surgical approach.

However, it remains non-obvious how to translate the wealth of information contained in a CFD solution into a rational selection of the best surgery for each patient [4]. In this work we describe our preliminary evaluation of Machine Learning (ML) towards this goal. We assess the inference capabilities of ML algorithms by estimating geometrical measures using only fluid dynamics features. We notice that our goal differs from the majority of the research that applies ML to fluid mechanics, where the efforts are devoted to the improvement of flow modeling, optimization and control [5].

METHODOLOGY

The preliminary nature of the work calls for a simplification of the problem, in terms of both the anatomies and the physical modeling, while at the same time maintaining its key features. For the CFD simulations, we employ a standard $k-\omega$ SST RANS turbulence model (tuned with preliminary Large Eddy Simulations), and a Gaussian process [6] is used for inference. From the anatomical standpoint, an original parametric CAD model of the upper airways is developed (Fig.1b) which replicates the main features of a real nasal cavity, but without the paranasal sinuses. The parametric model is then modified to mimic some of the most common anatomical variations observed in the ENT practice: 4 corresponding to asymptomatic variations of healthy noses, and 3 to pathological conditions typically leading to severe symptoms (anterior hypertrophy of the inferior turbinate, hypertrophy of the whole inferior turbinate, and anterior hypertrophy of the middle turbinate). Combinations of these parameters lead to 200 unique anatomies, which are used to generate a CFD dataset with the associated task of predicting the severity of single pathology expressed in terms of one parameter.

Adopting ML models over CFD output is not straightforward, since every CFD analysis produces large amounts of data. Even the relatively coarse RANS simulations considered here run on about one million cells, and each cell carries at least 7 real values (three spatial coordinates, three components of velocity and pressure). Learning on such highly-dimensional feature space requires an enormous amount of annotated data. Thus, CFD simulations cannot be directly an input for ML, and more compact descriptors are required. We resort to feature engineering, by devising a small number of features designed by experts, i.e. CFD engineers and ENT doctors. Examples of features are: a polynomial fit of pressure along the nose (Fig.2 a); a histogram of total travel times of tracers released at 200 specified locations (Fig2 b); the flow variables averaged over 5 specific cross-sections of the domain and smaller portions of these (Fig.2 c). In the end, the number of features is 342, which is still very high considering the number of samples.

*Corresponding author. E-mail: andrea.schillaci@polimi.it

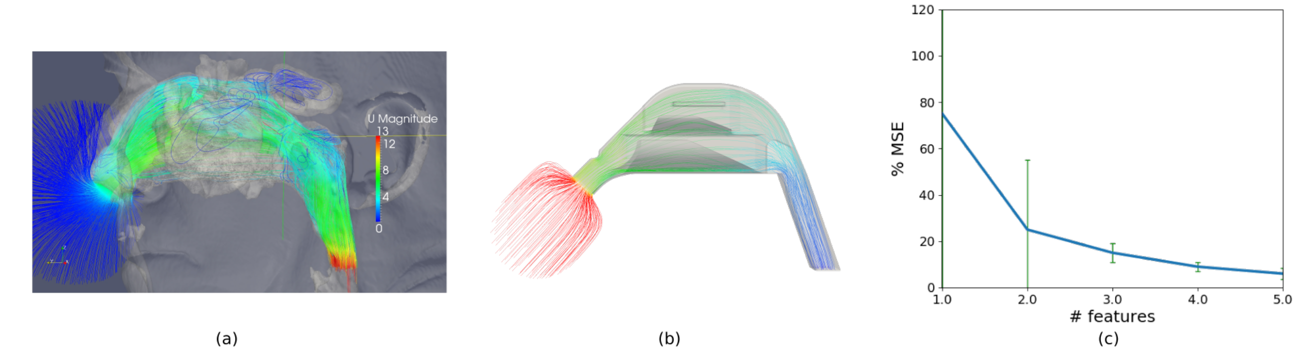

Figure 1: (a) Streamlines in the human upper airways (taken from [3]). (b) Streamlines in the simplified geometric model. (c) Mean square error of the prediction, versus the number of features. The vertical bar quantifies the variance.

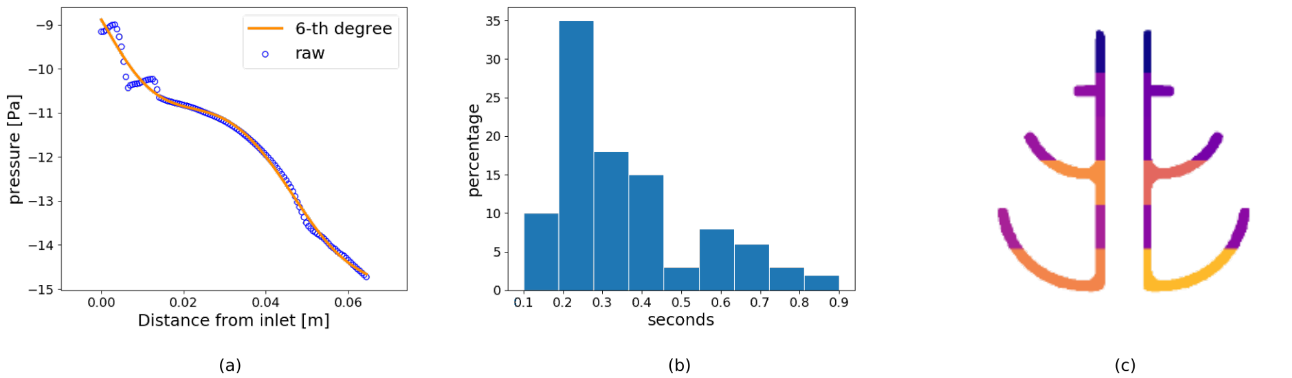

Figure 2: Example features. (a) Polynomially interpolated pressure. (b) Histogram of total travel times of tracers. (c) Flow variables averaged over 10 portions of a cross-section.

RESULTS AND CONCLUSIONS

Experiments performed by cross-validation over our dataset of 200 simulations, show that features extracted from CFD data can successfully infer the target measures of the CAD model. We performed feature selection to identify the most informative features, using both *Recursive Feature Elimination* and *Forward Feature Selection* by fitting *Extremely Randomized Trees* [7] as regression model. As an illustrative example, Fig.1c reports the results of a Gaussian Process trained on the most informative features for the anterior hypertrophy of the inferior turbinate, and shows that the mean square error of the prediction drops below 20%, when only 3 features are used. Remarkably, the *selected* features are often extracted from areas only indirectly affected by the geometrical modification, further indicating that CFD conveys important information. The most informative features are found to be the average flow values across the 5 slices.

CFD can have a large impact upon the ENT practice, as it provides functional *and* patient-specific information about the airflow in the human nose. In particular, our study indicates that features extracted from CFD data have the potential to identify pathologies even when accompanied by non-pathological variability. ML is thus a viable pathway to address those shortcomings that prevent CFD from being routinely deployed in clinical practice. The next step is to validate our study on more accurate CFD models (DNS), more realistic anatomies (CT scans of patients) and more realistic predictions (diagnosis of ENT specialists).

References

[1] Smith, K. A., Orlandi, R. R., & Rudmik, L. Cost of adult chronic rhinosinusitis: a systematic review. The Laryngoscope, 125(7), 1547-1556, 2015

[2] Sundh, C., & Sunnergren, O. Long-term symptom relief after septoplasty. Eur Arch Oto-Rhino-L, 272(10), 2871-2875, 2015

[3] Quadrio, M., Pipolo, C., Corti, S., Messina, F., Pesci, C., Saibene, A. M., Zampini, S. & Felisati, G. Effects of CT resolution and radiodensity threshold on the CFD evaluation of nasal airflow. Med Biol Eng Comput, 54(2-3), 411-419. 2016

[4] Quadrio, M., Pipolo, C., Corti, S., Lenzi, R., Messina, F., Pesci, C., & Felisati, G. Review of computational fluid dynamics in the assessment of nasal air flow and analysis of its limitations. Eur Arch Oto-Rhino-L, 271(9), 2349-2354, 2014

[5] Brunton, S., Noack, B., & Koumoutsakos, P. Machine learning for fluid mechanics. Annual Reviews of Fluid Mechanics, 2020.

[6] Rasmussen, C. E. Gaussian processes in machine learning. In Summer School on Machine Learning (pp. 63-71). Springer, Berlin, Heidelberg. 2003, February.

[7] Geurts, P., Ernst, D., & Wehenkel, L. Extremely randomized trees. Machine learning, 63(1), 3-42. 2006