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MACHINE LEARNING APPLIED TO THE PREDICTION OF TRUMPET BIFURCATION DIAGRAMS: TOWARDS A TOOL FOR TRUMPET DESIGNERS

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ABSTRACT

This work aims to develop a fast and easy-to-use program for the prediction of brass instrument bifurcation diagrams, with minimal supervision from the user. Using numerical continuation, more than ten thousand bifurcation diagrams are generated to train a machine learning model with trumpet impedances as inputs, and descriptors associated with the bifurcation diagrams as outputs. Our approach is based on the definition of virtual players and virtual trumpets to generate the training data. Different regression models are then considered and their performance is compared. The model finally selected shows high speed and great accuracy in predicting the descriptors. Moreover, the regression approach includes regularization which promotes sparsity, hence improving the interpretability of the model. This program then constitutes a potential tool for music instrument designers to easily predict the dynamical behavior of numerical prototypes.

Keywords: *machine learning, numerical continuation, brass instruments, physical modelling*

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1. BIFURCATION DIAGRAM OF A MODEL OF BRASS INSTRUMENT

The use of artificial intelligence in musical acoustics is a growing field of interest, with some recent examples of computational optimization or machine learning applications to design problematics in brass or bowed string instruments [1, 2]. In this study we evaluate the benefits of machine learning in order to elaborate a surrogate model for the prediction of the dynamical behaviour of trumpets.

In previous work, numerical continuation of a physical model of brass instrument was performed using the Asymptotic Numerical Method (ANM) [3]. Bifurcation diagrams could be computed, showing the evolution of periodic solutions with respect to the blowing pressure for different Bb trumpets defined by their acoustic input impedance (Fig. 1). Different "performance descriptors" could then be extracted from the bifurcation diagrams to characterize objectively the instrument. They include information about minimum blowing pressures, hysteresis behaviours, dynamic range, minimum and maximum acoustic pressure in the instrument over a given blowing pressure range. In the present study, given p_0 the quasi-static mouth pressure and p the acoustic pressure in the mouthpiece, we particularly focus on the following descriptors (Fig. 1):

- $Pmin1$: mouth pressure at the Hopf bifurcation
- $Pmin2$: mouth pressure at the fold bifurcation

- H: hysteresis (difference between $Pmin1$ and $Pmin2$)
- p_{min}: minimum value of the amplitude of p
- p_{max}: amplitude of p at a given offset mouth pressure from $Pmin2$
- D: dynamic range calculated as the difference between p_{max} and p_{min}.
- S: slope of the stable part of solution branch over the p_0 range covered between p_{min} and p_{max}

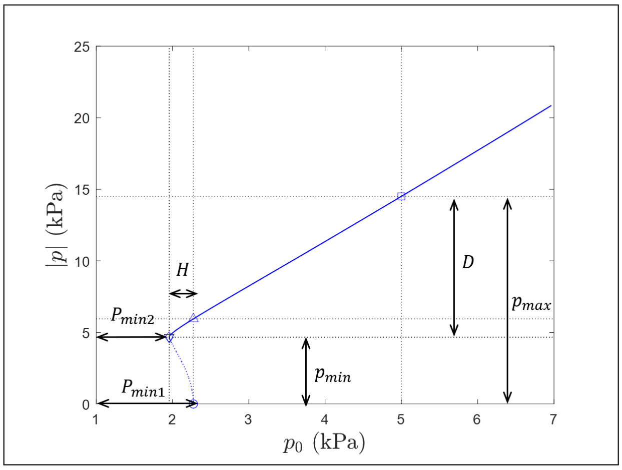

Figure 1. Bifurcation diagram (amplitude of p with respect to p_0) of a Bb trumpet for a Bb4 as presented in [3], with six performance descriptors highlighted.

Furthermore, to take into account the influence of the player's parameters (lip-model parameters) on the calculation results, bifurcation diagrams were also computed for several virtual players in this previous study [3]. This approach is interesting to quantify the robustness of the differences in performance descriptors between instruments, as well as to assess the sensitivity of each performance descriptor and each instrument to these variations. Besides, these numerical predictions offer some interesting perspectives for brass instrument designers, as they may provide some insights on the behaviour of prototypes of musical instruments, and contribute to guide design choices.

Nevertheless, these calculations remain computationally costly, and require a certain know-how in order to operate the continuation calculation. The question is therefore, the following: could we train a machine learning model to compute the bifurcation diagrams and the performance descriptors from trumpet input impedances, and then provide a fast and easy-to-use tool that could be used in the context of trumpet development?

2. MACHINE LEARNING APPROACH

To tackle this problem, a supervised approach is used to train a machine learning model in order to compute the performance descriptors over a batch of virtual musicians.

2.1 Dataset creation

Supervised approaches need a large amount of data to learn a given task. For the descriptor prediction, we used $n = 199$ virtual instruments and 47 virtual players. Each instrument is defined by $m = 44$ modal parameters that are associated to the 11 poles s_k and 11 residues C_k extracted from the the input impedance [3]:

$$Z(\omega) = Z_c \sum_{k=1}^{11} \frac{C_k}{j\omega - s_k} + \frac{C_k^*}{j\omega - s_k^*}, \tag{1}$$

where Z_c is the characteristic impedance of the instrument.

For each virtual instrument/player pair, we computed the bifurcation diagram and performance descriptors for a Bb4 ($f_0 \simeq 466$ Hz), using the continuation method described in [3]. Here, the regression task consists in predicting from the modal parameters of the impedance of any instrument, a descriptor value for each of the 47 virtual players. It can be formalized in the following way:

For each musician-descriptor pair, we want to solve

$$\min_{w \in \mathbb{R}^m} \frac{1}{2n} \|y - Xw\|_2^2, \tag{2}$$

where $X \in \mathbb{R}^{n \times m}$ is the matrix containing the modal parameters of the instruments, $y \in \mathbb{R}^n$ is the vector containing the descriptor values associated to each instrument, and $w \in \mathbb{R}^m$ contains the weights of the regression model.

2.2 Model training

Different methods were evaluated, including Xgboost [4], Support Vector Regression [5] and Least-Angle Regression [6].

By regularizing the problem (2) with the ℓ_1-norm, we obtain the Least Absolute Shrinkage and Selection Operator (LASSO) [7] formulation of the regression problem:

$$\min_{w \in \mathbb{R}^m} \frac{1}{2n} \|y - Xw\|_2^2 + \lambda \|w\|_1,$$

where $\lambda \in \mathbb{R}^+$ is the regularization strength. The best performances were obtained on the regularized regression problem solved with the Least-Angle Regression (LARS) algorithm. One benefit of this method is also to promote interpretability. We trained one LASSO model using the LARS and a 5-fold cross-validation procedure for each descriptor/player pair in order to select the best parameters for the model – less than 10 minutes on a regular laptop computer. Thus, the regression task consists in asking a model trained for a specific player, to predict a descriptor value from the modal parameters of any given instrument.

2.3 Performance on the test set

To ensure stability and reduce biases, we cross-validated the results using a 5-fold cross-validation procedure. Therefore, 80% of the 199 instruments are used as a train set to train the models. The remaining 20% of the instruments, not seen by the models, are used as a test set to compute performances. We compare the LASSO with a baseline. This baseline predicts the value of a specific descriptor by using the mean of this descriptor value in the training set. Tab. 1 shows averaged prediction performances for the LASSO models and the baseline.

Table 1. Relative error percentage mean and standard deviation for all virtual players and instruments for each descriptor. Performances are computed over the test set for the LASSO models and the baseline (mean of the train set).

Descriptor	LASSO (%)	Baseline (%)
Pmin2	0.54 ± 0.06	4.53 ± 0.43
D	0.56 ± 0.06	1.14 ± 0.10
pmaxL2	0.66 ± 0.07	1.58 ± 0.13
Pmin1	0.72 ± 0.11	5.72 ± 0.35
slope	0.86 ± 0.10	1.40 ± 0.13
pminL2	0.96 ± 0.10	4.08 ± 0.35
H	5.17 ± 1.41	35.49 ± 8.51

Although the baseline performances are relatively high, more accurate and consistent predictions are obtained for all performance descriptors with a mean relative error below 1% for most of them. Since the hysteresis H can be calculated from $Pmin1$ and $Pmin2$, we find a high prediction error since different values of $Pmin1$ and $Pmin2$ can lead to a same value of H. Therefore, this high raw error in H prediction can be compensated by taking the difference between the predicted $Pmin1$ and $Pmin2$.

An example of a prediction of $Pmin1$ descriptor for the 47 virtual players on three virtual instruments is depicted in Fig. 2. In terms of computational time, predicting all descriptors for 100 trumpets takes less than 5 seconds on a regular laptop computer. This figure highlights the ability of the proposed approach to exploit the diversity of virtual musicians to precisely estimate the distribution of each performance descriptor for new instruments.

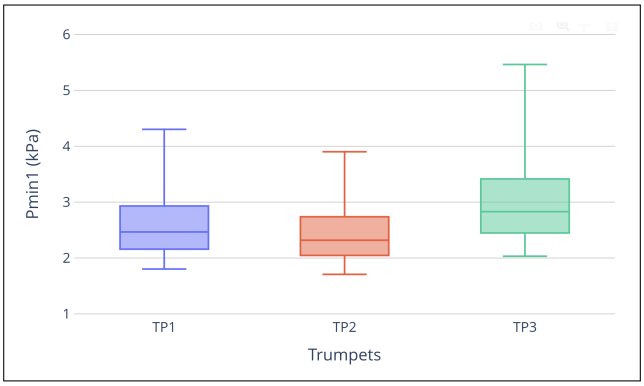

Figure 2. Box plot of $Pmin1$ descriptor prediction for the 47 virtual players on 3 test instruments (unseen during the model training).

2.4 Interpretability

The LASSO promotes sparsity in the selected variables to make the prediction. This makes the models easy to interpret as explained in [7]. Tab. 2 shows the importance of each modal coefficient in the prediction of the descriptor $Pmin1$ averaged over the 47 virtual players.

This table shows that the fourth and fifth poles and residues are the most important parameters for predicting $Pmin1$: more than 60% of the descriptor value is deduced from these parameters. This result seems coherent with the underlying mechanisms of sound production in the trumpet, since Bb4 corresponds to the 4th register of the instrument, with a fundamental frequency around 466 Hz lying between the fourth and fifth resonance peaks of the input impedance. Nevertheless, this trend – importance of the modal coefficients associated to the 4th and 5th impedance peaks – is not necessarily observed for all

Table 2. Mean and standard deviation of the importance of each modal coefficient in the prediction of the descriptor $Pmin1$ for the 47 virtual players. Only the seven most important modal coefficients are displayed.

Modal coefficient	Mean (%)	Std (%)
$\mathrm{Re}(C_4)$	17.89	0.79
$\mathrm{Re}(s_5)$	12.14	0.35
$\mathrm{Re}(s_4)$	11.21	0.32
$\mathrm{Re}(C_5)$	9.77	0.19
$\mathrm{Im}(s_4)$	6.15	0.27
$\mathrm{Re}(C_6)$	4.55	0.07
$\mathrm{Im}(c_4)$	4.03	0.10

the other descriptors, which suggests more complex relationships with the input impedance of the instrument.

3. CONCLUSIONS

We designed a simple, accurate, fast and interpretable machine learning approach able to predict trumpet performance descriptors using a set of virtual musicians. One particular limitation concerns the generalization of this approach to other dynamical behaviours such as direct bifurcations, that were not considered in this study. In future work, we then hope to extend this study to more notes and performance descriptors, which may involve different machine learning methods. We therefore wish to be able to predict bifurcation diagrams over a larger playing range, thus providing a global overview of the behaviour of the instrument.

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