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# A Neural Network for Acoustic Duct Mode Decomposition

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## ABSTRACT

Acoustic mode decomposition is commonly used to separate pressure wave components in flow ducts and established methods rely on mathematical descriptions of the wave motion. In this work, a new approach to mode decomposition is presented that uses artificial intelligence (AI) to separate the acoustic mode content. A neural network is trained with data gained from a small set of numeric solutions of the Linearized Navier-Stokes equation in the frequency domain in a straight duct. The network is tested on relevant experimental data. A good agreement with the analytical method is demonstrated in two applications with different flow conditions. We conclude that using AI for mode decomposition is a promising alternative to the standard method as it applies to a much broader set of aero-acoustic problems.

## 1. INTRODUCTION

Acoustic wave propagation in ducts including flow acoustic dispersion effects has been the topic of research since Kirchoff's well-recognized work in 1868 [1]. This seminal publication initiated 150 years of research; various studies investigated how to extend and generalize acoustic dispersion for different relevant applications. Recent work by Dokumaci [2] and Weng [3] generalized Kirchoff's formulation for ducts to include flow and turbulence. In our previous research, we showed that such solutions can improve noise prediction in some cases [4]. However, these latest models are still dependent on simplified assumptions regarding flow that produce errors in real applications. We investigated a case of this nature in Ref. [5]. Inaccuracies in the solutions of wave propagation in flow ducts amplify during the post-processing of experimental and numerical data that involves acoustic modal decomposition techniques, for example in the two-port method [6], or liner impedance reduction procedures [7].

In our latest research, we investigate the possibilities to use artificial neural networks to improve acoustic mode decomposition. Although machine learning is applied throughout many disciplines within acoustics, the literature on machine learning-based acoustic mode decomposition is sparse. To our best knowledge, the only existing study is Huang's work in Ref. [8], which focuses on the discussion of specific aspects of the decomposition of higher-order modes using compressed sensing.

With the contribution to the 2020 Forum Acusticum, we want to summarize our work on the topic. This extended abstract is intended as a short overview of the key aspect. The complete and detailed original article on which our presentation is based can be found in Ref. [9].

## 2. PROBLEM

Duct decomposition methods are used to split spatially sampled sound fields into upstream and downstream propagating aeroacoustic modes. This requires knowledge of the propagation and shape of such modes and leads to a multi-dimensional linear regression problem. Although the method is well-documented, see for example Ref. [4,10,11], there are common challenges when applying duct decomposition, namely a) to find explicit formulations for the mode-shapes and wave-numbers especially for non-standard applications, e.g., strongly disturbed flows, soft/rough walls, unusual duct geometries; and b) to solve the regression for ill-conditioned decomposition conditions, e.g., for adverse probe positioning or undersampled sound-fields.

## 3. IDEA

Machine learning delivers tools that efficiently and accurately solve regression problems and is applied to some areas within the field of acoustics [12–14], but to our best knowledge not to duct aeroacoustics yet. Therefore, the presented research is based on the idea of using those tools to decompose acoustic sound fields in ducts. The machine learning algorithm discovers the wavenumbers and mode shapes from numerical training data, whereas no explicit knowledge of the equations that govern the acoustic mode propagation is needed.

To create the training and validation data for the machine learning algorithm, the principle of superposition in linear acoustics is exploited. This allows us to expand large and inexpensive trainings-data sets from only a few fundamental solutions of the flow acoustic problem.

## 4. IMPLEMENTATION

The linear regression is implemented as a multi-layer perceptron feed-forward artificial neural network. Despite their simple structure, such networks are universal function approximators [15].

We implemented the network in Python's Tensor Flow [16] and Keras [17] environments. During our research, we varied the hyper-parameters of the network, for example, the number of neurons, the number of layers, and the activation functions.

The training data is computed solving the linearized Navier-Stokes Equations in the frequency domain, using modal excitation presented in Ref. [18]. We solve the

propagation of pure plane waves in upstream and in downstream directions. The considered cases were turbulent pipe flow with moderate Mach-numbers  $M=0.1, 0.2,$  and  $0.3$ . The numerical computation is carried out in 2 steps: i) a stationary flow field is computed using the Reynolds Averaged Navier Stokes (RANS) equations; ii) The Linear Navier Stokes Equation in the frequency domain are solved using the RANS solution as a background flow. Two solutions per training frequency are generated with upstream or downstream fluctuating volume forces to excite the planar acoustic waves. The computational domain is terminated with acoustically non-reflecting boundary conditions in the form of perfectly matched layers.

Training data is created as a superposition of complex weighted linear combinations of the base solutions. By this means, new training data could be dynamically created during the training process, which lowers the risk of overfitting the training set.

## 5. RESULTS

The trained network was tested on experimental and analytical data. The testing procedure was split into tests on unseen data for trained frequencies and tests on unseen data for untrained frequencies. We compared the network decomposition against the classical decomposition method performed with the `acdecom` python package [19]. Our key findings are:

1. Neural Networks can be used to learn acoustic wave decomposition. The accuracy compared to the classical solution was higher than 99% in the tested cases, when the network was trained under the same simplifications as assumed in the classical methods. However, we can include a high degree of flow-acoustic complexibility into numerical training data, which enables us to decompose sound fields in applications where the classical solutions are inaccurate.
2. The Network performance is equally high for trained and untrained frequencies. In our research, the network was trained on 20% of the decomposed frequencies only.
3. We found that despite the activation functions, where the softmax function outperformed the other tested functions, the layer and neuron structure was of minor importance for the decomposition quality. This makes the method robust and applicable in academic and industrial applications alike.

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