INTERNSHIP AND THESIS PROPOSAL

Autoencoders with physics-informed latent manifold: Application in acoustics.

CentraleSupélec - Paris-Saclay University Research Center (Laboratory of Mechanics Paris-Saclay)
ONERA - The French Aerospace Lab

Supervisors:

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- Prof. Eric Savin (CentraleSupélec - ONERA)
- Dr. Stefania Fresca (MOX - Department of Mathematics, Politecnico di Milano).

The internship shall be supervised jointly by the OMEIR team (Structures, Materials, Environment : Interactions and Risks) at Laboratoire de Mécanique de Paris-Saclay (LMPS), ONERA and MOX laboratory at Politecnico di Milano. It shall develop a transverse axis of research concerned with elastoacoustic wave propagation and machine learning, in order to develop numerical simulations based on physics and enriched by data. The internship shall initiate future collaborations between the partners around air and ground transport, considering uncertainty quantification and surrogate modeling by statistical learning.

Candidate Profile: M.Sc. student in applied mathematics, mathematical engineering, physics, computer science for a **6 months internship** at Laboratory of Mechanics Paris-Saclay. Applicants shall have a background in applied mathematics, data science (python libraries, GPU computing), statistical learning.

Duration: 6 months.

Salary: 600 euros/month.

Main objectives: This internship aims at developing a new strategy to blend the outcome of physics-based numerical simulations with massive experimental database, such as in situ data routinely recorded for monitoring purposes. The proposed approach relies on generative deep learning techniques (Generative Adversarial Networks or Diffusion Models) with a twofold purpose:
- Finding low-dimensional nonlinear representations of both synthetic and experimental data;
- Training stochastic generators of fake experimental responses conditioned to the physics-based simulation results.

Keywords: #gan, #diffusionmodels, #XAI, wave propagation, radiative transfer.

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Project Outline:
The methodology we wish to extend in this work has initially been developed by Gatti & Clouteau [1] in the context of earthquake simulation. The authors employed three-dimensional high-fidelity numerical models to render synthetic acceleration time-histories on a large region. This tool allows to account for the complex physics of the earthquake phenomenon, but it is still limited to a low-frequency range prediction, due to the associated computational cost. In order to span the large uncertainty on the high-frequency part of the signal, whose signature is strictly related to complex scattering patterns at small wavelength, a databases of millions of broad-band seismic signals—recorded worldwide at seismological networks—was used to train a deep adversarial auto-encoder. The latter was taught to extract meaningful hidden features from experimental data and encode them into a "latent Gaussian manifold." Those features were then used to generate realistic broad-band signals, as stochastic realizations of the same low-frequency synthetic part, produced by numerical analysis. In this way, the parameter dimensionality that is responsible of the large uncertainty of the outcome of high-fidelity numerical simulation is not modeled directly (for the lack of resolution) but learnt from the data. Therefore, the hybrid signals resembles recorded earthquake time-histories in a broad-band frequency range. The scope of the internship is to extend the above-mentioned strategy and to apply it to aerospace models (viscoelasticity, acoustics, etc). The main objective is to strengthen the physics constraints on the adversarial learning scheme, i.e. to find a robust and non-intrusive algorithm to disentangle the latent space according to different wave propagation phenomena taking place at different scales (see Lee & Carlberg [2] or Li et al. [3]). In other words, the deep convolutional encoder proposed in [1] will be forced to infer a set of independent Gaussian components of the latent space, each one representing a scattering phenomenon taking place at a definite scale. Thus, the theory of radiative transfer will be adopted in order to unify the wave propagation problem at different wavelength and constraint the learning phase accordingly.
The project is multidisciplinary since it relies on both machine learning techniques and algorithms, and advanced physical models in acoustic and elastic wave propagation phenomena. It aims to design GANs for the construction of surrogate models trained from multi-fidelity, simulated and experimental databases, such as images or time series, while constraining their latent manifolds by the involved physical phenomena. In particular, it is desirable to constrain high-frequency wave fields with wave propagation models pertaining to these regimes.

References
[1] F. Gatti, D. Clouteau. Towards blending physics-based numerical simulations and seismic databases using Generative Adversarial Network. Computer Methods in Applied Mechanics and Engineering 372, 113421 (2020).
[2] K. Lee, K. T. Carlberg. Deep Conservation: A latent-dynamics model for exact satisfaction of physical conservation laws. Proceedings of the AAAI Conference on Artificial Intelligence 35(1), 277-285 (2021).
[3] X. Li, C. Lin, R. Li, C. Wang, F. Guerin. Latent space factorisation and manipulation via matrix subspace projection. In Proceedings of the 37th International Conference on Machine Learning (III, H. D., Singh, A., Eds.), Proceedings of Machine Learning Research 119, 5916-5926 (2020).