Master internship and thesis offer

Neural Network prior and full Bayesian sampling for inverse problems

**Scientific context:** Inverse problem, deconvolution, deep learning, Bayesian strategy.

**Signal-image-vision issues:** Prior learning, posterior sampling, conditional generators...

**Involved tools:** Invertible neural networks, stochastic sampling, MCMC, Langevin and Hamilton.

**Possible application fields:** Imaging in physics, astronomy, medicine, remote sensing, industry.

**Computing environment:** Matlab, PC.

**Location:** Groupe Signal – Image, IMS, Talence, France.

**Duration internship:** Six months starting in January or February 2021.


**Doctoral study:** The internship will open to a PhD thesis on the subject.

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The fast development of neural networks and deep learning methodologies opens the way to new solutions for large scale inverse problems [1–3]. In particular, in the Bayesian framework [4], the prior distribution can be learned from a bunch of examples characteristic of the field of interest considered. This contrasts with the standard methods based on more general all-purpose priors (see figure below) usually designed within restricted parametric distribution families [5].

Whatever the approach, standard or neural network, the Bayesian strategy provides a tool of choice to include uncertainty quantification and statistical analysis of the solutions, in particular via posterior sampling of unknowns given measurements. See [6, 7] for the neural network approach or [4, 8] for a more general view.

Such tools for image reconstruction and uncertainty quantification are of major interest in a wide range of modalities for various fields: physics, astronomy, medicine, remote sensing, industry,... A focus could be put on the domain of aerospace and the field of fluid mechanics, for example related to turbulent flow measurement, such as tomographic reconstruction of gas density for aerodynamics and propulsion [9, 10] or particle image velocimetry [11]. In such cases, the realism of the bunch of examples can be ensured by numerical simulations thanks to well-controlled physical models.

The associated prior will be next combined to the distribution of the measurements (likelihood) to provide the posterior, the latter being sampled by means of an MCMC algorithm, for instance in the AGEM framework [12]. On the methological side, this framework is presently tied to a particular class of networks (the denoising autoencoders) and we plan to generalize to invertible network architectures [7] that enable explicit manipulation of sample likelihood, a potential asset for sampling algorithms, such as Langevin or Hamilton MCMC samplers.
In addition, the AGEM framework presents another essential interest in practice: it affords adaptive tuning to operating conditions not met during the learning phase. In particular, it enables to consider different extensions toward hyperparameter estimation. Besides, AGEM exploits a Monte Carlo EM approach for hyperparameter estimation, and it is potentially more efficient to develop fully Bayesian approaches where hyperparameters themselves are attributed a prior [5, 13].

A first instance of this methodology (learning, sampling, imaging including uncertainties) will be developed in the context of the internship: select a simple network architecture, gather a first learning database (already available), learn and test the model. The objective of the thesis is to proceed on the design, implementation and assessment of such approaches on cases of increasing complexity. Regarding the field of fluid mechanics, more complex flows and more constrained observation conditions (turbulent flows, scarcer measurements). The developed posterior samplers will be applied to the statistical analysis of flow reconstructions, including hyperparameter estimation and uncertainty quantification.

The methodology will be demonstrated on experimental data gathered from various experimental facilities developed at ONERA: Multiview holographic bench [10], particle image velocimetry [11]. In order to improve the generalization capability of our networks to experimental data, the original learning database build on physically sound simulations could be enriched with high resolution measurements.

References


