Master internship

Self-calibrated and self-adaptive image deconvolution: Bayesian strategy, diffusion model prior and stochastic sampling

Scientific context: Inverse problem, deconvolution, Bayesian strategy, self-calibrated / self-adaptive.

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

Involved tools: Diffusion model, posterior sampling and Gibbs algorithm.

Possible application fields: Medicine and biology, physics and astrophysics, archaeology,. . .

Computing environment: Matlab, Parallel Computing, Automatic Differentiation, Deep Learning.

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

Duration internship: Five-six months starting at the beginning of 2026.

Supervisors: Jean – François GIOVANNELLI, Groupe Signal – Image, IMS, Talence, France.

Doctoral study: The internship may open to a PhD thesis on similar subjects.

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Context — A broad variety of measurement systems have become widespread in recent years, requiring processing tools adapted to important amounts of large data sets and reconstruction of high dimensional objects. In this context, processing tools must be entirely automated and cannot demand for human assistance in order to tune parameters. This is far more crucial in inverse problems [1] for one main reason: methods are founded on regularization (required by ill-possedness) and then appeal for hyperparameters to balance a compromise between various types of information. Additionally, modern measurement systems are complex and require models with various parameters. A threefold problem has then to be solved [2–4]: from a unique observation (*i.e.,* unsupervised scheme) estimate parameters for object and noise (self-adapted issue) as well as system parameters (self-calibrated question), in parallel with the object itself. In addition, a more advanced question arises: model selection (*e.g.,* select model for noise or measurement system within a list of candidate). These questions, regarding parameter estimation and model selection are a main open problem in data science and this is the core issue of the work.

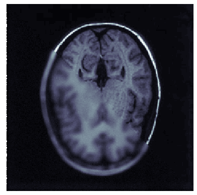
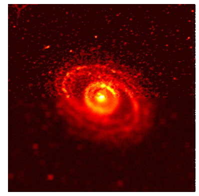
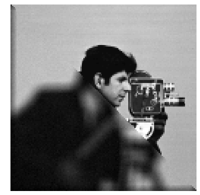
Methodological framework — From the methodological standpoint, the investigations come within the framework of hierarchical models and Bayesian strategies [5, 6]. This framework has become a cornerstone tool in the field of inverse problems [1] since it allows to include numerous variables, possibly with complex interactions and to account for diverse sources of information (properties of unknown object, measurement systems, noise and signal level,. . .) [7]. Ultimately, the methods rely on optimal estimation / selection that are computed by guaranteed stochastic sampling of a posterior distributions [5, 6].

Prior model and diffusion — The proposed work draws on the latest advances in artificial intelligence for inversion: diffusion models [8–11]. Among the various classes of recent models, this class of model has proven to be the most effective for modeling probability distribution for images. Firstly, it allows neural network parameters to be calibrated from a database of examples characteristic of the considered field of interest, in a relatively simple and, to a certain extent, robust manner. Furthermore, this class of model offers the possibility of efficiently generating new examples, with a remarkable ability to reproduce complex structures. Their use in inversion, within the Bayesian framework, is becoming increasingly prevalent.

Noise and measurement system parameters — This prior for the unknown object will be next combined to the distribution of the measurements, in a usual manner. Additionally it will also be combined to prior distributions for noise parameter (*e.g.,* a gamma density) and some system parameters (*e.g.,* a uniform density). The full posterior will then be sampled by means of a Gibbs algorithm [6, 12]. It will rely on a (i) direct Gamma distribution for the noise level, (ii) Metropolis-Hastings step for the system parameters and (iii) standard one for the object itself [8–10]. In a second step, we could consider other tools such as Langevin or Hamilton samplers.

Model selection — Regarding this area of the work, an optimal selection function in a clearly stated sense [5, 6, 13, 14] relies on the posterior probability for each model that is based on evidence, which itself requires the marginalisation of unknown parameters. This aspect presents a major difficulty and we will first investigate state-of-the-art methods starting by the Chib approach [15, 16]. We could then consider some other tools [13, 14, 17], *e.g.,* (proper) harmonic expectation, thermodynamic integration or Laplace approximation,. . .

Application — Such tools for image reconstruction (and uncertainty quantification) are of major interest in a wide range of modalities for various fields. Regarding the application, several fields could be considered: medicine and biology, physics and astrophysics, remote sensing, industry,. . . A focus could be put on one specific domain, according to the trainee's preference.

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