PhD Proposal – PR[AI]RIE-PSAI 2026

Deep Learning for Non-Invasive Imaging Through Strongly Scattering Media

1. Environment of the Project

The project and the PhD thesis will take place within the framework of the French AI-Clusters PR[AI]RIE-PSAI. This project is rooted in **Biomedical Imaging**, one of the core research areas of the PR[AI]RIE-PSAI program. It will be under the co-direction of Sebastien Popoff and Alexandre Aubry (CNRS, Institut Langevin), and in collaboration with Arthur Goetschy and Baptiste Hériard-Dubreuil (ESPCI, Institut Langevin) The work will be done at the Langevin Institute (1, rue Jussieu, Paris), part of ESPCI-PSL.

Inclusion. This position is open to all candidates regardless of gender, nationality, disability, or socio-economic background. Recruitment will follow OTM-R principles (European Charter for Researchers) with a minimum four-week open posting on the PR[AI]RIE-PSAI website. Applications from underrepresented groups in physics and computer science are particularly encouraged.

2. Context and Motivation

Light passing through a strongly scattering medium, such as a thick biological tissue, undergoes multiple scattering events that tend to randomize its propagation. However, the response of such a system is *not* stochastic as long as the medium remains static : it is fully deterministic and can, in principle, be learned. By measuring the transmission matrix of a strongly disordered medium [1], researchers at Institut Langevin demonstrated that we really can see through a scattering medium. Yet this technique requires access to both sides of the medium, which fundamentally limits its application to non-invasive imaging.

In more realistic approaches, one only has access to one side of the medium. We can define and measure a reflection matrix that links the wavefronts arriving on and reflected off the medium. While this object does not give direct access to the transmission properties of a random medium, it holds information both about the propagation medium and the hidden object to image. In the past 10 years, we developed approaches to separate these contributions and perform reconstruction of images deeper than using standard imaging approaches, both in ultrasound [2] and optical imaging [3].

However, when the light is randomized by too many scattering events in an inhomogeneous medium, these contributions become difficult to discriminate. Moreover, in biomedical applications, the object to recover can be the inhomogeneous medium itself. To tackle these issues, we recently started using differentiable models akin to deep learning frameworks to model the propagation medium, with each trainable parameter representing spatial physical properties of the medium we want to study [4].

3. A hybrid approach

First attempts to use deep learning frameworks for imaging through complex media relied on *off-the-shelf* models developed for image processing, with limited success. This can be explained by the fact that scattering tends to randomize and spread the signal coming from an object over a large area, while standard models, such as convolutional ones, rely on a hypothesis of multiscale locality of the information.

In recent years, this paradigm has changed with the development of *physics-informed neural networks* that use layers mimicking physical phenomena, such as wave propagation. The idea is that tailoring a trainable mathematical model closer to the physical equations naturally decreases the dimensionality of the solution space while providing better convergence properties. For thin or weakly scattering media, the propagation properties of the system can be modeled by the effect of one or a few planes where the optical phase is perturbed [5].

However, when the light undergoes more scattering events, the model becomes more complex and the uniqueness of the solution and the convergence of the optimization are not guaranteed. Physically, this implies that a trained model can match the measured reflection properties without correctly describing the transmission ones, leading to a failure to reconstruct images in the deep layers of a random medium. Moreover, the reflection properties, including the reflection matrix, are dominated by contributions originating from shallow depths, hence not penetrating deep into the medium where the important signals lie.

The idea is, instead of trying to simultaneously optimize all the parameters of the full model, to use physical measurements for regularization and gradually train the model, starting from parameters closer to the surface before going deeper and deeper.

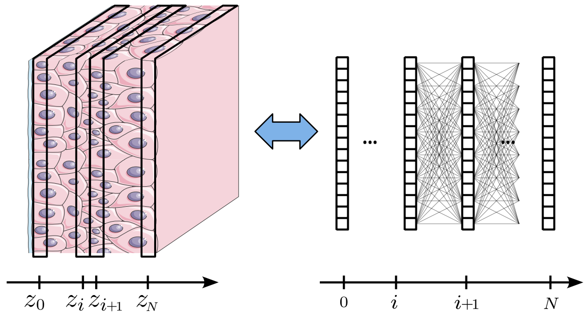

FIGURE 1 – **Physics-informed neural network for light propagation in scattering media.** (Left) The physical system, a scattering medium such as a biological tissue, where the inhomogeneities can be modeled as a succession of planes. (Right) A deep learning framework where each layer represents a scattering plane. Coupling between layers can be engineered to satisfy physical insight about light propagation and scattering while having trainable parameters representing the physical properties of the medium.

4. Methodology and Objectives

The goal of the project is to develop physics-informed networks using regularization based on experimental measurements to recover images deep inside scattering optical media akin to biological tissues.

Models - We will use models that are typically used for numerical simulations, but instead of computing the effect of a known configuration, we will relax the degrees of freedom as trainable parameters.

1/ For a medium in which light is mostly scattered in the forward direction, one can neglect the light reflected by the medium itself, which can then be effectively modeled as a succession of phase plates at different depths. This is similar to the principle of numerical simulations based on the so-called *beam propagation method*. The left-to-right directionality of this approach makes its implementation quite straightforward using deep learning frameworks. Each trainable parameter represents the index of refraction, or equivalently the phase shift, at each position of the different planes.

2/ In more realistic scenarios, light measured in reflection comes both from the object to image and from backward scattering due to the inhomogeneity of the propagation medium. A photon going through the scattering medium can undergo multiple scattering events in the forward and backward directions. A model that follows the path of the light would be difficult to implement in a way compatible with a backward-propagation optimization scheme. Instead, we can rely on other approaches, like the transfer matrix one, in which each layer is represented by a linear operator that links incoming to outgoing light instead of left-to-right fields. Such systems are famously numerically unstable without proper regularization, which we will discuss in the following paragraph.

3/ Another approach is to use the expression of the scattered field as a series, with each term representing a different occurrence of scattering events. We use the Dyson equation :

$$G = G_0 + G_0 V G = G_0 + \sum_{n=1}^{\infty} G_0 \left(V G_0\right)^n = G_0 + G_0 V G_0 + G_0 V G_0 V G_0 + \cdots \tag{4.1}$$

where $G_0(\mathbf{r}, \mathbf{r}'; \omega)$ is the free-space Green's function, representing the electromagnetic field at position $\mathbf{r}$ due to a point dipole source at $\mathbf{r}'$ propagating in a homogeneous background medium of permittivity ε_b ; $G(\mathbf{r}, \mathbf{r}'; \omega)$ is the full Green's function, which accounts for all multiple scattering events and encodes the complete electromagnetic response of the inhomogeneous medium ; and $V(\mathbf{r}) = (\omega^2/c^2)\, \delta\varepsilon(\mathbf{r})$ is the scattering potential, proportional to the local dielectric contrast $\delta\varepsilon(\mathbf{r}) = \varepsilon(\mathbf{r}) - \varepsilon_b$, which vanishes outside the scatterers. Each successive term in the series corresponds to an increasing number of scattering events : $G_0 V G_0$ describes single scattering, $G_0 V G_0 V G_0$ double scattering, and so on, with the Dyson equation resumming this Born series to all orders.

The series formulation allows us to build a forward model with trainable parameters representing the perturbation of the dielectric constant $\delta\varepsilon(\mathbf{r})$. Such an approach was successfully numerically studied in the case of large scattering objects for optical diffraction tomography [6].

Training, cost functions, and physical regularization - The main physical input we want our model to fit is the reflection matrix that can be measured non-invasively from one side of the system. Thus, the first contribution of the cost function is the quadratic error of the measured reflection matrix compared to the one predicted by the model.

As stated before, the more complex the model is, the higher the chances of falling into local minima. We need to guide the optimization to reach a solution as close as possible to the physical system.

A first trick will be to first train the shallowest layers, representing either lower depths or lower orders of scattering events, as they account for the main energy contributions of the reflection matrix, and then gradually train the following ones.

We envision that this will not be sufficient for more complex systems, as the contributions we are interested in for imaging deep in inhomogeneous media correspond to layers with small contributions to reflection. To help convergence and regularize the system, we will use two different strategies. 1/ Add more information about the system by measuring the multispectral reflection matrix, which generalizes the reflection matrix to different wavelengths [7]. 2/ Use intermediate experimental measurements during the optimization scheme. Once the first n layers have been trained, we can use the first part of the model to focus light at the corresponding depth z_n. We can then acquire a new matrix whose inputs correspond to sources located at depth z_n. It will allow to enhance the sensitivity of the system to large depths whose contributions would otherwise be drowned by shallower-depth signals. This matrix will be used to train the next layers, and so on, in a similar fashion to the iterative layer-peeling approach used to trace multiple scattering trajectories from the reflection matrix [8].

5. Work Programme

We divide the project into tasks of increasing complexity.

Year 1 – Validation of the approach through a simple phase-plate model. To assess the validity of the approach, we will use the simplest model of phase plates. We will use as a physical medium a succession of small-angle thin diffusers and we will place an object to image behind it. The reflected light is assumed to mainly originate from reflections on the object. We will measure its reflection matrix, and a model based on forward scattering will be trained to match the measurements and learn the parameters representing the object.

Year 2 – Imaging through thick scattering media via the transfer matrix approach. We will move to strongly scattering samples where backward scattering can no longer be neglected. The propagation model will be based on transfer matrices, where each layer links incoming and outgoing fields on both sides, and the physical regularization strategy developed in Year 1 will be extended to stabilize the optimization of these inherently ill-conditioned operators. We will validate the approach on controlled experimental samples of increasing optical thickness and benchmark reconstruction depth against standard reflection-matrix imaging methods.

Year 3 – Deep tissue imaging.

In this last part, the object to image is the scattering medium itself. This is typically the situation for imaging organs such as the liver or breast. We will use the approach based on the Dyson series, where the perturbation term $\delta\varepsilon(\mathbf{r})$ is also the physical quantity we want to recover.

6. References

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