Application of Physics-Informed Neural Networks to Maxwell equations

Alexandre Pugin, *Stéphane Lanteri, Stéphane Descombes*

Université Côte d'Azur, Centre Inira d'Université Côte d'Azur

alexandre.pugin@inria.fr

Maxwell's equations govern the propagation of electromagnetic waves. Solving them is necessary to design metamaterials in radar, antenna, cloaking and metalenses technologies for example. Currently, simulations are predominantly conducted using numerical methods such as the Finite Element Method (FEM) and the Finite Difference Method (FDM). Simulations with these methods can become computationally intensive in the case of three-dimensional domains with complex geometries. This represents a strong limitation if the ultimate goal is to perform numerical optimization for example, which requires many simulations for a large set of design parameters. Hence, we would like to use neural networks as surrogate models, possibly with lower accuracy for shorter simulation times.
Physics-Informed Neural Networks (PINNs) have seen a surge in interest over the last five years after the original article from Raissi et al.[1] was published. This paradigm allows one to model the solution of systems of partial differential equations with little to no data provided. However, Maxwell's equations remain poorly explored with PINNs despite the incentives. There are only a few works dealing with PINNs to solve Maxwell equations. The goal of Chen et al.[2] resembles ours, as they want to use PINNs to design metamaterials. However, in contrast to us, they solve inverse problems, i.e. they have data dictating what the electromagnetic field should look like and from there they use PINNs to retrieve the effective permittivity of metamaterials. In this respect, Baldan et al.[3] is closer to us as they solve a parametric problem, i.e. for a set of given parameters, they predict the electromagnetic field. But unlike us, they do so in the magnetostatic setting . We want to solve Maxwell's equations in a more general setting where the magnetic field is time-dependent. The goal of this work is to lay the groundwork to eventually apply PINNs to solve parametric electromagnetic wave propagation problems in three-dimensional domains. To do so, we will start by solving problems in two-dimensional spaces.

References

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