Ray Tracing and Physics-Informed Neural Networks

Diogo Duarte[1], Ramon C. F. Araújo[1], Paulo Douglas S. de Lima[1], João M. de Araújo[1], Tiago Barros[2]. Gilberto Corso[3].

[1] Departamento de Física Teórica e Experimental, Universidade Federal do Rio Grande do Norte, Natal, RN, 59078-970, Brazil.
[2] Departamento de Engenharia de Computação e Automação, Universidade Federal do Rio Grande do Norte, Natal, RN, 59077-080, Brazil.
[3] Departamento de Biofísica e Farmacologia, Universidade Federal do Rio Grande do Norte, Natal, RN, 59078-970, Brazil.

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Abstract

The ray tracing is a powerful technique to estimate the propagation of a trajectory normal to the wave front in heterogeneous media. This technique solves a differential equation based on Snell's law to obtain the slopes and trajectory of a given wavefront. In addition, the physical problem of ray tracing is expressed as a partial differential equation (PDE). The ray tracing is widely used in first arrival time estimation, illumination, tomography, and in time-lapse seismic processing. In this work, we explore the ray tracing solution using a Machine Learning (ML) approach. Indeed, we follow a recent trend in ML called physics informed neural networks, which plugs into the network's loss function the PDEs and boundary conditions that express the physical laws of interest. A certain number of points are sampled from the equation's domain and used as inputs to the network. In the context of ray tracing, such points are space coordinates within the region in which the wave is propagating. The neural network is then trained to output the PDE solution at the sampled positions by minimizing the loss function. If training is carried out with a representative sampling of the equation's domain, it is expected that the resulting neural network is able to calculate the PDE solution with good accuracy at any point throughout the domain of analysis. In this approach we use the deep neural network architecture, that is a universal approximator, to solve the ray tracing PDE, thus obtaining the solution alternatively to traditional numerical methods, such as finite differences or finite elements. Besides, the neural network is not trained with empirical or synthetic ray tracing solution, rather it uses the automatic differentiation (autodiff) to estimate the gradients and find the optimal solution for given boundary conditions. By its turn, the automatic differentiation works by breaking down a complex function into a series of elementary operations, such as addition, multiplication, and exponentiation. Each operation is associated with a local derivative, which describes how the output of that operation changes with respect to its inputs; this was developed in the ML context, and now it has become the center of the physics-informed neural networks. This work was developed using the Python language, with the GradientTape package from the Tensorflow library for calculating the derivatives of the loss both with respect to the internal parameters of the network and the input attributes (ordered pairs (x, y)). For optimization, we used Adam, which requires less memory and usually converges faster. Additionally, ray tracing is done numerically using MATLAB for result comparison. The preliminary results of the physics informed neural network to the ray tracing problem are promising. Further studies are necessary to compare the computational cost of the ML solution with a traditional ray tracing solution, based on numerical discretization.