

# ANN Estimations of the Absorption Coefficient in Multi-Region Heterogenous Media: MoC Solutions as Training Data

Nelson G. Roman<sup>1</sup>, Pedro H. A. Konzen<sup>2</sup>  
PPGMAP/IME/UFRGS, Porto Alegre, RS

The estimation of the medium absorption coefficient from external measurements can be stated as an inverse problem [5, 6], and has important applications in optical medicine [8], including in optical tomography [2]. In this work, we propose a framework based on artificial neural networks (ANNs) to estimate the absorption coefficient in multi-region heterogeneous media. The associated direct transport problem [4] is given as

$$-1 < \mu < 1, \mu \neq 0 : \frac{1}{c} \frac{\partial I}{\partial t} + \mu \frac{\partial I}{\partial x} + \sigma_t I(t, \mu, x) = \sigma_s \Psi(t, x), \quad (t, x) \in (0, t_f] \times (a, b), \quad (1a)$$

$$-1 < \mu < 1 : I(0, \mu, x) = 0, x \in [a, b], \quad (1b)$$

$$\mu > 0 : I(t, \mu, x) = q(t, \mu), \quad t \in [0, t_f], \quad (1c)$$

$$\mu < 0 : I(t, \mu, x) = 0, \quad t \in [0, t_f], \quad (1d)$$

where  $I(t, \mu, x)$  [W/sr] is the particle intensity at the time  $t$  [ps], in the direction  $\mu$  [sr], and at the point  $x$  [cm],  $c$  [cm/ps] is the average speed of light in the medium,  $\sigma_t(x) = \kappa(x) + \sigma_s(x)$  [1/cm] is the total absorption coefficient,  $\kappa(x)$  [1/cm] is the absorption coefficient, and  $\sigma_s(x)$  [1/cm] is the scattering coefficient. The average scalar flux is denoted by  $\Psi(t, x) = \frac{1}{2} \int_{-1}^1 I(t, \mu', x) d\mu'$ . Based on the model given in [1], the only source is a laser pulse given by

$$q(t, \mu) = w \left( \frac{|\mu - \mu_s|}{\delta_\mu} \right) w \left( \frac{|t - \tau_s - \delta_t|}{\delta_t} \right), \quad (2)$$

where  $\mu_s$  is the laser direction,  $\delta_\mu$  its angular spread,  $\tau_s$  its activation time,  $\delta_t$  its temporally center, and  $w(\nu)$  is the window function

$$w(\nu) = \begin{cases} 1 & , \nu = 0, \\ \exp((2e^{-1/|\nu|}) / (|\nu| - 1)) & , 0 < \nu < 1, \\ 0 & , |\nu| \geq 1. \end{cases} \quad (3)$$

The objective is to estimate the absorption coefficient  $\kappa(x)$  from detector measurements  $d_0(t) = \Psi(t, a)$  and  $d_1(t) = \Psi(t, b)$ ,  $t \in [0, t_f]$ . We propose to estimate  $\kappa$  as a piece-wise constant function. The medium is partitioned into  $n_c$  cells, which determines the resolution of the estimations. A multi-layer perceptron (MLP) neural network [3] is built to give the  $\boldsymbol{\kappa} = (\kappa_i)_{i=1}^{n_c}$  estimations from discrete detectors measurements  $\boldsymbol{d} = \{(d_0(t_j), d_1(t_j))\}_{j=1}^{n_d}$ , where  $n_d$  is the number of measurements in discrete times. The ANN is trained from a data set  $\{(\boldsymbol{d}^{(s)}, \boldsymbol{\kappa}^{(s)})\}_{s=1}^{n_k}$  computed from solutions

<sup>1</sup>ngroman1992@gmail.com

<sup>2</sup>pedro.konzen@ufrgs.br

of the direct problem (1). The direct solver is based on the Method of Characteristics (MoC), and it has already been detailed in our previous work [7]. Therefore, the framework couples an efficient direct solver with a general-purpose non-linear regression model.

As a work in progress, we present here a preliminary test case. The medium is assumed to have the total absorption coefficient  $\sigma_t = 1$ ,  $a = 0$ ,  $b = 1$ , and the parameters of the laser pulse are  $\mu_s = 1.0$ ,  $\delta_\mu = 1$ ,  $\tau_s = 0.0$ ,  $\delta_t = 120$ . The direct solver has been used to produce a training set  $\{(\mathbf{d}^{(s)}, \boldsymbol{\kappa}^{(s)}(x))\}_{s=1}^{n_k}$  with  $\mathbf{d}^{(s)} = \{(d_0(t_j), d_1(t_j))\}_{j=1}^{n_d}$ ,  $t_j = 10j$ ,  $n_d = 6$  and each output vector  $\boldsymbol{\kappa}^{(s)}(x)$  contains  $n_c = 10$  piecewise constant absorption coefficients distributed over the domain, defined as

$$\boldsymbol{\kappa}^{(s)}(x) = \left( \kappa_1^{(s)}, \kappa_2^{(s)}, \dots, \kappa_{n_c}^{(s)} \right), \quad (4)$$

with  $\kappa_i^{(s)} = 0.1 + (s - 1)0.1$ ,  $s = 1, 2, \dots, n_c = 10$ .

Further work will include the training of the ANN and the evaluation of the estimations for different resolution setups. The framework is expected to be a powerful alternative for estimating the absorption coefficient in multi-region heterogeneous media.

## Acknowledgments

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001.

## References

- [1] O. P. Bruno and A. Prieto. “Spatially dispersionless, unconditionally stable FC–AD solvers for variable-coefficient PDEs”. In: **Journal of Scientific Computing** 58 (2014), pp. 331–366. DOI: 10.1007/s10915-013-9734-8.
- [2] E. L. Gaggioli and O. P. Bruno. “Parallel inverse-problem solver for time-domain optical tomography with perfect parallel scaling”. In: **Journal of Quantitative Spectroscopy and Radiative Transfer** 290 (2022), p. 108300. DOI: 10.1016/j.jqsrt.2022.108300.
- [3] S. Haykin. **Neural Networks and Learning Machines**. 3a. ed. New Jersey: Pearson, 2009. ISBN: 9780131471399.
- [4] M. F. Modest. **Radiative Heat Transfer**. 3a. ed. New York: Elsevier Science, 2013. ISBN: 9780123869906.
- [5] F. D. Moura Neto and A. J. Silva Neto. **An Introduction to Inverse Problems with Applications**. Springer, 2014. ISBN: 978-3642325571.
- [6] M. N. Özisik and H. R. B. Orlande. **Inverse Heat Transfer: Fundamentals and Applications**. 2nd. CRC Press, 2021. ISBN: 9781003155157.
- [7] N. G. Roman, P. C. Santos, and P. H. A. Kozen. “ANN-MoC method for inverse transient transport problems in one-dimensional geometry”. In: **Latin-American Journal of Computing** (2024). DOI: 10.5281/zenodo.12191947.
- [8] L. V. Wang and H. Wu. **Biomedical Optics: Principles and Imaging**. Wiley, 2012. ISBN: 9780470177006.