

Hybrid Knowledge and Data-Driven Neural Networks for Diffuse Optical Tomography Reconstruction in Medical Imaging

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Abstract : Diffuse Optical Tomography (DOT) is an emergent medical imaging technique which employs NIR light to estimate the spatial distribution of optical coefficients in biological tissues for diagnostic purposes, in a noninvasive and non-ionizing manner. DOT reconstruction is a severely ill-conditioned problem due to prevalent scattering of light in the tissue. In this contribution, we present our research in adopting hybrid knowledgedriven/data-driven approaches which exploit the existence of well assessed physical models and build upon them neural networks integrating the availability of data. Namely, since in this context regularization procedures are mandatory to obtain a reasonable reconstruction [1], we explore the use of neural networks as tools to include prior information on the solution. 2. Materials and Methods The idea underlying our approach is to leverage neural networks to solve PDE-constrained inverse problems of the form $\mathcal{D} * = \mathcal{D} \mathcal{D} \mathcal{D} \mathcal{D} \mathcal{D}(\mathcal{D}, \mathcal{D})$, (1) where \mathcal{D} is a loss function which typically contains a discrepancy measure (or data fidelity) term plus other possible ad-hoc designed terms enforcing specific constraints. In the context of inverse problems like (1), one seeks the optimal set of physical parameters \mathcal{q} , given the set of observations \mathcal{y} . Moreover, $\hat{\mathcal{y}}$ is the computable approximation of \mathcal{y} , which may be as well obtained from a neural network but also in a classic way via the resolution of a PDE with given input coefficients (forward problem, Fig.1 box \square). Due to the severe ill conditioning of the reconstruction problem, we adopt a two-fold approach: i) we restrict the solutions (optical coefficients) to lie in a lower-dimensional subspace generated by auto-decoder type networks. This procedure forms priors of the solution (Fig.1 box \square); ii) we use regularization procedures of type $\mathcal{J} * = \mathcal{J} \mathcal{J} \mathcal{J} \mathcal{J} \mathcal{J} \mathcal{J}(\mathcal{D}, \mathcal{D}) + \mathcal{J}(\mathcal{D})$, where $\mathcal{J}(\mathcal{D})$ is a regularization functional depending on regularization parameters which can be fixed a-priori or learned via a neural network in a data-driven modality. To further improve the generalizability of the proposed framework, we also infuse physics knowledge via soft penalty constraints (Fig.1 box \square) in the overall optimization procedure (Fig.1 box \square). 3. Discussion and Conclusion DOT reconstruction is severely hindered by ill-conditioning. The combined use of data-driven and knowledgedriven elements is beneficial and allows to obtain improved results, especially with a restricted dataset and in presence of variable sources of noise.

Keywords : inverse problem in tomography, deep learning, diffuse optical tomography, regularization

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