Neural Bloch-McConnell Fitting (NBMF): Physics-Informed Clinical CEST/MT MRF Quantification Network

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INTRODUCTION: Magnetic resonance fingerprinting (MRF)-based quantification of CEST and semi-solid (ss) MT requires a computationally demanding dictionary synthesis and matching¹ or a lengthy supervised neural network (NN) training². Unsupervised learning³ can circumvent dictionary generation, yet it still requires a lengthy training procedure and is

incompatible with pulsed saturation and multi-pool imaging. The goal of this work was to develop a rapid training-set-free ssMT/CEST-MRF reconstruction method, learning directly from the acquired data via clinical-scan-compatible physical modeling and unsupervised learning.

METHODS: An efficient Bloch-McConnell ODE numerical solver was implemented over an auto-differentiation framework, chained to simulate MRF sequences and embedded within a physics-informed self-supervised learning framework, yielding the Neural Bloch-McConnell-Fitting (NBMF) pipeline (**Fig. 1**). Five healthy volunteers were scanned at two imaging sites using a 3D whole-brain ssMT/CEST MRF protocol⁴ and their quantitative brain parameter maps were extracted.

RESULTS: In an amine phantom experiment, NBMF was able to reconstruct the vials' composition with similar fidelity as dictionary matching. In healthy volunteers (**Fig. 2a-c**), NBMF was able to retrieve GM/WM quantitative parameter values for the ssMT and amide in line with literature (**Fig. 2d,e**). The neural reconstructor yielded by NBMF within minutes of joint fitting & training was able to process new

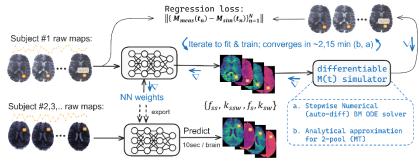


Fig. 1. Neural Bloch-McConnell Fitting (NBMF) pipeline.

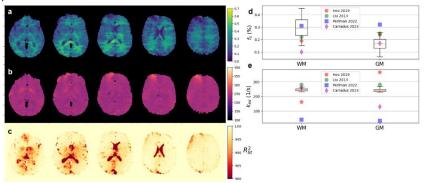


Fig. 2. (a-b) Quantitative CEST maps reconstructed using NBMF, alongside the residual error (c) and comparison to previous works (d-e).

unseen subjects in seconds with good consistency, especially for ssMT and amide proton volume fraction quantification.

DISCUSSION: BM fitting-based reconstruction is computationally challenging even for equilibrated Z-spectra and is considered impractical for the 'general case' (non-steady-state, multi-pool pulsed-saturation) required in clinical CEST-MRF. This work presents an auto-diff numeric BM solver that enables rapid fitting for the first time (to the best of our knowledge). The same framework also jointly trains a reusable neural reconstructor, which facilitates a real-time (order of seconds) full-brain quantification when presented with additional subjects and patients.

CONCLUSION: NBMF dramatically accelerates the entire quantitative ssMT/CEST-MRF pipeline towards clinical applications, accelerating the preparation phase per new protocol and replacing dictionary generation, dot-product matching, and neural-network training with a one-stop-shop rapid alternative. The pipeline and specifically the differentiable BM simulator block can easily be modified for fitting conventional multi-B₁ Z-spectra. The innovative use of auto-diff numeric ordinary differential equation (ODE) solver could extend broadly across quantitative imaging modalities and general inverse problems involving fitting an ODE-governed model to experimental data.

ACKNOWLEDGMENTS: The authors thank Tony Stöcker and Rüdiger Stirnberg for their help with the 3D EPI readout. This project received funding from the Horizon Europe program (ERC, BabyMagnet, project no. 101115639), the Ministry of Innovation, Science and Technology, Israel, and a grant from the Tel Aviv University Center for AI and Data Science.

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