Technology Offer

Processing Magnetic Resonance Data via Machine Learning-Enhanced Non-Linear Regression

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Abstract

This invention describes an advanced method and apparatus for processing magnetic resonance (MR) data, integrating machine learning to address key challenges in MR imaging analysis. The process involves collecting MR data, applying a machine learning model to estimate initial parameters, and refining these through regression to generate precise parameter maps (e.g., T1/T2 relaxation times, CEST metrics). This technology enhances the speed, accuracy, and reliability of diagnostic imaging applications, particularly in complex cases like brain tissue analysis and disease detection, where conventional MR data processing falls short.

Background

Traditional MR data processing depends on complex regression-based methods to analyze biological tissue accurately. These approaches, however, often struggle with obtaining correct initial parameters, which can result in slow processing times and errors. Existing solutions - like iterative down sampling - have not effectively addressed these limitations, and applying machine learning to MR data is still typically limited to black-box models without explicit verification and transparency. This invention addresses key limitations of conventional MR data processing by providing an improved method and apparatus for generating accurate parameter maps with reduced processing time and fewer artifacts. The core innovation combines machine learning with nonlinear regression to streamline the estimation of input parameters essential for MR data analysis.

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This MR data processing method employs machine learning to streamline parameter estimation in non-linear regression models. The MR data from an MRI scanner are processed through a regression model using starting parameters provided by a neural network or support vector machine (Fig. 1). This machine learning estimator can be applied either directly in the MRI system for real-time analysis or offline for post-processed data, providing adaptability. By dividing MR data into voxel-level inputs, the technology generates highly accurate parameter maps based on Bloch equations or their adaptions, relaxation models, magnetic field mapping models or other complex MR signal models. Configured for rapid adaptation, the neural network typically operates with hundreds of neurons across multiple layers, enabling faster and more reliable MR data analysis (Fig. 2).

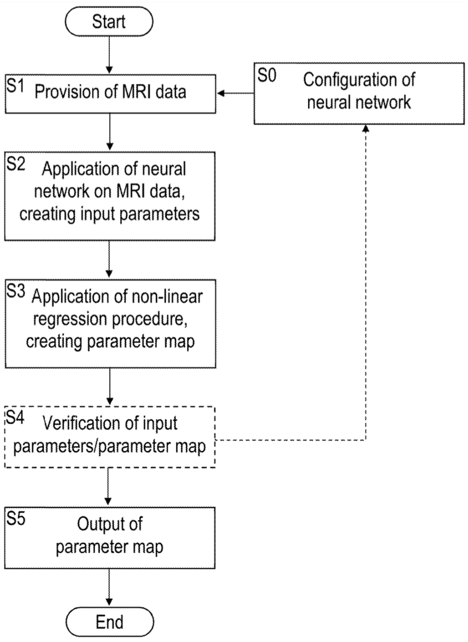

Figure 1: Flowchart of the MR data processing method integrating machine learning for improved initial parameter estimation, enabling accurate and efficient generation of tissue-specific parameter maps through nonlinear regression (Zaiss et al., 2021).

Advantages

- Significantly reduces overall data processing time. It has already been shown that the processing time can be decreased from approximately 6.5 minutes to 2 seconds when using NN. This is an improvement by a factor of 195 (Zaiss et al., 2021).
- Minimizes imaging artifacts by optimizing initial parameter estimates.
- Improves diagnostic reliability with model-based verification.
- Allows both real-time and offline deployment for greater flexibility.
- Enhances accuracy in complex imaging scenarios, including low signal-to-noise conditions.

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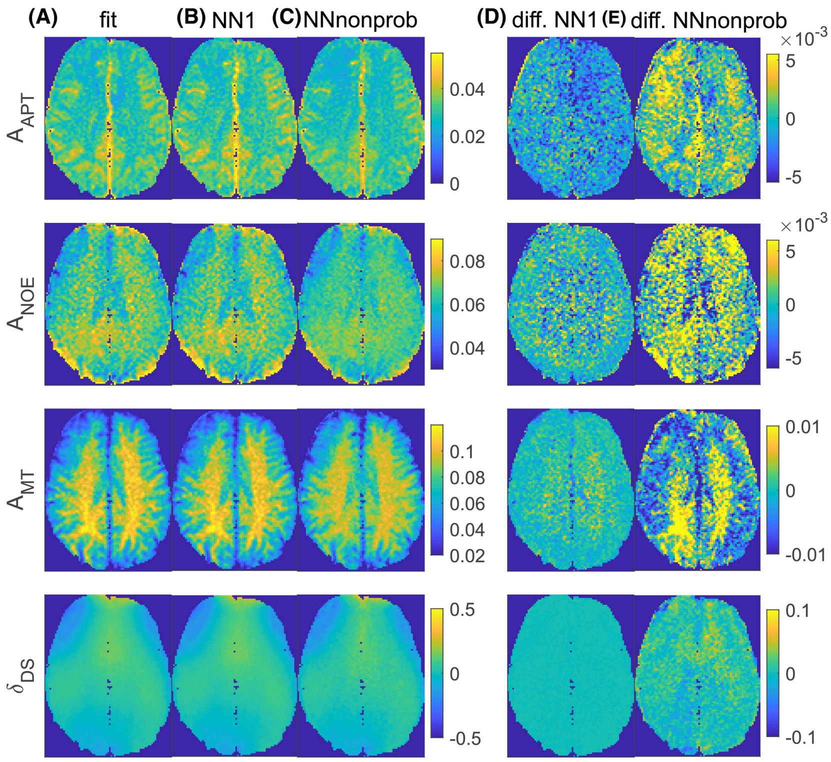

Figure 2: Comparison of MR image parameter maps generated by different methods. Panel (A) shows parameter maps of MR imaging data created using conventional Lorentzian fitting, capturing key tissue features like contrast between gray and white matter. Panel (B) displays the same parameter maps generated by a neural network model (NN1), which closely mirrors the accuracy of traditional methods but with a processing that is 195 times faster (Zaiss et al., 2021). In contrast, Panel (C) shows predictions from a non-probabilistic neural network model (NNnonprob), which has greater error and weaker contrast. Panels (D) and (E) illustrate the difference maps for NN1 and NNnonprob, respectively, confirming that NN1 provides higher accuracy and consistency for complex tissue mapping. Rows correspond to the parameters APT, NOE, and MT amplitude and δ_{DS} (Glang et al., 2020).

Potential applications

- High-resolution imaging for brain tissue differentiation.
- Quantitative mapping of T1 and T2 relaxation times in various tissues.
- Spectroscopic MR imaging (MRSI) for detailed clinical diagnostics.
- CEST imaging, particularly in the evaluation of tumors and pH-sensitive environments.
- Real-time MR imaging for monitoring dynamic biological processes such as perfusion and diffusion.

Patent Information

US11168235B2 (Application: 29.08.2019)

Publications

Zaiss et al., „Method and device for processing MR data using machine learning for parameter estimation," US Patent 11,169,235, 9. November 2021.
Glang et al. DeepCEST 3T: Robust MRI parameter determination and uncertainty quantification with neural networks—application to CEST imaging of the human brain at 3T. *Magnetic resonance in medicine*, 2020, 84. Jg., Nr. 1, S. 450-466.

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