Abstract #01940 ISMRM ABSTRACT

Hybrid 2D CNN-Transformer Achieves Fast and Robust Ktrans Mapping of FUS-Induced BBB Opening

Primary: Acquisition & Reconstruction - Image Reconstruction: AI 〉 **Secondary:** Diffusion - Diffusion Analysis & Visualization 〉 **Presentation:** Oral, PowerPitch Oral, Traditional Poster, Digital Poster 〉 **Keywords:** PERMEABILITY MACHINE LEARNING/ARTIFICIAL INTELLIGENCE DYNAMIC CONTRAST ENHANCED MRI BLOOD-BRAIN BARRIER ANIMAL MOUSE MODEL

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Impact

We introduce 2D ConvFormer, a state-of-the-art model for K^{trans} mapping of FUS-induced BBB opening achieving a >50x acceleration over the Tofts model. It enables robust, rapid quantification from both full and low-dose DCE-MRI, demonstrating superior resilience to noise and motion.

Synopsis

Motivation: Conventional Tofts model-based K^{trans} mapping is slow, susceptible to noise and motion, and gadolinium (GBCA) dose remains a safety concern.

Goals: To develop a robust and accelerated K^{trans} quantification model for both full and reduced (3.3%) GBCA dose DCE-MRI.

Approach: We propose a Hybrid 2D CNN-Transformer (2D ConvFormer) that uses 2D CNNs for local and Transformers for global spatiotemporal feature integration. It was validated against ST-CNN and Tofts on mouse DCE-MRI, including low-dose and simulated degradation data.

Results: 2D ConvFormer achieves a >50x speed-up with superior robustness to noise and motion over Tofts and outperforms the state-of-the-art ST-CNN in both full and low-dose.

Introduction

The blood-brain barrier (BBB) critically limits the systemic therapy options for central nervous system (CNS) diseases, including brain tumors, Alzheimer's disease or Parkinson's disease by blocking drug delivery [1-4]. Focused ultrasound (FUS) reversibly disrupts the BBB, creating a therapeutic window that requires precise quantification [5]. The volume transfer constant (K^{trans}), derived from dynamic contrast-enhanced (DCE)-MRI, measures microvascular permeability and blood flow, enabling visualization and quantification of BBB opening. [6].

However, the gold-standard Tofts model is computationally intensive, often requiring >1 hour per mouse brain, and is susceptible to noise and motion. It also necessitates gadolinium-based contrast agents (GBCAs), which pose risks for patients with renal impairment [7, 8]. The spatiotemporal CNNs (ST-CNN) proposed by Lee et al. showed success in low-dose DCE-MRI [9]. In this study, we propose a Hybrid 2D CNN-Transformer (2D ConvFormer) architecture that achieves state-of-the-art performance in full and low-dose DCE-MRI and demonstrates superior speed, resilience to noise and motion, and potential for scan time reduction compared to both Tofts and ST-CNN models.

Methods

Mouse DCE-MRI data was acquired 12 hours after FUS-induced BBB disruption (Fig. 1a). The DCE-MRI protocol included: 1) baseline T1W scans, 2) 80 T1W scans after a 3.3% GBCA dose (0.165 mmol/kg), and 3) 84 time points after the remaining 96.7% (full) dose. Raw images underwent NIFTI conversion, robust within-subject registration, and manual brain extraction (Fig. 1b). Ground truth K^{trans} maps (Fig. 1c) were generated by Tofts model fitting to the full-dose, 84-timepoint data, which was then thresholded by zeroing values outside the range -0.02 and 0.05 to remove outliers. Noise and motion were simulated using TorchIO for relevant experiments.

The 2D ConvFormer architecture (Fig. 1d) predicts the central voxel's K^{trans} from $7 \times 7 \times T$ spatiotemporal patches, an approach suitable for our limited dataset (10 scans). Patches are processed by 2D CNN blocks for local feature extraction. The features are tokenized and, crucially, concatenated with three auxiliary tokens: a CLS token, a muscle-based AIF reference token, and a pre-contrast signal token. These T+3 tokens are fed into a Transformer encoder, which uses an efficient dynamic tanh function instead of a layer normalization [10]. The output CLS token is passed to an MLP for final prediction. The model was trained using MAE loss and an Adam optimizer (LR=1e-3, batch=256) with five-fold cross-validation on an NVIDIA Quadro 6000 GPU. Evaluation metrics for the whole brain included Pearson correlation coefficient (PCC), Spearman's correlation coefficient (SCC), Concordance correlation coefficient (CCC), normalized root mean squared error (NRMSE), Kullback–Leibler (KL) divergence, structural similarity index measure (SSIM), peak signal-to-noise ratio (PSNR) and DICE for the opening mask, which was generated using a Gaussian Mixture Model (GMM).

Results

2D ConvFormer achieved new state-of-the-art performance, surpassing ST-CNN in most scenarios. Qualitatively (Fig. 2), 2D ConvFormer showed superior structural fidelity and lower residuals than ST-CNN in full and 3.3%-dose data for positive and negative controls. Quantitatively (Fig. 3), 2D ConvFormer outperformed ST-CNN on all metrics in the 84-timepoint scenarios (both full and low-dose) and maintained high robustness under simulated noise and motion (Fig. 4). In low-dose acquisitions, 2D ConvFormer exhibited significant improvements over Tofts model ($p<0.001$ for PCC, CCC, and NRMSE). While the performance gap narrowed in simulated reduced acquisition time, 2D ConvFormer still showed improvements over ST-CNN in CCC and SSIM. Furthermore, 2D ConvFormer generated a significantly improved BBB opening mask quality over ST-CNN, as demonstrated by Dice scores (Fig. 4c) and 3D map comparisons (Fig. 5).

Discussion

Our 2D ConvFormer model provides a significant advancement for K^{trans} mapping. Most critically, 2D ConvFormer accelerates reconstruction by >50 times

compared to the iterative Tofts model (approx. 1.5 minutes vs. >1 hour), enabling near-real-time feedback. 2D ConvFormer also proved highly robust to simulated noise and motion. In state-of-the-art comparisons, 2D ConvFormer achieved new state-of-the-art performance, clearly outperforming the ST-CNN in full 84-timepoint acquisitions for both full and 3.3% GBCA doses. This high performance is likely due to the hybrid architecture's ability to learn global temporal dependencies. It demonstrates the feasibility of simultaneous dose and scan time reduction, paving the way for safer clinical translation.

Conclusion

We introduced 2D ConvFormer, a novel Hybrid 2D CNN-Transformer, for K^{trans} mapping. 2D ConvFormer achieves state-of-the-art, robust reconstruction from full-dose and low-dose (3.3%) DCE-MRI under simulated noise and reduced-time conditions. By reducing the reconstruction time by 50-fold compared to the Tofts model, 2D ConvFormer provides a practical, faster, and safer alternative for BBB permeability quantification.

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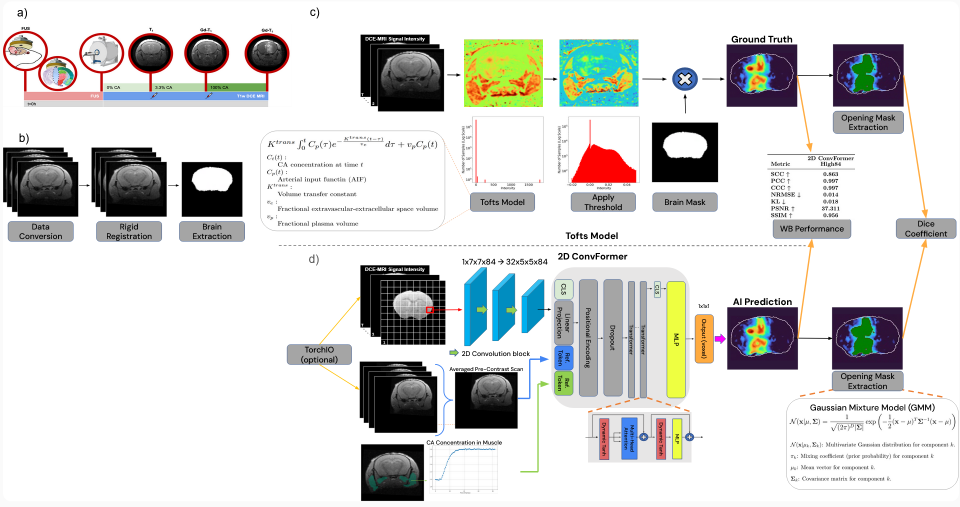
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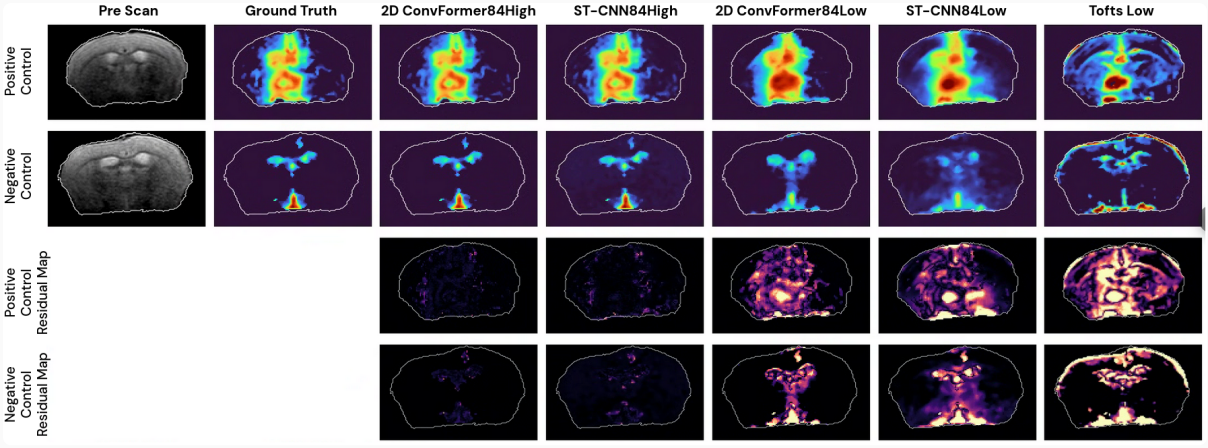
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Figures and Tables



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Figure 1: *Overview of the workflow.* ***(a)*** *Mouse DCE-MRI protocol detailing baseline, low-dose (3.3%), and full-dose (96.7%) GBCA acquisitions.* ***(b)*** *Image preprocessing steps: Data Conversion, Rigid Registration, and Brain Extraction.* ***(c)*** *Ground truth Ktrans map generation using the Tofts model.* ***(d)*** *Proposed 2D ConvFormer architecture, which uses 2D CNNs and a Transformer encoder with dynamic tanh function to predict Ktrans from 7x7xT patches and auxiliary reference inputs (muscle AIF, pre-contrast scan).*



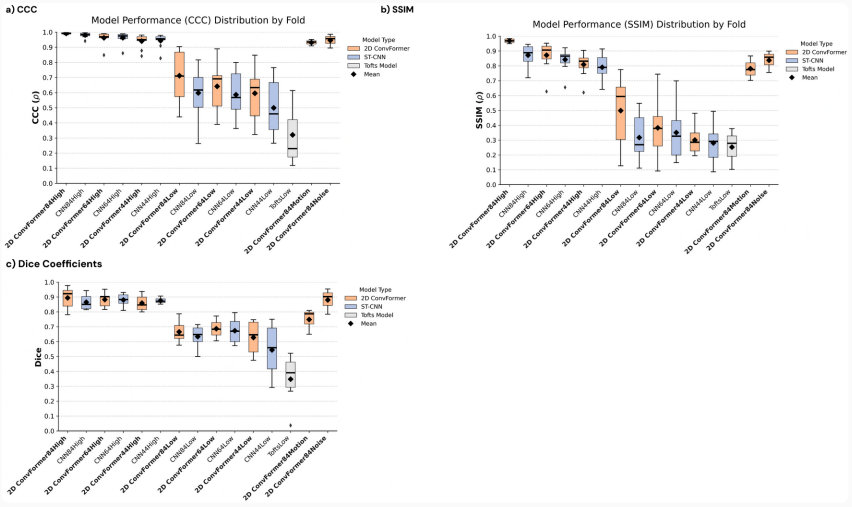
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Figure 2: *Qualitative comparison of predicted K^{trans} maps for positive (BBB-disrupted) and negative control regions. Top two rows (turbo colormap): K^{trans} predictions. 2D ConvFormer (High and Low dose) demonstrates superior structural fidelity and agreement with the Ground Truth compared to ST-CNN and ToftsLow. Bottom two rows (magma colormap): Residual maps. The 2D ConvFormer predictions show visibly lower error (darker residuals) than ST-CNN and Tofts, particularly in the low-dose scenario.*

Metric	2D ConvFormer High84	ST-CNN High84	2D ConvFormer Noise84	2D ConvFormer Motion84	2D ConvFormer Low84	ST-CNN Low84	Tofts Low84
Positive Control							
SCC ↑	**0.863**	0.858	0.854	0.814	**0.642**	0.523	0.390
PCC ↑	**0.997**	0.995	0.989	0.957	**0.922**	0.850	0.625
CCC ↑	**0.997**	0.994	0.986	0.952	**0.902**	0.816	0.614
NRMSE ↓	**0.014**	0.018	0.028	0.054	**0.082**	0.110	0.137
KL ↓	**0.018**	0.108	0.049	0.075	**0.091**	0.495	0.269
PSNR ↑	**37.311**	34.794	31.130	25.388	**21.763**	19.204	17.275
SSIM ↑	**0.956**	0.887	0.858	0.775	**0.601**	0.453	0.279
Negative Control							
SCC ↑	**0.933**	0.499	0.480	0.752	**0.607**	0.431	0.220
PCC ↑	**0.991**	0.981	0.897	0.911	**0.724**	0.708	0.217
CCC ↑	**0.991**	0.973	0.895	0.909	**0.695**	0.681	0.171
NRMSE ↓	**0.010**	0.0167	0.034	0.0304	**0.051**	0.055	0.146
KL ↓	**0.009**	0.806	0.0479	0.0197	**0.084**	0.830	0.098
PSNR ↑	**39.996**	35.539	29.443	30.353	**25.879**	25.117	16.692
SSIM ↑	**0.983**	0.720	0.755	0.8670	**0.727**	0.548	0.377

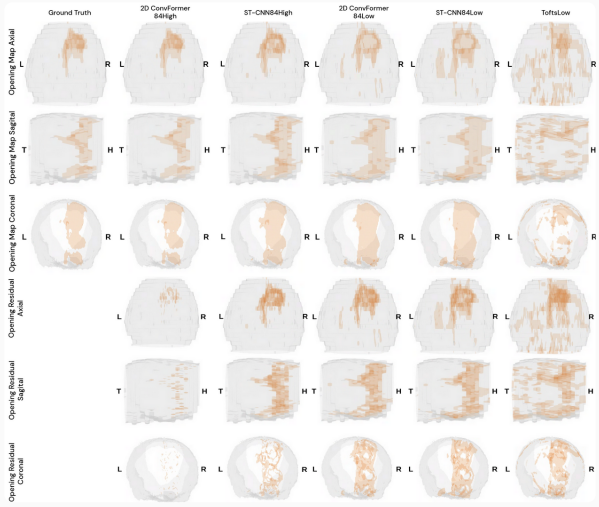
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Figure 3: *Quantitative comparison of model performance for the whole brain. Metrics include Spearman (SCC), Pearson (PCC), and Concordance (CCC) Correlation Coefficients, NRMSE, KL Divergence, PSNR, and SSIM. 2D ConvFormer outperforms the baseline ST-CNN in the full-dose full-timepoint (High84) scenario. In the low-dose full-timepoint (Low84) scenario, 2D ConvFormer significantly surpasses both ST-CNN and Tofts models. It also maintains high performance under simulated noise and motion.*



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Figure 4: *Performance comparison under different acquisition time, simulated degradations, and full/ low-dose for the whole brain. Box plots compare a) Concordance Correlation Coefficient (CCC), b) Structural Similarity Index (SSIM), and c) Dice Coefficients for the BBB opening mask. 2D ConvFormer (orange) consistently outperforms ST-CNN (blue) across reduced time points (84, 64, 44) in both high and low-dose settings. It also shows superior robustness to simulated motion and noise.*



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Figure 5: *3D visualization of the generated BBB opening masks and corresponding residuals. Top 3 rows (Opening Map): 2D ConvFormer (High and Low dose) accurately reconstructs the shape and extent of the opening in all views (Axial, Sagittal, Coronal), closely matching the Ground Truth. Bottom 3 rows (Opening Residual): 2D ConvFormer shows improved residual error than ST-CNN. ToftsLow exhibits significant false positives and negatives, aligning with the poor Dice scores seen in Fig. 4c.*