HUMMID: High-fidelity Ultra-fast Macrostructure and Microstructure brain Imaging using Deep learning

Yuhang He[1, 2, 3], Jialan Zheng[2,4], Hongjia Yang[2], Yifei Chen[2], Zihan Li[2], Mingxuan Liu[2], Qiuyun Fan[5], Yi Liao[6], Haibo Qu[6], Qiyuan Tian[2], Jie Lu[1, 7], Ziyu Li[8]

[1]Department of Radiology and Nuclear Medicine, Xuanwu Hospital, Capital Medical University, Beijing, China;

[2]School of Biomedical Engineering, Tsinghua University, Beijing, China;

[3]School of Precision Instrument and Opto-Electronics Engineering, Tianjin University, Tianjin, China;

[4]Tanwei College, Tsinghua University, Beijing, China;

[5]Academy of Medical Engineering and Translational Medicine, Medical College, Tianjin University, Tianjin, China;

[6]Department of Radiology, West China Second University Hospital, Sichuan University, Chengdu, China;

[7]Beijing Key Laboratory of Magnetic Resonance Imaging and Brain Informatics, Beijing, China, Xuanwu Hospital, Beijing, China;

[8]Oxford University Centre for Integrative Neuroimaging, FMRIB, Nuffield Department of Clinical Neurosciences, University of Oxford, Oxford, UK.

(Purpose + Method and Materials + Results + Conclusion = 2387 characters)

Purpose (800 characters)

Quantifying macro- and microstructural features of human brain is vital for studying healthy and pathological changes. Assessments of macrostructural brain morphology typically rely on high-resolution T1w images from long scan times (e.g., ~5 min for 1 mm iso.). Diffusion MRI (dMRI) reveals tissue microstructure and brain connectivity but needs lengthy angular samplings (e.g., ~5 min for 2 mm iso. and 32-62 directions). The combined scan time (~10 min) limits the feasibility of brain structure mapping in clinical use. This study aims to enable ultrafast, high-fidelity T1w and dMRI using deep learning. Using just six diffusion-weighted images (DWIs) along optimal diffusion directions and a single b=0 image volume (~0.5 min scan time), the proposed method (HUMMID) accurately reconstructs both macro- and microstructural features, enabling ultrafast brain morphology and connectivity mapping for wider clinical applications.

Method and Materials (619 characters)

HUMMID consists of two concatenated U-Nets. The first one generates high-quality T1w from 6 DWIs along optimized diffusion directions and 1 b=0 image. The second one uses residual learning to map the input to high-SNR DWIs. T1w (1 mm iso.) and dMRI data (2 mm iso., b = 1000 s/mm^2, 50 directions) of 130 subjects (56 for training, 14 for validation, 60 for evaluation) from UK Biobank were used. Six DWIs along optimized directions were synthesized from fitted tensors—using 6 directions for the input and all 50 for the reference. On evaluation data, analyses included brain segmentation and cortical surface reconstruction (FreeSurfer), DTI (FSL), and tractography (TrackVis) to assess the fidelity of the generated T1w and dMRI data.

Results (569 characters)

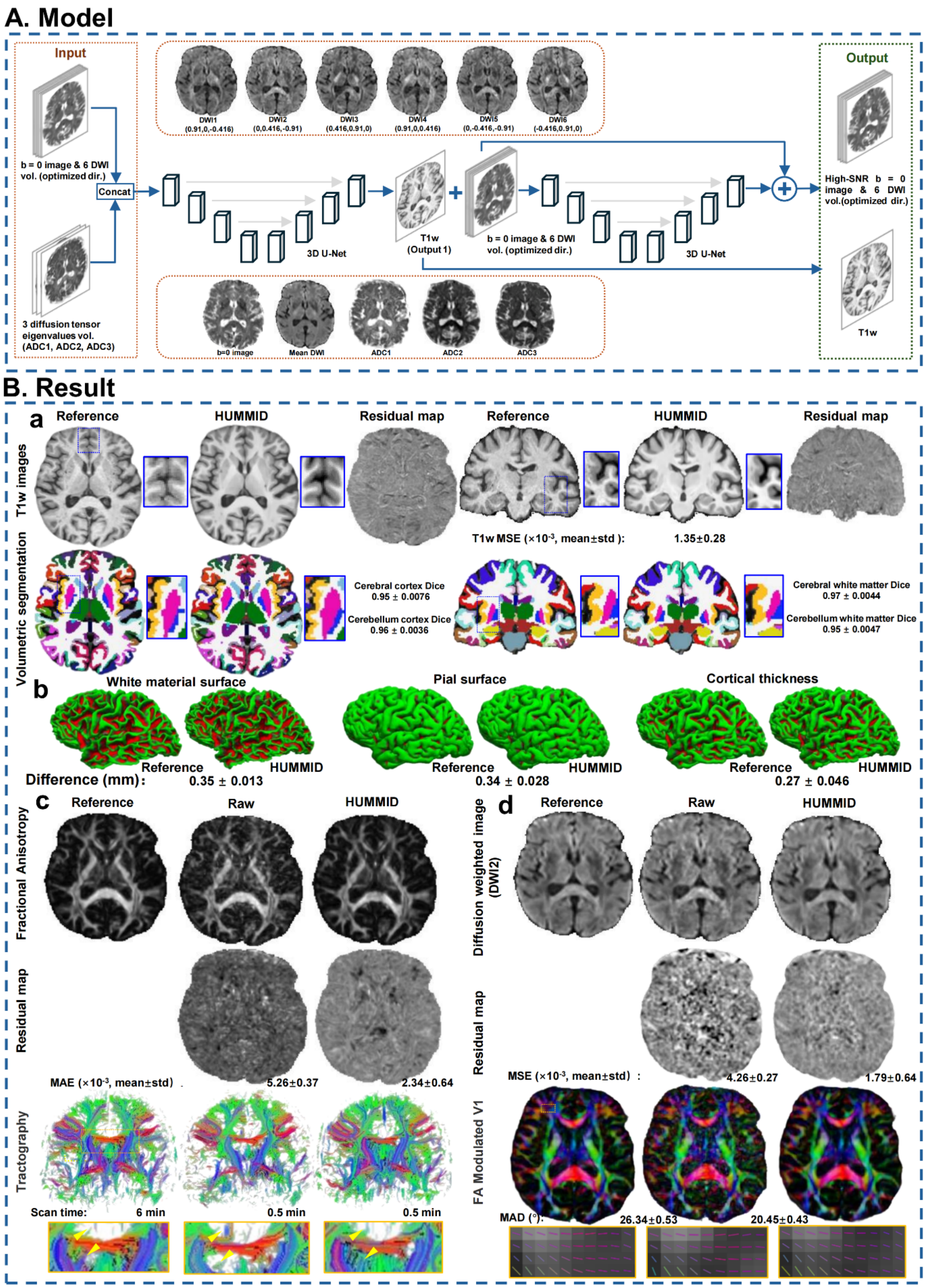
HUMMID synthesized high-quality T1w images similar to native ones, which produced accurate brain segmentations compared to those from native images, with Dice coefficients higher than 0.95 for white matter and cortex. Reconstructed cortical surfaces from synthesized and native T1w data were highly similar, with whole-brain mean difference as 0.35, 0.34, and 0.27 mm for gray-white surface, pial surface, and cortical thickness. HUMMID also effectively improved the SNR of input dMRI data. The whole-brain averaged mean error for fractional anisotropy reduced by 56%. The tracked fibers from HUMMID exhibited patterns more similar to those from reference DTI data.

Conclusion (173 characters)

HUMMID generates high-SNR anatomical and dMRI data from six-direction dMRI input, showing the potential in high-SNR brain morphology and microstructure mapping within clinically feasible scan times.

Clinical Relevance/Application (226 characters)

By reducing 93% scan time while preserving image quality, HUMMID has the potential to facilitate brain morphology and microstructure mapping in patients with severely limited scan tolerance, such as stroke patients or young children with neurological conditions.



A. Model
Input
b = 0 image & 6 DWI vol. (optimized dir.)
Concat
3 diffusion tensor eigenvalues vol. (ADC1, ADC2, ADC3)
DWI1 (0.91,0,-0.416)
DWI2 (0,0.416,-0.91)
DWI3 (0.416,0.91,0)
DWI4 (0.91,0,0.416)
DWI5 (0,-0.416,-0.91)
DWI6 (-0.416,0.91,0)
3D U-Net
T1w (Output 1)
b = 0 image & 6 DWI vol. (optimized dir.)
3D U-Net
b=0 image
Mean DWI
ADC1
ADC2
ADC3
Output
High-SNR b = 0 image & 6 DWI vol.(optimized dir.)
T1w
B. Result
a
Reference
HUMMID
Residual map
Reference
HUMMID
Residual map
T1w images
T1w MSE (×10⁻³, mean±std):
1.35±0.28
Volumetric segmentation
Cerebral cortex Dice 0.95 ± 0.0076
Cerebellum cortex Dice 0.96 ± 0.0036
Cerebral white matter Dice 0.97 ± 0.0044
Cerebellum white matter Dice 0.95 ± 0.0047
b
White material surface
Pial surface
Cortical thickness
Reference
HUMMID
Reference
HUMMID
Reference
HUMMID
Difference (mm):
0.35 ± 0.013
0.34 ± 0.028
0.27 ± 0.046
c
Reference
Raw
HUMMID
Fractional Anisotropy
Residual map
MAE (×10⁻³, mean±std)
5.26±0.37
2.34±0.64
Tractography
Scan time:
6 min
0.5 min
0.5 min
d
Reference
Raw
HUMMID
Diffusion weighted image (DWI2)
Residual map
MSE (×10⁻³, mean±std) :
4.26±0.27
1.79±0.64
FA Modulated V1
MAD (°):
26.34±0.53
20.45±0.43