Pilot Tone–Guided 3D Head Motion Correction Enhanced by Pretrained 2D U-Net Regularization

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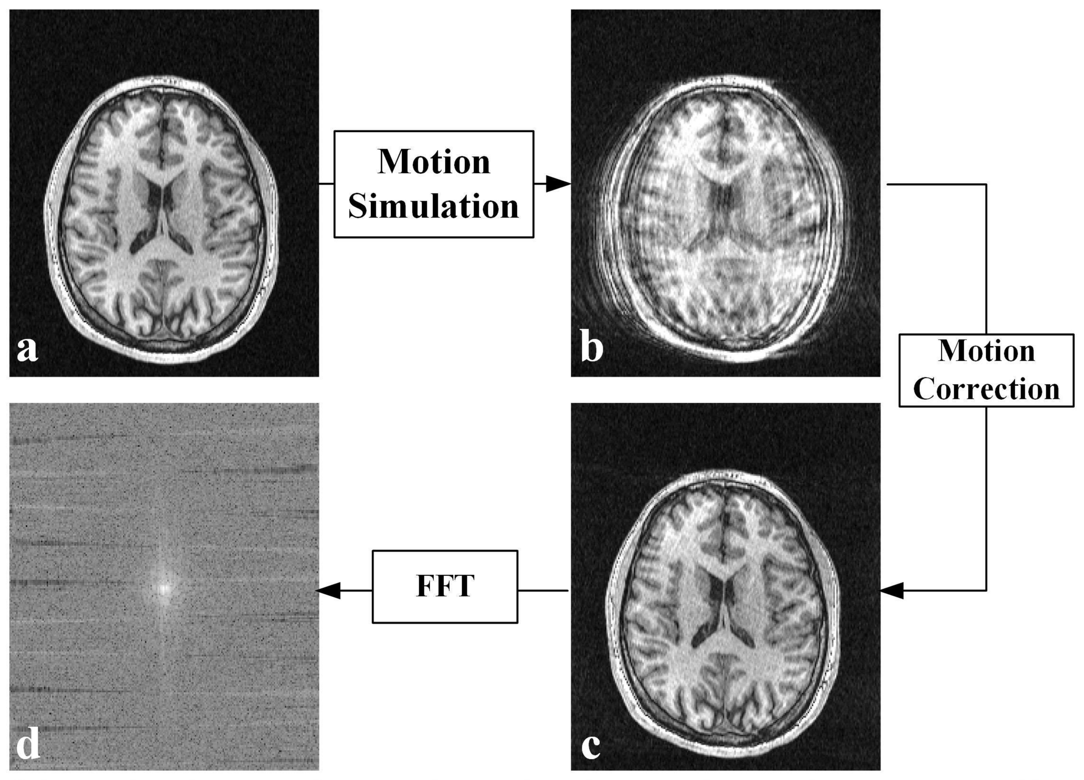
Introduction

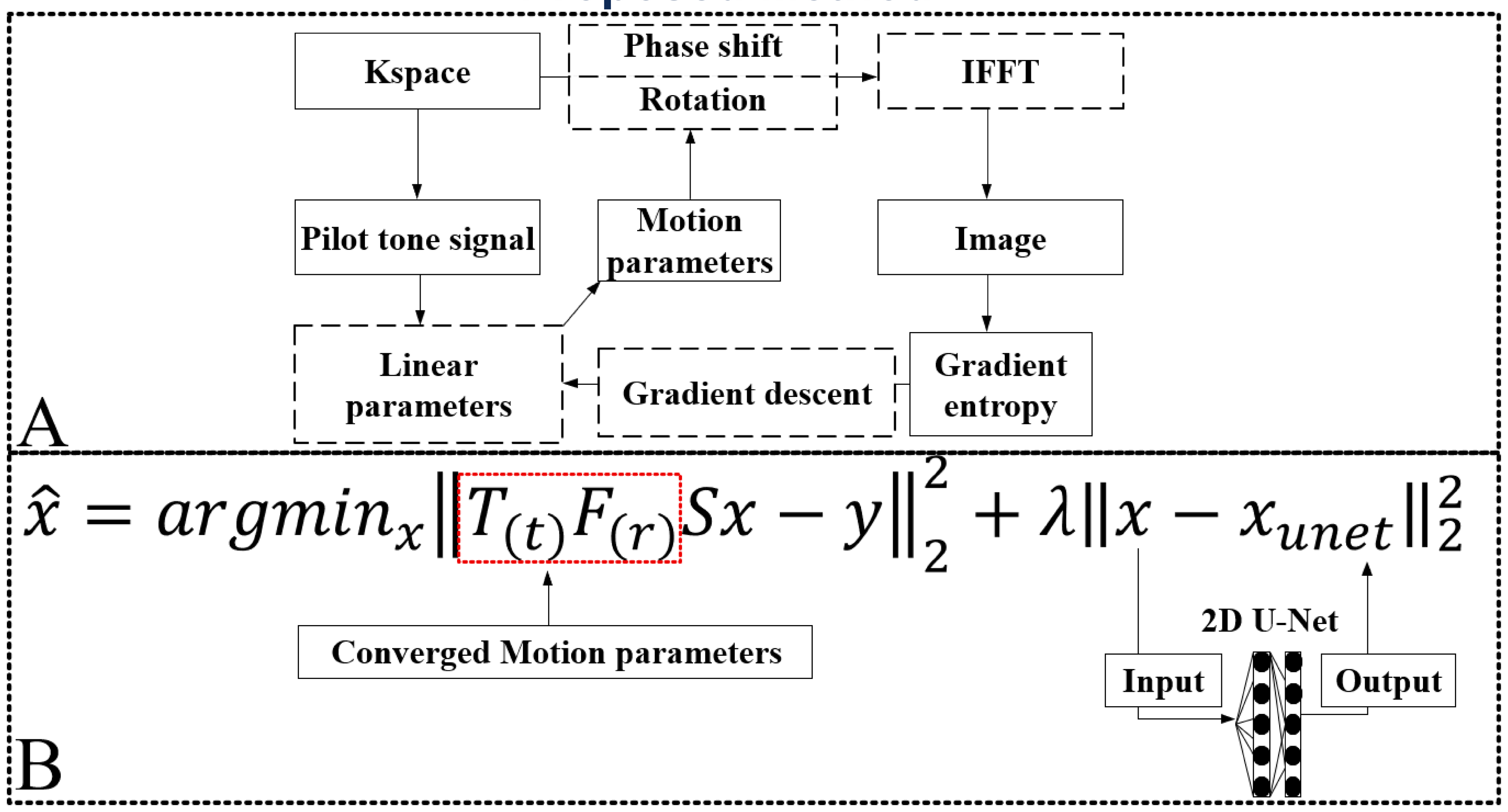


Simulation of motion-induced under-sampling artifacts. (a) Motion-free reference image. (b) Motion-corrupted image. (c) Motion-corrected image using ground-truth motion parameters, showing residual under-sampling artifacts. (d) Corresponding k-space of (c), with black regions indicating under-sampled gaps caused by motion during acquisition.

Problem: To compensate for head rotations that occurred during the acquisition, motion correction algorithms need to counter-rotate the corresponding k-space data, thus producing 'wedge-shaped' undersampled regions in k-space. These undersampled regions, in turn, lead to image artifacts often perceived as a loss of SNR.

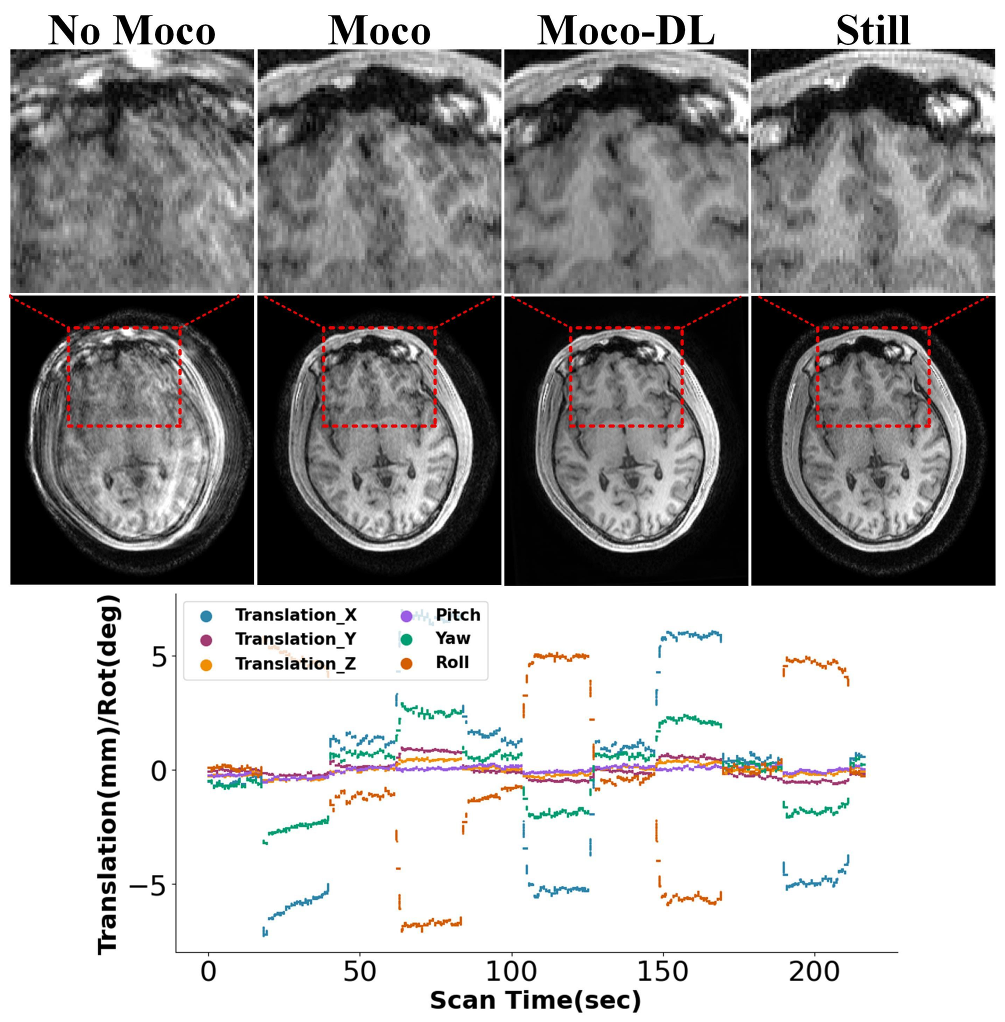
Solution: We found that a hybrid framework — 3D motion correction first, followed by a pretrained 2D U-Net as a regularization term — can effectively correct for motion while mostly avoiding such undersampling artifacts.

Proposed Method



Overview of the proposed motion correction and reconstruction framework. (A) A traditional motion compensation algorithm, in which k-space phase ramps and rotations compensate for the patient's rigid-body head motion. (B) The proposed modification: within the minimization step of (A), a regularization term based on a pre-trained U-Net is added. The 3D image is sliced into 2D inputs for the U-Net, and the difference between the U-Net output and its input serves as the regularization term. The U-Net model was developed previously and used as downloaded. x_unet: U-Net output; y: k-space data; T(t): translation phase ramps; F(r): k-space rotations; S: coil sensitivities; λ = 0.8.

Results — Volunteer (Instructed Movements)



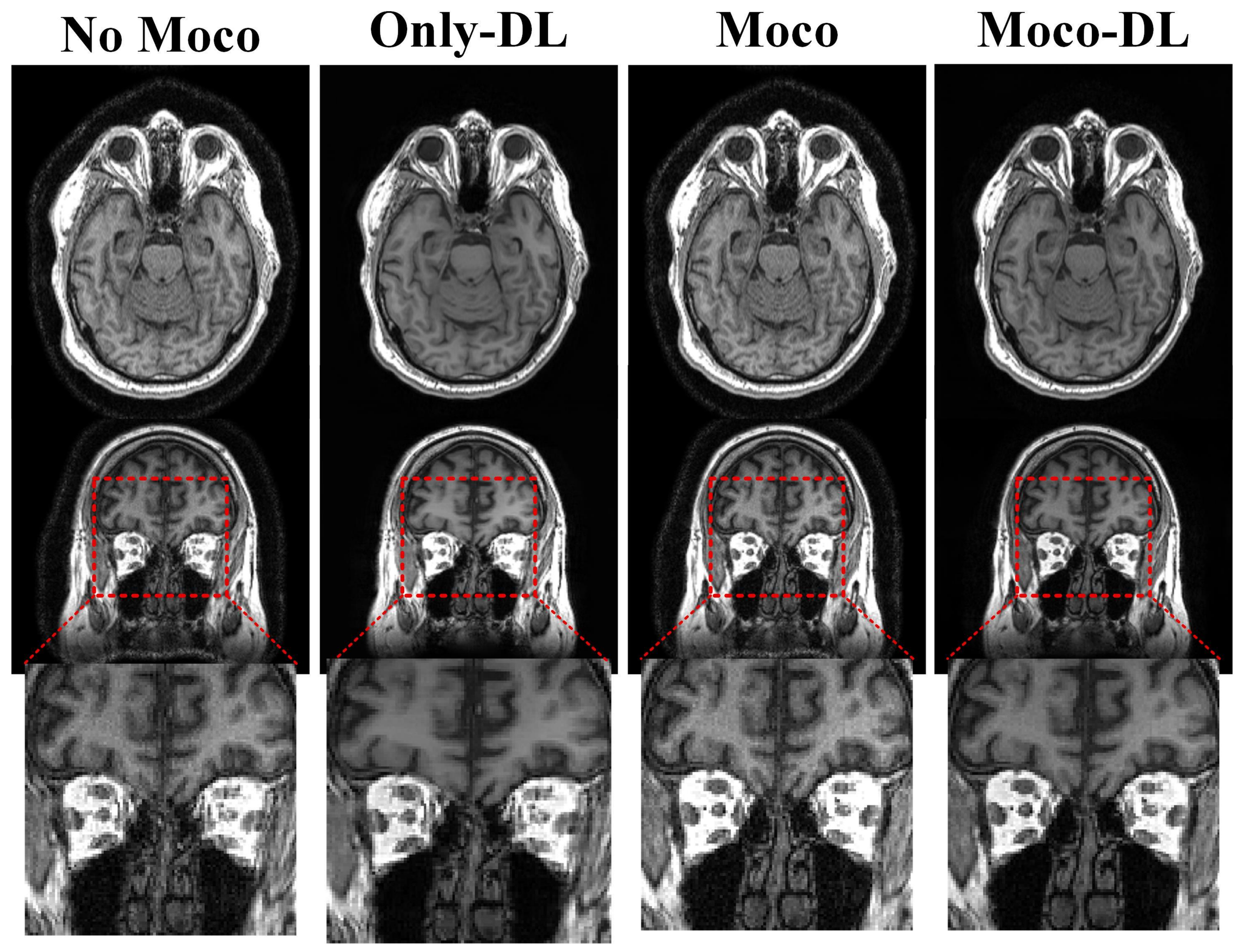
The volunteer was instructed to change position, in a manner of her/his choosing, every few seconds. In this dataset, the volunteer changed position 10 times, over a range of (~±5°, ±5 mm):

MoCo → a clear improvement over the 'no MoCo' image can be seen

MoCo-DL → further increase the SNR and reduce artifacts compared to the Moco one

Still → This is the 'reference' image, obtained in a separate scan with the volunteer instructed to remain still

Results — Patient (Mild Motion)



Axial and coronal slices are shown from one patient who moved subtly during the 3D MPRAGE scan. This illustrates that in common, clinically relevant cases of slight patient motion, the approach can still help sharpen the image. Moreover, combining our traditional MoCo processing with the DL model yielded visibly better results than either method alone.

Discussion & Conclusion

Hybrid framework: We integrated a pretrained 2D U-Net denoiser model into the regularization term of a more traditional motion correction method.

Better image quality: Combining traditional and U-Net approaches yielded higher SNR and fewer residual artifacts than either method alone.

Efficient & practical: Low GPU usage and a processing time of ~110 s per 3D volume was achieved here, using an off-the-shelf PC.

References

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