The effect of intra-scan motion on AI reconstructions in MRI

Laurens Beljaards[1] L.R.BELJAARDS@LUMC.NL
[1] *Department of Radiology, Leiden University Medical Center, Leiden, The Netherlands*

Nicola Pezzotti[2,3] NICOLA.PEZZOTTI@PHILIPS.COM
[2] *Philips Research,* [3] *Eindhoven University of Technology*

Christophe Schülke[2] CHRISTOPHE.SCHUELKE@PHILIPS.COM

Matthias J. P. van Osch[1] M.J.P.VAN_OSCH@LUMC.NL

Marius Staring[1] M.STARING@LUMC.NL

Editors: Under Review for MIDL 2022

Abstract

MRI can be accelerated via (AI-based) reconstruction by undersampling k-space. Current methods typically ignore intra-scan motion, although even a few millimeters of motion can introduce severe blurring and ghosting artifacts that necessitate reacquisition. In this short paper we investigate the effects of rigid-body motion on AI-based reconstructions. Leveraging the Bloch equations we simulate motion corrupted MRI acquisitions with a linear interleaved scanning protocol including spin history effects, and investigate i) the effect on reconstruction quality, and ii) if this corruption can be mitigated by introducing motion-corrupted data during training. We observe an improvement from 0.819 to 0.867 in terms of SSIM when motion-corrupted brain data is included during training, demonstrating that training with motion-corrupted data can partially compensate for motion corruption. Inclusion of spin-history effects did not influence the results.

Keywords: Motion Corruption, Fast MRI, Undersampling, AI-Based Reconstruction

1. Introduction

MR acquisition is a time consuming process, making it susceptible to patient motion during scanning. MRI can be accelerated by acquiring only a fraction of k-space and using a reconstruction technique that leverages prior knowledge about the data to reconstruct the image. Recent research using AI-based reconstruction techniques has been successful, but generally assumes an ideal setting without intra-scan motion. Yet, even a few millimeters of motion can introduce severe blurring and ghosting artifacts, necessitating re-acquisition.

In this short paper we investigated the effects of rigid-body motion on AI-based reconstructions. We simulated motion corrupted MRI acquisition with a linear interleaved scanning protocol, and optionally added spin history effects to the modelling. We then explored the merit of incorporating spin history effects with respect to reconstruction quality, and investigated whether the use of the simulated data during training is able to mitigate the effects of intra-scan motion.

Table 1: Median performance on 4× undersampled data against fully sampled still images.

	no motion			2D motion			3D motion			3D motion + Bloch + spin-history			3D motion + Bloch		
	SSIM	NMSE	PSNR	SSIM	NMSE	PSNR	SSIM	NMSE	PSNR	SSIM	NMSE	PSNR	SSIM	NMSE	PSNR
$\mathcal{F}$(zero filled)	0.569	0.111	21.0	0.484	0.167	18.9	0.476	0.173	18.8	0.281	0.467	14.9	0.332	0.364	15.9
$\mathcal{R}_{\text{still}}$	**0.953**	**0.006**	**34.2**	0.835	0.054	24.7	0.819	0.061	24.1	0.181	1.398	10.4	0.368	0.486	15.1
$\mathcal{R}_{\text{motion2D}}$	0.917	0.023	28.6	**0.878**	**0.037**	**25.9**	**0.867**	**0.044**	**25.2**	0.603	0.289	17.1	0.657	0.216	18.3
$\mathcal{R}_{\text{motion}}$	0.911	0.024	28.2	0.874	0.038	25.7	0.866	0.045	25.0	0.598	0.292	17.1	0.657	0.222	18.2
$\mathcal{R}_{\text{motion+spin}}$	0.829	0.088	23.0	0.788	0.106	21.8	0.782	0.106	21.7	**0.694**	**0.176**	**19.3**	0.697	0.177	19.2
$\mathcal{R}_{\text{motion+bloch}}$	0.844	0.068	23.7	0.802	0.096	21.9	0.798	0.096	22.0	0.684	0.181	19.1	**0.720**	**0.152**	**19.8**

2. Methods

We synthesize motion corrupted scans by applying a 3D affine motion pattern to a given still image over a series of timesteps to simulate the motion of the subject in the scanner. During each timestep, we apply a 3D shift and rotation in image space, optionally apply excitation and relaxation to tissue in image space, and finally convert to k-space to sample relevant k-space lines according to a linear interleaved multi-slice pattern, resulting in a motion corrupted k-space. Excitation and relaxation is modelled by the Bloch equations, as motion may move unexcited tissue into the scan slice, causing spin history artifacts. The motion parameters are extracted from the (RealNoiseMRI Challenge, 2021) dataset, where subjects were asked to perform nodding motion during the scan. The motion parameters have median (max) shifts and rotations of 0.37 (2.9) mm and 0.4 (3.9) degrees.

For reconstruction we use our deep-learning unrolled iterative scheme (Pezzotti et al., 2020), only passing the center slice to the network. We use a 10 block network, slices of shape 160 by 160, and the still images as an exact uncorrupted ground truth.

3. Experiments and Results

Four motion corrupted datasets and corresponding models were generated respectively using 2D motion ($\mathcal{R}_{\text{motion2D}}$), 3D motion ($\mathcal{R}_{\text{motion}}$), 3D motion with relaxation and excitation following the Bloch equation to model spin history effects ($\mathcal{R}_{\text{motion+spin}}$), and 3D motion with excitation and relaxation using unselective RF-pulses to suppress spin history effects while keeping the intensity similar for a fair comparison ($\mathcal{R}_{\text{motion+bloch}}$). The reconstruction models were initially trained for 1.7M iterations with one slice per iteration on uncorrupted brain T1, T2 and FLAIR images from the NYU FastMRI dataset (Knoll et al., 2020), and subsequently fine-tuned for 1M iterations on synthetic T1 data on the four corrupted datasets, respectively. We used 4x undersampling and 8% central fraction, and an NVIDIA Quadro RTX 6000 GPU. A baseline model $\mathcal{R}_{\text{still}}$ was also finetuned on still T1 data. The effect of the various types of motion on the reconstruction quality is shown in Table 1.

The effect of motion. The introduction of motion caused a large decrease in reconstruction quality of $\mathcal{R}_{\text{still}}$. In comparison, the models that were fed motion corrupted data during training displayed better performance when confronted with motion-corrupted data, although decreased sharpness can be observed in the image. On still data, the performance of the motion-induced models decreased compared to $\mathcal{R}_{\text{still}}$, suggesting that these small models sacrificed some 'still' prediction quality to improve at motion correction. For larger models with 24 blocks on data of size 320 by 320 we observed no significant difference in terms of SSIM, namely 0.875 for $\mathcal{R}_{\text{still}}$, 0.876 for $\mathcal{R}_{\text{motion+bloch}}$, and 0.873 for $\mathcal{R}_{\text{motion+spin}}$.

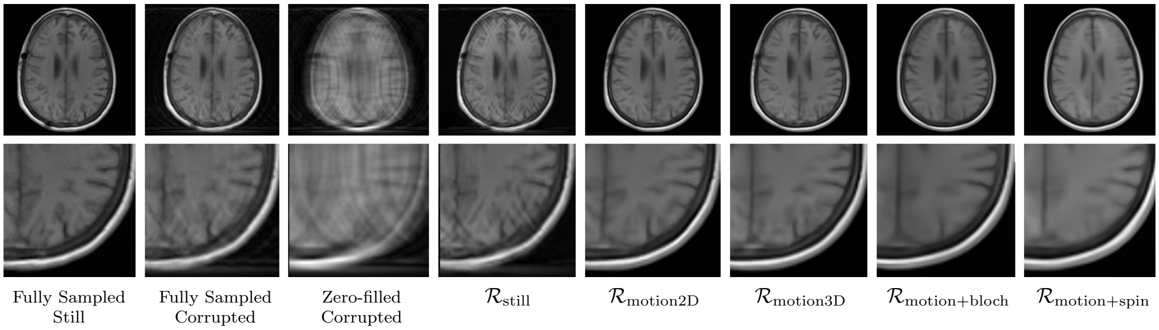

Figure 1: Predictions of the models on undersampled motion corrupted data.

Spin history modelling. The similarity between the performance of $\mathcal{R}_{\text{motion+bloch}}$ and $\mathcal{R}_{\text{motion+spin}}$ in Table 1 shows that the added effect of training with spin history is very small, making it difficult to justify the increased complexity it introduces to the simulation.

Data consistency. The reconstruction technique incorporates a learned data consistency modifier, allowing the data consistency to be imposed less strongly if beneficial for performance. We measured a decreased weighing of the first data consistency term from 1.00 for $\mathcal{R}_{\text{still}}$ to 0.65 for $\mathcal{R}_{\text{motion}}$, and of the remaining terms from an average of 0.71 to 0.13. This decrease in weighing occurred in all of the motion-induced models. The change in data consistency strength indicates that it is beneficial for the motion-induced models to have more freedom to compensate for motion in the measured k-space.

4. Discussion and Conclusion

We investigated the effect of motion on reconstruction, and demonstrated that training with motion corrupted data can alleviate negative effects on reconstruction quality. The modelling of spin history effects via Bloch equations did not yield improvements. The motion-induced models imposed data consistency less strongly, which may be restored by incorporating explicit motion compensation in the architecture. A potential limitation of this study is the use of a smaller network, that does not achieve diagnostic quality.

In conclusion, finetuning by training with synthetic motion corrupted data can enhance the motion robustness of existing deep learning based reconstruction approaches.

Acknowledgments. This work was in part funded by Philips Research.

References

Knoll et al. FastMRI: A publicly available raw k-space and DICOM dataset of knee images for accelerated MR image reconstruction using machine learning. *Radiology: Artificial Intelligence*, 2:e190007, 01 2020.

Pezzotti et al. An adaptive intelligence algorithm for undersampled knee MRI reconstruction. *IEEE Access*, 8:204825–204838, 2020.

RealNoiseMRI Challenge. Neurobiology Research Unit, Rigshospitalet, Copenhagen, Denmark. 2021. URL realnoisemri.grand-challenge.org. Accessed: 22-04-22.