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Evaluating Rigid Motion-Affected, U-NET-Estimated Q-Matrices with Parallel RF Transmission

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1 Synopsis

Motivation:

Patient motion may exacerbate SAR exposure, and may necessitate large corrective safety factors. A position adaptive safety model would facilitate high-performance scanning without compromising safety.

Goal(s):

We test the efficiency of using neural networks for estimating the effect of patient motion on local SAR for ultrahigh-field MRI.

Approach:

We trained U-Nets to estimate the effect of patient motion on Q-matrices, and compared network-estimated SAR with ground-truth after-motion SAR for realistic parallel-transmit pulses.

Results:

Patient motion has a statistically-significant effect on local SAR, but network-estimated safety models can recover a faithful representation of the ground-truth after-motion local SAR.

Impact:

The proposed approach needs a smaller corrective safety factor, which may enable higher-performance scanning without compromising safety, when using ultrahigh-field MRI for subjects who may not remain still.

2 Introduction

Safety models are used to calculate the specific absorption rate (SAR) during MRI in order to ensure safe scanning. These models may range from consisting of multiple virtual body models positioned at multiple possible patient positions within the coil to one centralized body model. Irrelevant patient positions may be unnecessarily restrictive whereas an over-simplistic safety model will not be representative enough [1]. Depending on the safety model, the calculations may be highly-misleading, considerably limiting scanning performance on one end of the spectrum and yielding substantially unsafe pulses

on the other end [2]. Adapting a representative safety model to the actual patient position would ensure high-performance scanning without compromising safety.

Within-scan patient motion can alter the location and intensity of local SAR, leading to safety concerns [2]. To adapt safety models to patient motion, recent proof-of-concept work used neural networks (NNs) [3]. In this simulation-based study, we test the efficiency of using neural networks for estimating the effect of patient motion on local SAR with various parallel-transmit pulses designed for an initial position. We compared peak spatial (local) SAR (psSAR) values calculated using neural network estimated (NNe) Q-matrices [4] to the actual (i.e., ground-truth; GT) psSAR values after simulated patient motion.

3 Methods

We created and preprocessed data identically to Ref. [3], converting [5] combinations of Q-matrices to the so-called intermediate local SAR (ilSAR) distributions for certain parallel-transmit channel weights. Pairs of initial and post-motion ilSAR distributions were then used to train neural networks. Because ilSAR distributions have smooth and low-frequency spatial variations with limited fine detail, we observed over-fitting during training. To minimize over-fitting, we reduced the training dataset size by a third, and replaced conditional generative adversarial network (cGAN) with U-Net architecture [6] (Figure 1) that consisted of five downstack and four upstack layers as opposed to the eight and seven, respectively, used in the cGAN architecture. We used 3x3 filters, 40 epochs, and a higher decay rate of $\beta_1 = 0.9$ in the Adam optimizer. Similar to [7] we trained separate networks for rightward (R) and posteriorward (P) motion of 5 mm, which were then cascaded to estimate the effect of different amounts of motion; i.e., 2xR5 and 1xP5 network were cascaded for R10 P5 motion. Neural-network estimated ilSAR distributions were converted from ilSAR back to Q-matrices, which were used in psSAR calculations.

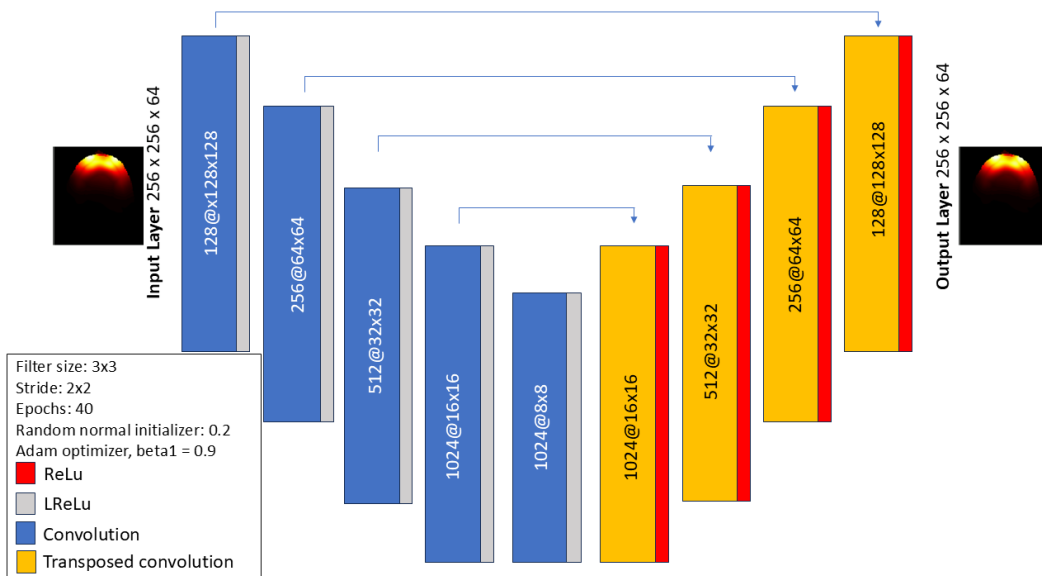


Figure 1: The neural network architecture. Five downstack layers are joined by skip connections to four upstack layers. Activation functions were leaky-ReLu for the convolution layers in the encoder path and ReLu for the deconvolution layers in the decoder path. Other parameters were selected as: filter size, 3x3; stride, 2x2; number of epochs, 40; $\beta_1 = 0.9$. Each network was trained for four hours on a DGX v-100 GPU in Linux using Tensorflow 2.4 in Python 3.7.

Parallel-transmit (pTx) pulses with 1, 2, 3, 4, or 5-spokes were designed [8, 9] for seven different slices between the cerebellum and the crown using B1+ maps and Q-matrices from the initial position, similar to the literature [2]. To simulate the effect of patient-motion, local SAR distributions were also calculated using GT and NNe Q-matrices and compared with the initial local SAR distribution (Figure 2). In other words, we assume knowledge of the ideal safety model, and exclude the mismatch between the safety model and the actual body in order to focus on the effect of motion and the correction our models provide. We hypothesized that patient-motion has a substantial effect on psSAR which can be corrected using neural networks. We tested the hypothesis using a two-sample Kolmogorov-Smirnov test [10, 11] on psSAR values from 35 pulses that were designed for initial and evaluated at 11 other positions each, yielding 385 samples.

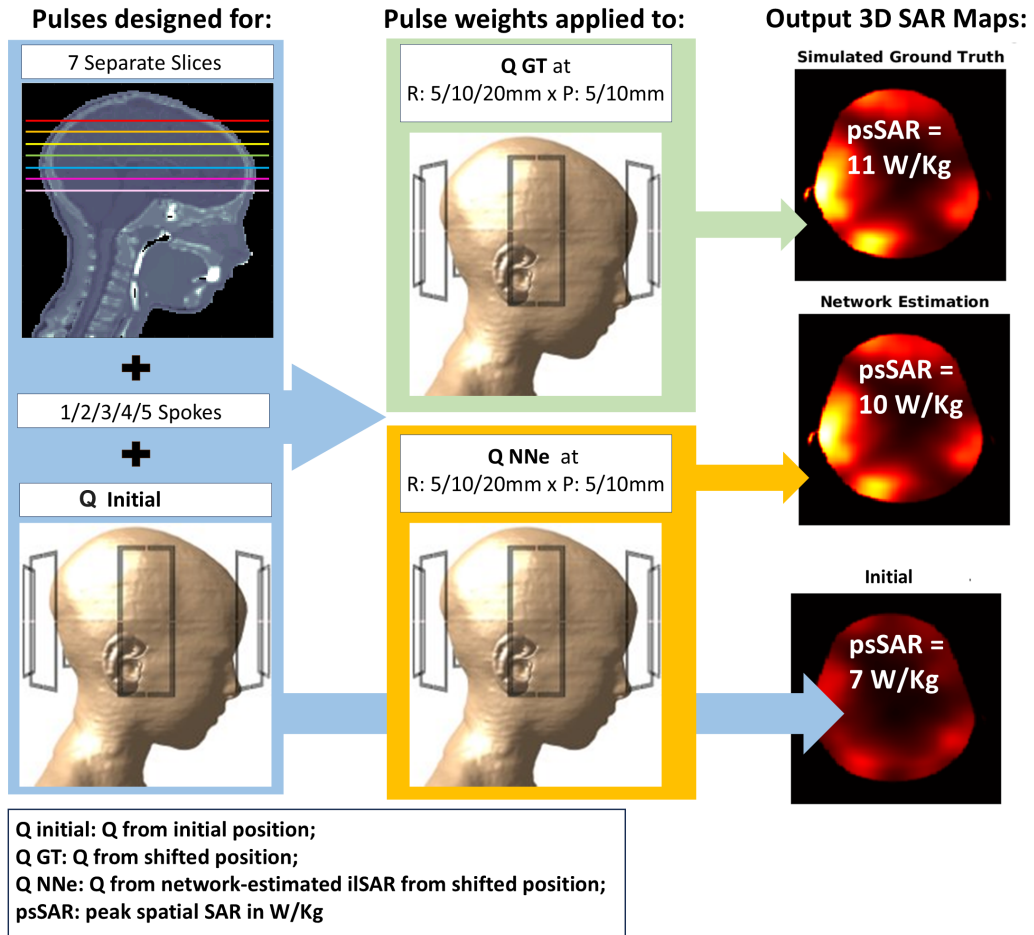


Figure 2: pTx pulses are designed for the initial position with 1/2/3/4/5 spokes for 7 slices. The SAR distribution at 11 other positions were calculated using the same pulse weights, and resulting psSAR values were compared. Example case shown for a 2-spokes pulse evaluated after a R:20 mm, P:10 mm displacement.

4 Results and Discussion

Figure 3 compares SAR distributions for the case where network estimation performance was the worst. The initial distribution highly underestimates SAR whereas the network estimated safety model provides a visually nearly-identical estimation of the ground-truth SAR distribution.

3D SAR from R10, P5 Displacement

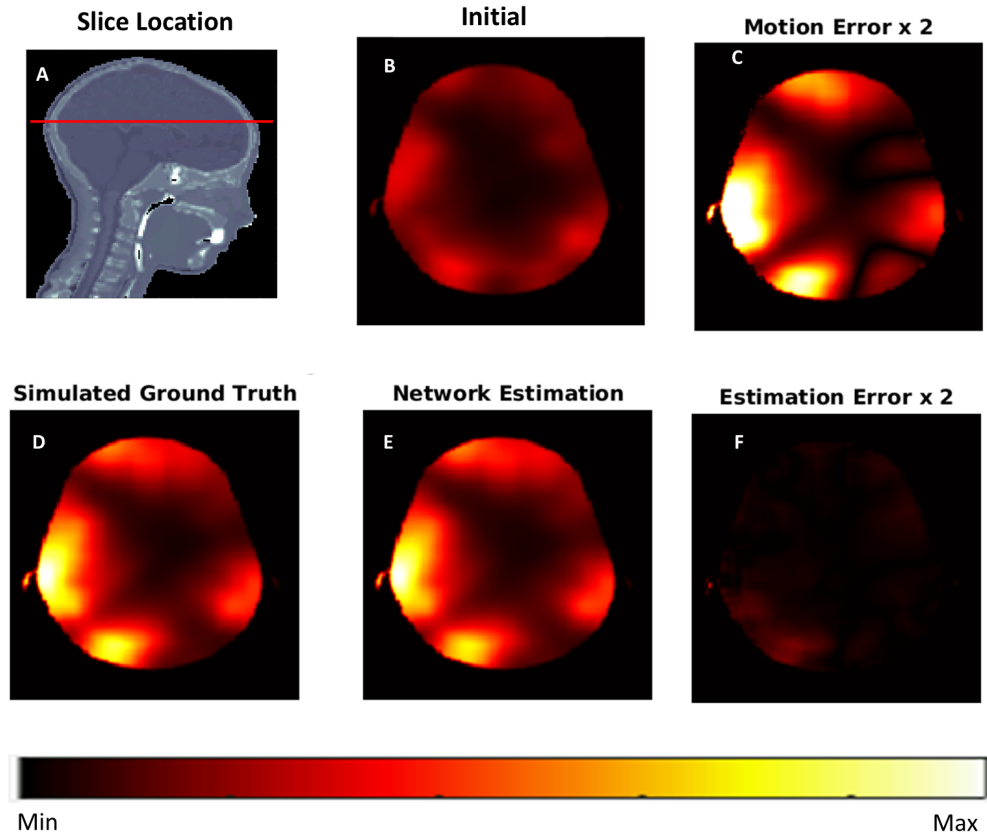


Figure 3: Maximum intensity projections (onto the axial plane) of 3D SAR distributions for R:10 mm P:5 mm motion. The case where the network estimation performance was the worst was selected. A: a 3-spoke pTx pulse was designed for the indicated slice. D: Ground Truth SAR distribution after motion. B-C: Initial SAR distribution and error compared to the ground-truth SAR. E-F: Network estimated SAR distribution and error compared to the ground-truth. The errors were intensified two-fold for clarity using the same color scale.

Figure 4 compares the estimation error in psSAR with the motion-caused error for all pulses designed. Across all cases, psSAR was underestimated by up to 2.14-fold by the initial SAR distribution whereas the worst case underestimation was only 1.25-fold for the network estimated safety model. I.e., the results suggest that a lower safety factor can be applied when using the proposed method (1.25) as opposed to the initial method (2.14) (Figure 5). Figure 5 shows that initial safety model fails to capture the range of SAR values after motion, which are successfully recovered by the network-estimated safety model.

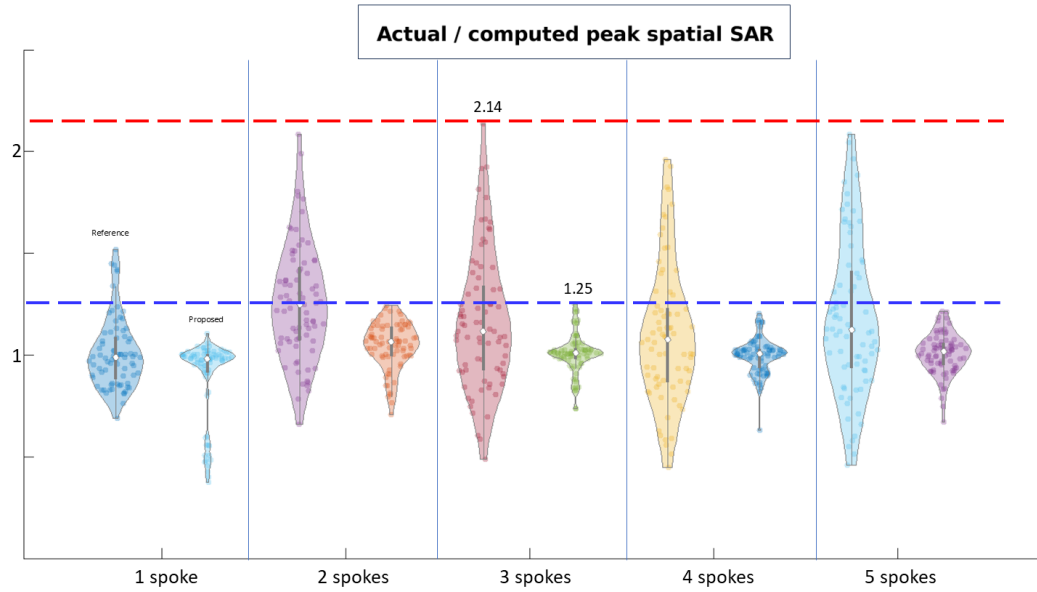


Figure 4: The ratio of ground-truth psSAR to initial and network-estimated psSAR values are shown. Distributions show GT/Initial and GT/NNe ratios of psSAR values, for different pulse types across all 7 slices. Within each spoke panel, the left distribution is for GT/initial, and the right distribution is for GT/NNe. Worst case underestimation for each case is emphasized by the dashed lines (red for initial, blue for network-estimated), with the corresponding corrective safety factor indicated above. Boxplots depict inter-quartile range.

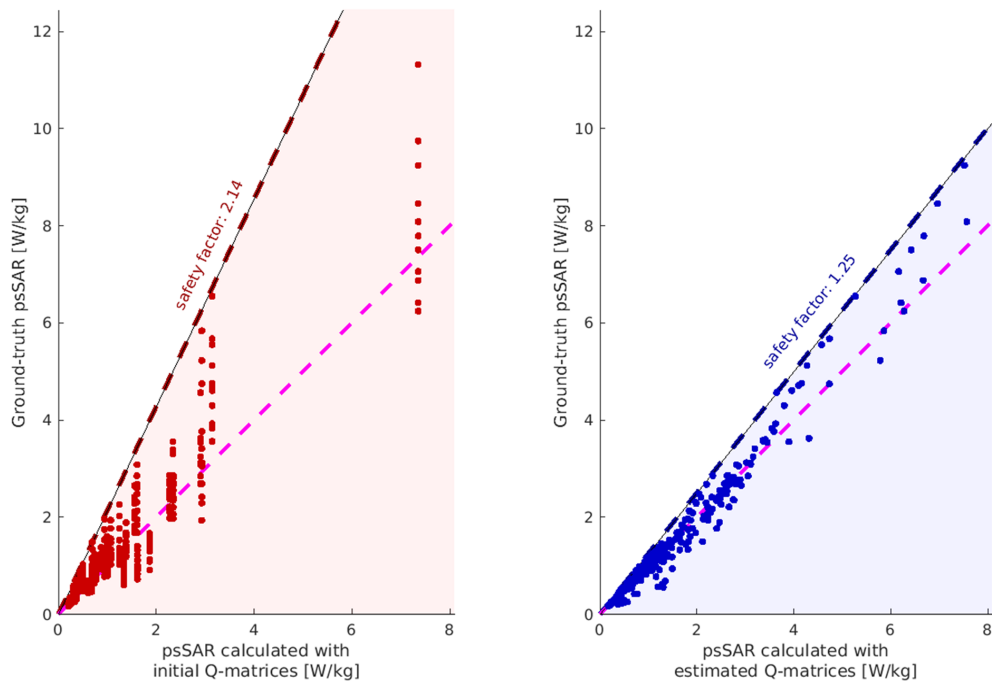


Figure 5: Initial and network-estimated psSAR values are plotted against ground-truth SAR. Left: initial psSAR vs motion-affected (ground-truth) SAR. Right: network-estimated psSAR vs motion-affected Q-matrices. The pink dashed line is the identity line. Initial safety model fails to capture the variations in after-motion SAR and leads to underestimated psSAR calculations. Worst-case SAR underestimation is much lower for network-estimated safety models, which represent after-motion SAR faithfully.

The Kolmogorov-Smirnov test established that the effect of patient-motion on psSAR was significant ($D(385) = 0.10$, $p = 0.035$) while the difference between

between the ground-truth and network-estimated psSAR values was insignificant ($D(385) = 0.03$, $p = 0.99$), supporting our hypothesis.

5 Conclusion

We tested the efficiency of using neural networks for estimating the effect of patient motion on local SAR with various realistic pTx pulses. While patient motion has a significant effect on psSAR, calculations using network-estimated Q-matrices provide a faithful representation of the ground-truth psSAR after motion, and require a smaller corrective safety factor. The proposed method can therefore improve the safety and effectiveness of ultrahigh-field MRI pTx acquisition.

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