Learning-based Motion Artifact Removal Networks (LEARN) for Quantitative R_2^* Mapping

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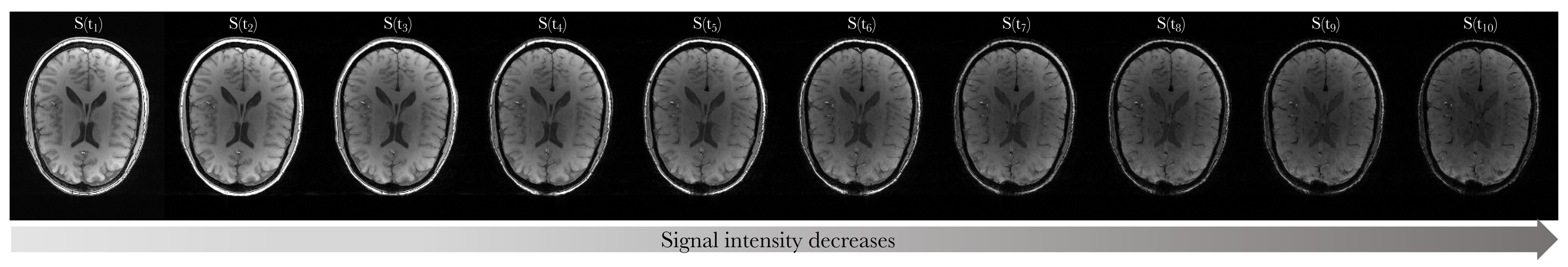
Abstract

- **Purpose**: To introduce two novel learning-based motion artifact removal networks (LEARN) for the estimation of quantitative motion- and $B0$-inhomogeneity-corrected R_2^* maps from motion-corrupted multi-Gradient-Recalled Echo (mGRE) MRI data.
- **Methods**: We *train* two convolutional neural networks (CNNs) to correct motion artifacts for high-quality estimation of quantitative $B0$-inhomogeneity-corrected R_2^* maps from mGRE sequences. The first CNN, LEARN-IMG, performs motion correction on complex mGRE images, to enable the subsequent computation of high-quality motion-free quantitative R_2^* (and any other mGRE-enabled) maps using the standard voxel-wise analysis or machine-learning-based analysis. The second CNN, LEARN-BIO, is trained to directly generate motion- and $B0$-inhomogeneity-corrected quantitative R_2^* maps from motion-corrupted magnitude-only mGRE images by taking advantage of the biophysical model describing the mGRE signal decay.

Background

- **mGRE images**: Multi-Gradient-Recalled-Echo (mGRE) sequences accompanied by correction of magnetic field inhomogeneity artifacts are used in different MRI applications to produce quantitative maps related to biological tissue microstructure in health and disease.

mGRE images $S(t)$



- **R_2^* estimation with biophysical model**: R_2* is one such quantitative map that can be estimated from mGRE signals. In the R_2^* approximation, the mGRE signal from a single voxel can be expressed as:

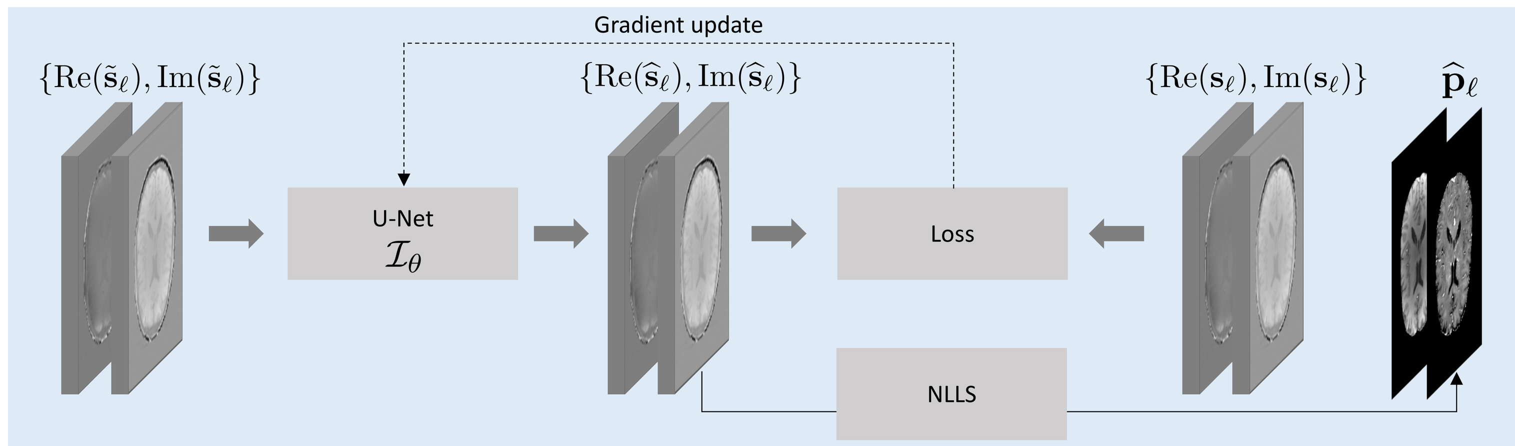
$$S(t) = S_0 \cdot \exp(-R_2^* \cdot t - i\omega t) \cdot F(t), \qquad (1)$$

where t denotes the gradient echo time, $S_0 = S(0)$ is the signal intensity at $t = 0$, and ω is a local frequency of the MRI signal. The complex valued function $F(t)$ describes the effect of macroscopic magnetic field inhomogeneities on the mGRE signal.

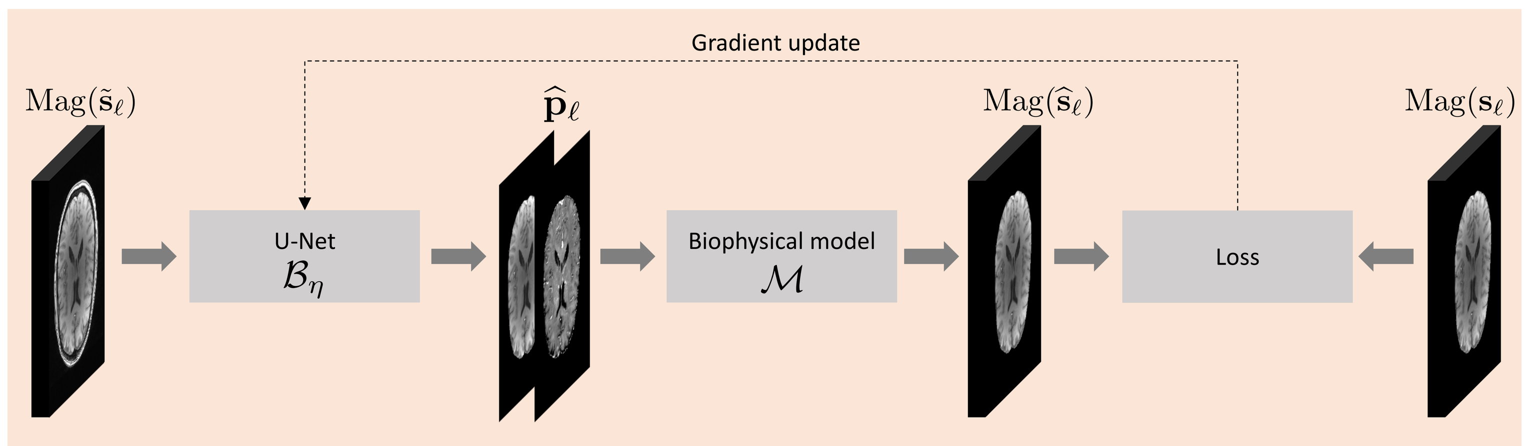
- **Challenges**: However, involuntary physical motion and subtle anatomical fluctuations during the mGRE signal acquisition can lead to undesirable artifacts during the estimation of these quantitative maps. It is therefore important to develop methods that reduce the sensitivity of the estimated quantitative maps to the motion artifacts in the MR images.
- **Our approaches**: Deep learning (DL) methods have also been recently introduced for motion-correction in MRI due to their speed and quality of reconstruction. Despite the recent activity, DL is yet to be investigated in the context of quantitative $B0$-inhomogeneity-corrected estimation of R_2^* maps from mGRE signals. One of the key challenges in this context is the sensitivity of the quantitative maps to the motion artifacts.

Methods

- **Our two learning-based approaches**: We propose two convolutional neural networks (CNNs) for recovering high-quality quantitative R_2^* maps from the motion-corrupted mGRE images. Both of our methods, referred to LEARN-IMG and LEARN-BIO, are trained on motion-free mGRE images and their simulated motion-corrupted counterparts.
- **Supervised learning LEARN-IMG**:LEARN-IMG follows the traditional supervised training strategy in order to correct the motion on the complex mGRE images. The high-quality motion-free and $B0$-inhomogeneity-corrected R_2^* maps can be subsequently computed by applying the standard non-linear least squares (NLLS) analysis that also accounts for the effect of background $B0$ field gradients (herein we use Voxel Spread Function (VSF) approach [?]) on the motion-corrected output images.

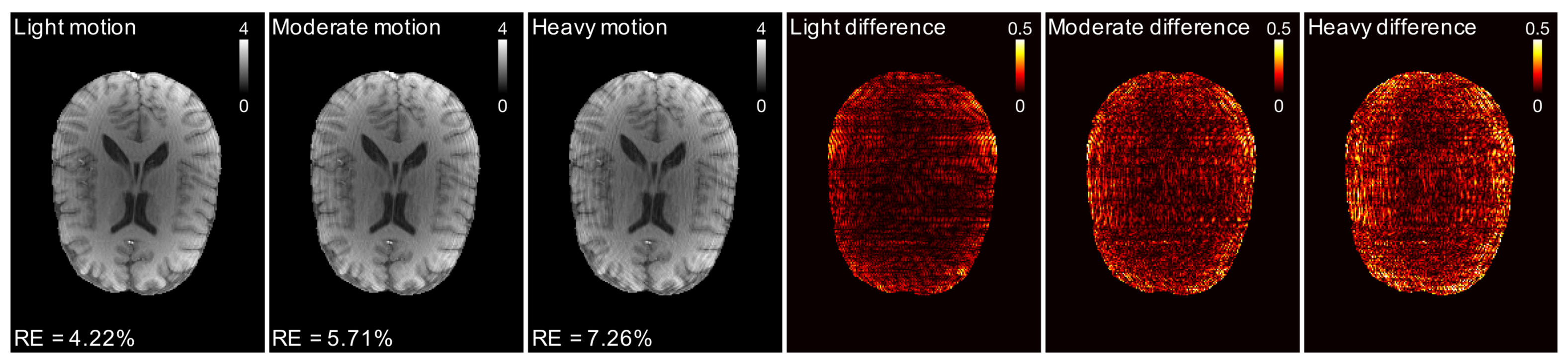


- **Self-supervised learning LEARN-BIO**:LEARN-BIO is trained to directly map the magnitude-only motion-corrupted mGRE images to motion-free and and $B0$-inhomogeneity-corrected R_2^* maps. The key feature of LEARN-BIO is that it is fully self-supervised, in the sense that it is trained using only the mGRE images and the biophysical model connecting the mGRE signal with biological tissue microstructure.



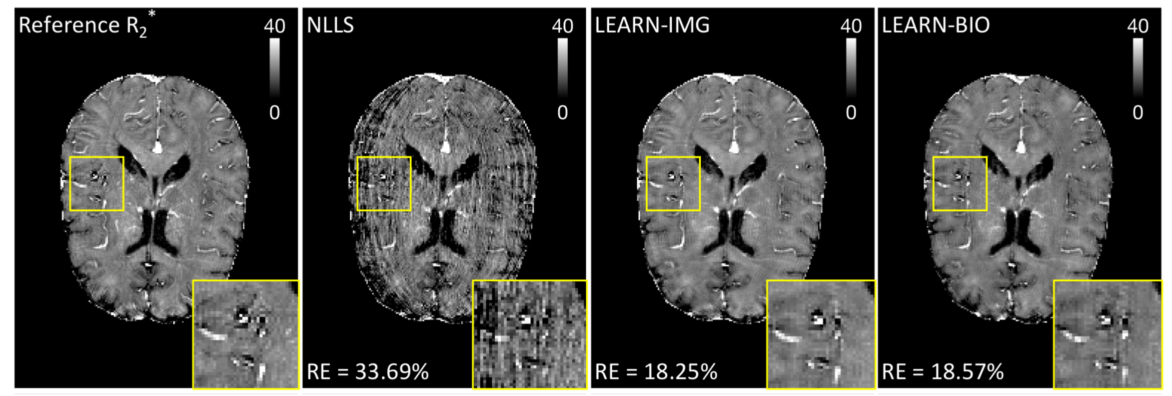
Data Generation

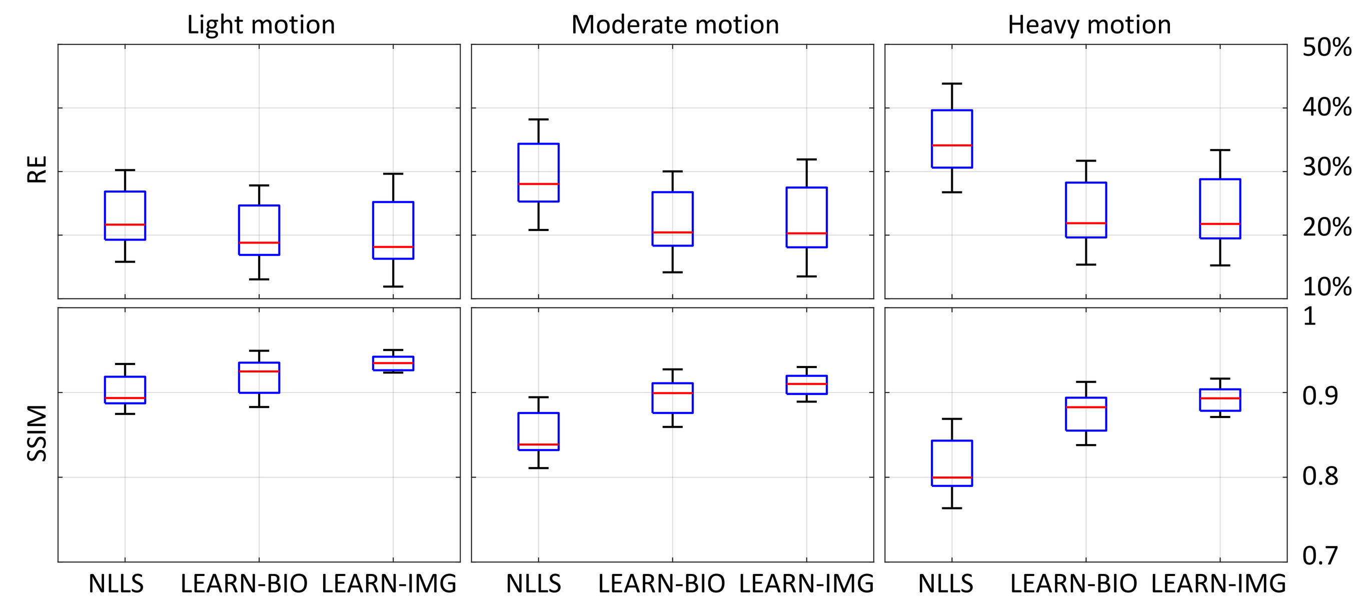
- **Motion artifacts simulation procedure**: We introduce a general motion synthesis procedure that generates motion-corrupted mGRE images for training our CNNs by replacing k-space data of the given motion-free images with the k-space data of its moved counterparts. Examples of motion corrupted images generated by our procedure are shown in the figure below.



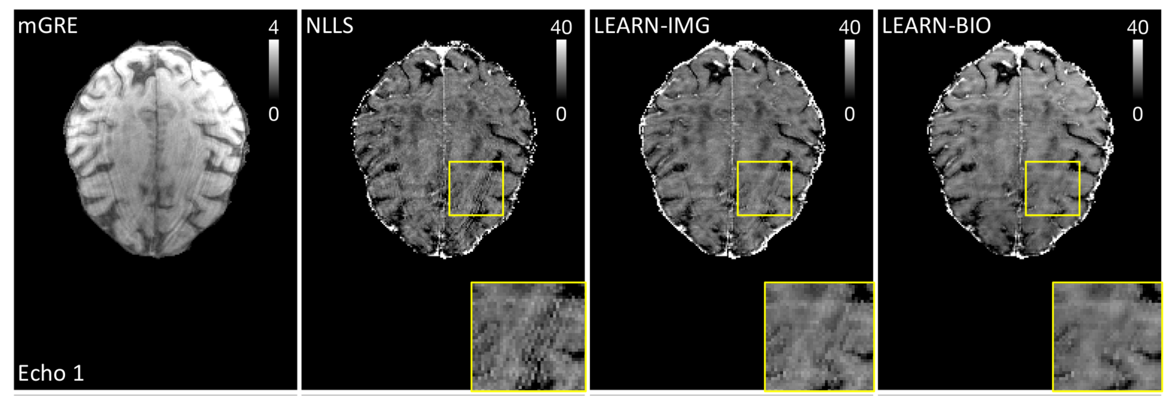
Main Results

- **Results on synthetic data**: LEARN-IMG consistently gives the best performance over the synthetic data in our different corruption scenarios, with LEARN-BIO closely following with similar results.





- **Results on experimental data**: The capability of our CNN models is further elaborates on experimental data, showing a practical application of our approaches on removing real-world motion artifacts and keeping feature details. Thanks to the power of our deep neural networks, our approaches constantly outperform NLLS both qualitatively and quantitatively, providing 3D R_2^* maps in a matter of seconds as compared with many hours required by NLLS analysis.



Conclusion

- **Conclusion**: Both LEARN-IMG and LEARN-BIO can enable the computation of high-quality motion- and $B0$-inhomogeneity-corrected R_2^* maps. LEARN-IMG performs motion correction on mGRE images and relies on the subsequent analysis for the estimation of R_2^* maps, while LEARN-BIO directly performs motion- and $B0$-inhomogeneity-corrected R_2^* estimation. Both LEARN-IMG and LEARN-BIO jointly process all the available gradient echoes, which enables them to exploit spatial patterns available in the data. The high computational speed of LEARN-BIO is an advantage that can lead to a broader clinical application.

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