Fast and robust motion correction of cardiovascular magnetic resonance T1-mapping using data-driven convolutional neural networks for generalisability

Ricardo A. Gonzales[1], Qiang Zhang[1], Bartłomiej W. Papież[2, 3], Konrad Werys[1], Elena Lukaschuk[1], Iulia A. Popescu[1], Matthew K. Burrage[1], Mayooran Shanmuganathan[1], Vanessa M. Ferreira[1], and Stefan K. Piechnik[1]

[1]Oxford Centre for Clinical Magnetic Resonance Research (OCMR), Division of Cardiovascular Medicine, Radcliffe Department of Medicine, University of Oxford, Oxford, United Kingdom
[2]Nuffield Department of Population Health, University of Oxford, Oxford, United Kingdom
[3]Big Data Institute, Li Ka Shing Centre for Health Information and Discovery, University of Oxford, Oxford, United Kingdom

Background

Quantitative cardiovascular magnetic resonance (CMR) T1-mapping has shown promise for advanced tissue characterisation in routine clinical practice[1]. However, T1-mapping is prone to motion artefacts, which affects its robustness and clinical interpretation[2]. Current methods for motion correction on T1-mapping are model-driven with no guarantee on generalisability, limiting its widespread use. Emerging data-driven deep learning approaches have shown good performance in general image registration tasks. It is desirable to develop a deep learning method for T1-mapping motion correction that is also generalisable.

Methods

We designed a convolutional neural network (CNN) solution for fast and robust motion artefact correction in T1-maps (ShMOLLI), developed using the UK Biobank imaging dataset. The CNN combines an encoder-decoder architecture[3] for producing deformation fields with warping layers[4] to apply such deformation to the feature maps in a coarse-to-fine manner (Fig. 1). The training set comprised of 1536 mid-ventricular T1-maps with strictly no motion, which were synthetically deformed to simulate motion artefacts. The model was evaluated on 200 samples with severe motion (n=50), moderate motion (n=100) and mild to no motion (n=50). For validation, 3 human experts visually assessed for motion in the T1-map, with motion scores ranging from 0% (strictly no motion) to 100% (very severe motion).

Results

The proposed model successfully and rapidly (<1 second per T1-map) suppressed a wide range of motion artefacts (Fig. 2). Overall, it significantly reduced motion scores from 37.1±21.5 to 13.3±10.5 (p<0.001). In each assessed category, the motion scores were significantly reduced from 55.8±18.7 to 18.6±14.3 (severe motion), from 35.5±18.9 to 12.7±9.2 (moderate motion), and from 21.7±13.8 to 9.4±6.4 (mild to no motion; all p<0.001). In an exploratory study, the proposed model achieved a better registration than the traditional inline motion correction method[5] (Fig. 3), subject to further investigation.

Conclusion

The presented data-driven deep learning CNN model is effective and robust for correction of artefacts from myocardial motion in T1-maps. It can be adapted and generalised to enhance parametric mapping methods, paving the way towards reliable quantitative medical imaging for immediate clinical interpretation.

References

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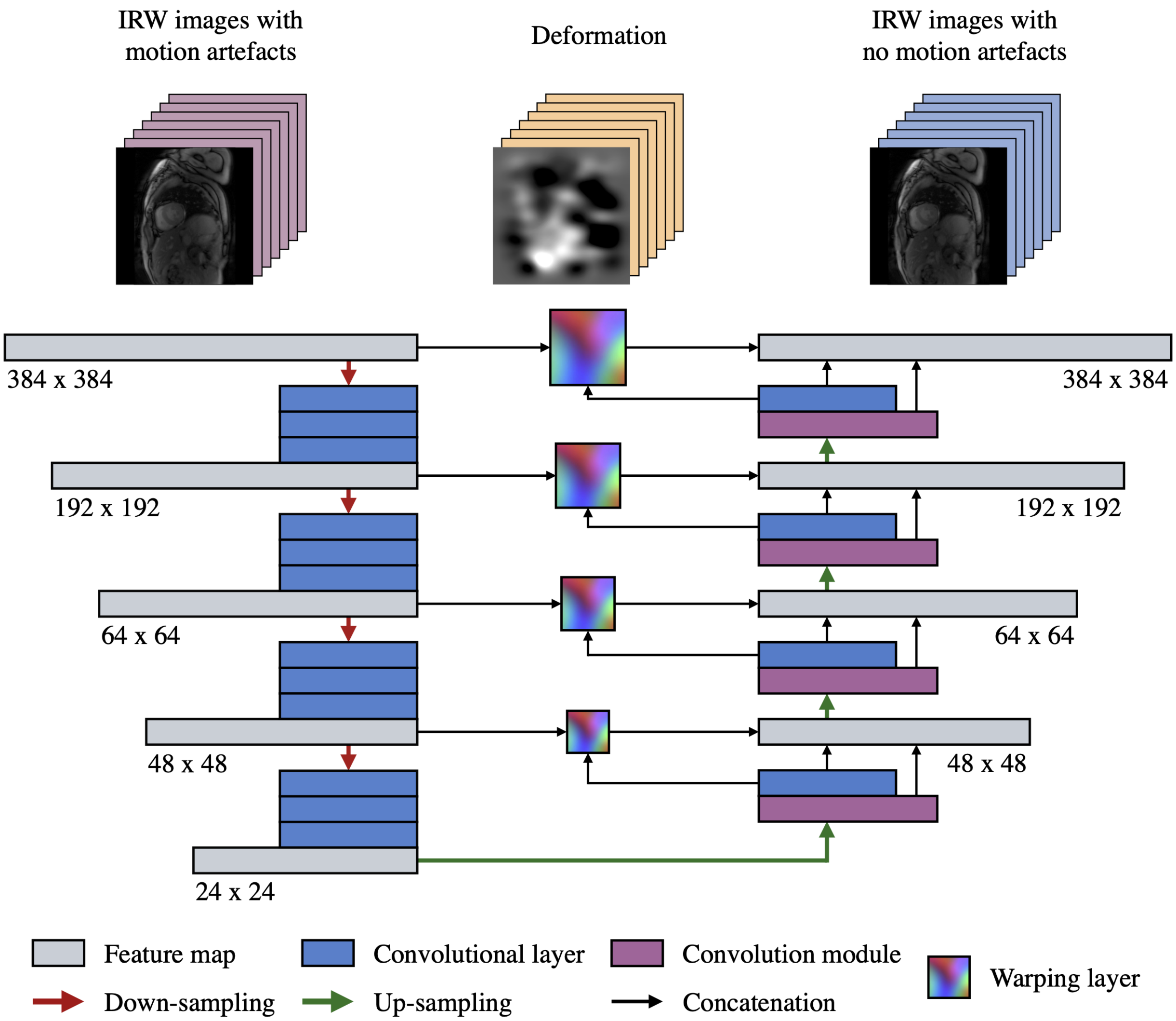

Figure 1. Structure of the proposed motion correction convolutional neural network. A stack of 7 inversion recovery-weighted (IRW) images from T1-mapping is input into the encoder-decoder structure on a per-channel basis. The warping layers estimate the optical flow from all the channels at each scale. The last warping layer generates the deformation required to correct the motion artefacts.

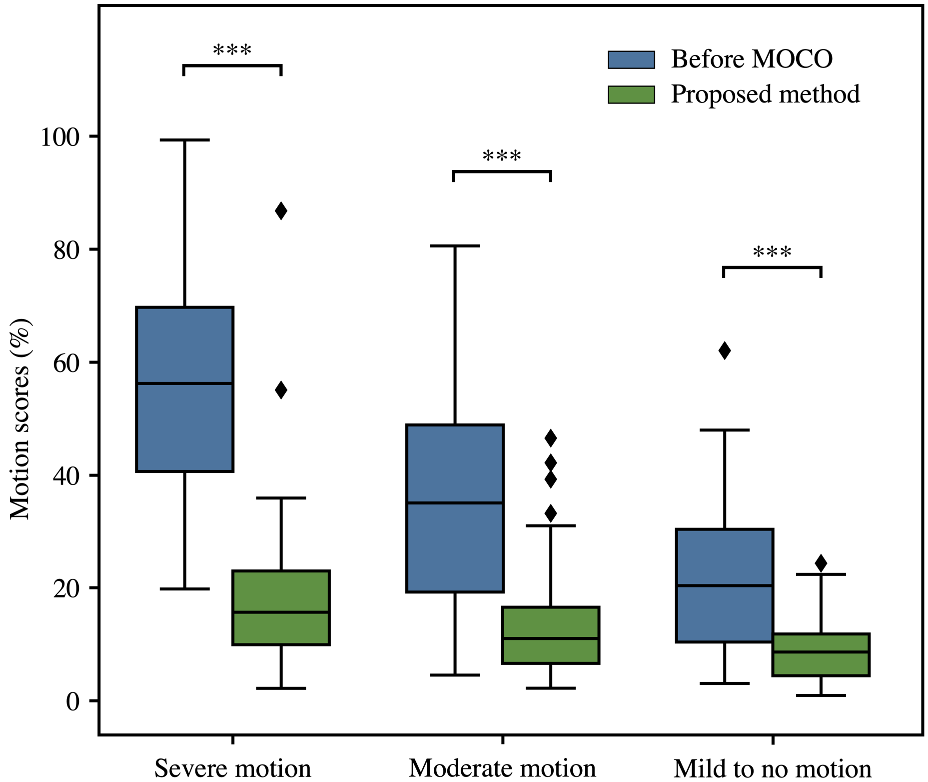

Figure 2. Performance of the proposed method in motion correction of T1-maps. Box and whisker plot of motion scores in non-parametric terms of three data groups, before (blue) and after motion correction by the proposed method (green). *** p<0.001

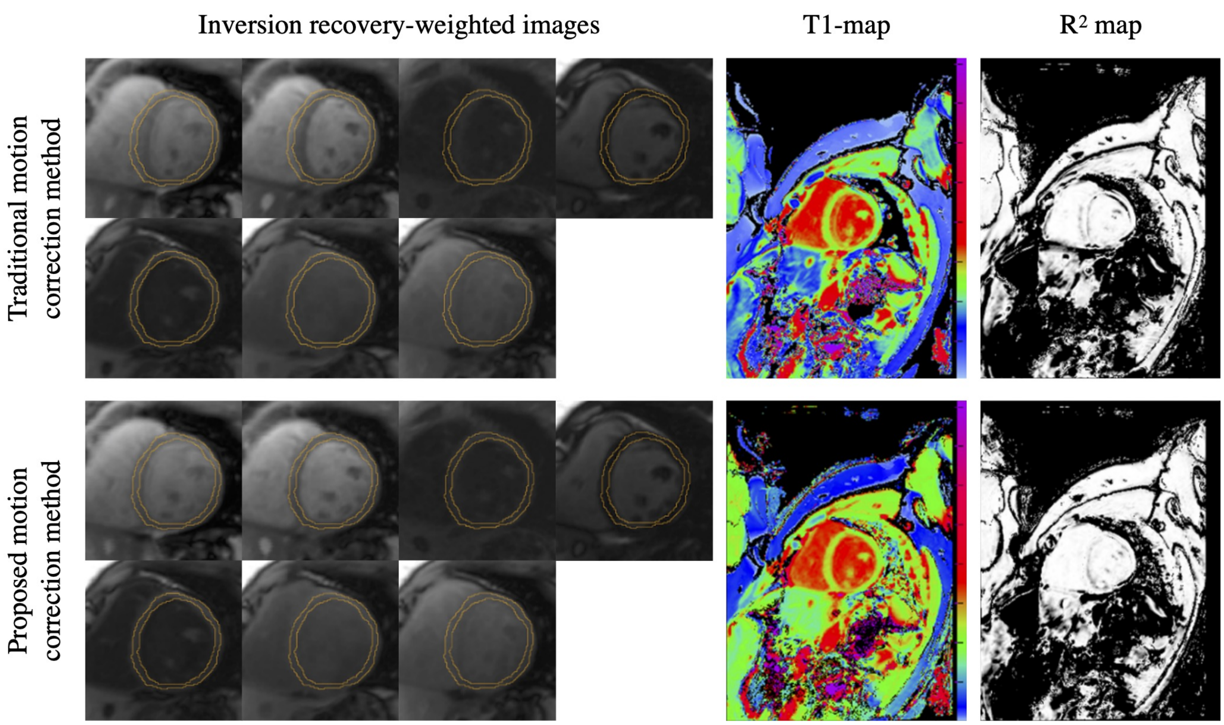

Figure 3. Performance of the traditional motion correction method (first row) compared against the proposed data-driven CNN method in motion correction of T1-maps. Each inversion recovery-weighted image is overlaid by identical myocardial contours for identifying motion.