

Exploring deep learning for MRI sequence transformation

James A. Grant-Jacob¹, Chris Everitt², Robert W. Eason¹, Leonard J. King² and Ben Mills¹

¹University of Southampton, United Kingdom, ²University Hospital Southampton, United Kingdom

Over the past four decades, Magnetic Resonance Imaging (MRI) [1] has become an indispensable tool for imaging the human body, and is now extensively utilised for the investigation of a wide variety of clinical conditions. In comparison with other imaging techniques such as conventional radiography [2] or ultrasound [3] however, MRI can be time-consuming and expensive [4] in some cases, taking in excess of 30 minutes per patient and costing up to around £1000, depending on the number and type of sequences employed, each of which takes several minutes to acquire. Thus, there is interest in developing faster MRI scans to improve patient throughput, reduce cost and provide a better patient experience.

The various MRI image series correspond to different pulse sequences, which are used to display varying tissue characteristics. Since most series are carried out sequentially, being able to convert from one to another could substantially reduce scan times.

In this study, we used deep convolutional neural networks [5] to generate T2 SPACE images from T1 VIBE images (figure 1). This process involved training a network on T1 VIBE images of the left hand, to generate equivalent T2 SPACE images of the left hand. The neural network was then tested on the right hand T1 VIBE images to generate T2 SPACE images.

Analysis of the results indicated that the neural network considered the structures in the surrounding ~ 1 cm when converting to T2, hence implying that the neural network was able to identify structural relationships between the sequences. However, some features measuring < 2 mm differed between the actual and generated T2 images, and grid patterning was evident from the generated T2 images.

Utilising deep learning for sequence transformations could enable faster MRI scanning due to reduced sequences with resulting increased throughput, reduced cost, improved patient experience and reduced patient waiting times. Additional work, such as synergising physics-based modelling with neural networks, will however be required to optimise image quality and show that deep learning can accurately recreate T2 characteristics from T1 images.

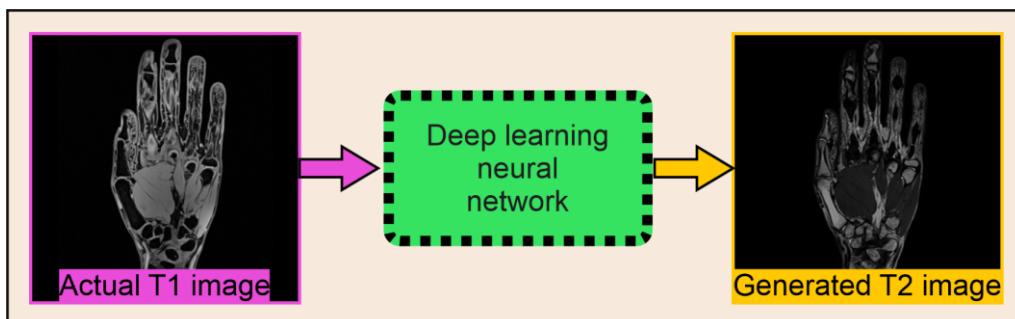


Fig. 1. Concept for using deep learning to transform a T1 VIBE sequence image into T2 SPACE sequence image.

- [1] Erasmus, L. J. *et al. South African Med. J.* 8, 13 (2004).
- [2] Frankel, R. I. *West. J. Med.* 164, 497 (1996).
- [3] Wells, P. N. T. *et al. J. R. Soc. Interface* 8, 1521–1549 (2011).
- [4] Rua, T. *et al. Bone Joint J.* 101-B, 984–994 (2019).
- [5] Grant-Jacob, J. A. *et al. Environ. Res. Commun.* (2020).