Ultra fast image reconstruction for real-time MRI-guided radiotherapy by removing undersampling artefacts using deep learning

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ABSTRACT SUBMISSION FORM

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PRESENTATION TITLE

Ultra fast image reconstruction for real-time MRI-guided radiotherapy by removing undersampling artefacts using deep learning

AUTHOR(S)

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ABSTRACT

Purpose: MRI-guided radiotherapy using hybrid MRI-linac systems opens up to opportunity to acquire MR data during treatment for beam guidance. Unfortunately, MRI is an inherently slow imaging modality. A simple method to reduce acquisition times is to acquire less data, at the cost of undersampling artefacts in the reconstructed images. These artefacts can be significantly reduced using iterative reconstructions, such as compressed sensing, but these are time-consuming and therefore not suitable for real-time processes. The goal of this work is to use deep learning to shift the time-consuming processing steps prior to treatment to enable undersampling artefact removal in real time. In this initial study, we focussed on 2D radial MRI.

Materials & Methods:
MR imaging: Data of four healthy volunteers were acquired on a 1.5T MR-RT system (Ingenia, Philips, Best, the Netherlands) to train, test and validate the deep learning network. Fully sampled radial 2D balanced steady-state free precession (bSSFP) images were acquired in the brain (TR/TE = 4.6/2.3ms, FOV = 256x256x100mm^3, pixel size = 1x1mm^2, slice thickness = 5mm). 20 dynamics were acquired at 20 different slice locations to increase. Data were retrospectively undersampled with a factor 8 to simulate an accelerated image acquisition.
Deep learning: A small U-Net with 4 down-sampling and 4 up-sampling steps was implemented in TensorFlow. Using 2D convolution and non-linear activation functions, features were extracted from input data and recombined to generate output images. For training, 80% of the data was used and data augmentation was used to generate 38400 input images. Input data of the network were the undersampled images, while the label data, which had to be trained, consisted of the undersampling artefacts. These were calculated by subtracting the undersampled image from the fully sampled image. Only magnitude data were used. Training was performed on a Tesla P100 (NVIDIA, Santa Clara, CA, USA) for 100 epochs with a batch size of 1. After training, the network was validated on 320 2D slices by comparing the prediction with the gold standard using the structural similarity (SSIM).

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Results: Training of the network took 25-30 hours. Figure 2 shows a validation example, where the artefact image was calculated from an undersampled image using the trained network. An artefact-free image (Fig. 1d) was constructed by subtraction of the prediction from the input. Most streaking was removed, but some fine details were missing as compared to the ground truth. Average SSIM was 0.86±0.03. The forward evaluation of the network took only 8 milliseconds, as a result of the limited network size.

Conclusions: These initial results show the feasibility of deep learning artefact removal for radially undersampled images for MR-guided radiotherapy. Future studies will focus on generating more extensive trainings sets, complex input data, and implementation on the MRI-Linac. By transferring the time-consuming training step to the pre-treatment phase, the ultra-fast forward evaluation can be used for real-time tracking purposes.

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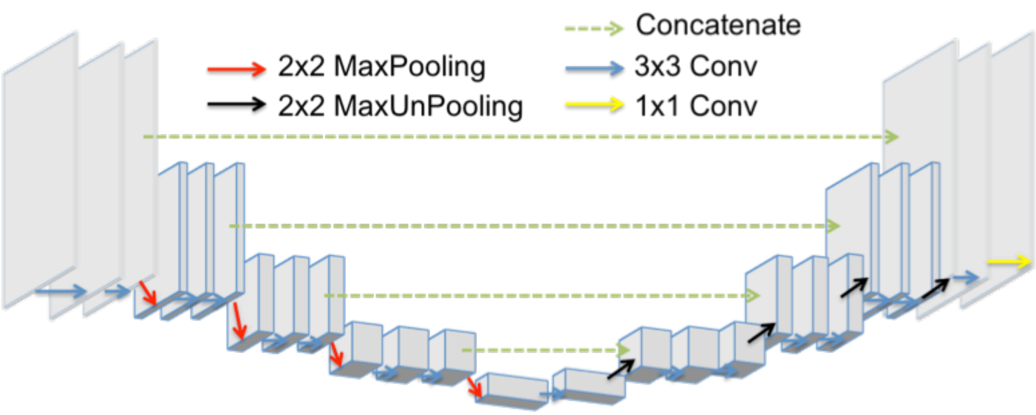

Figure 1 Graphical representation of the implemented U-Net, showing the different layers and steps within each layer.

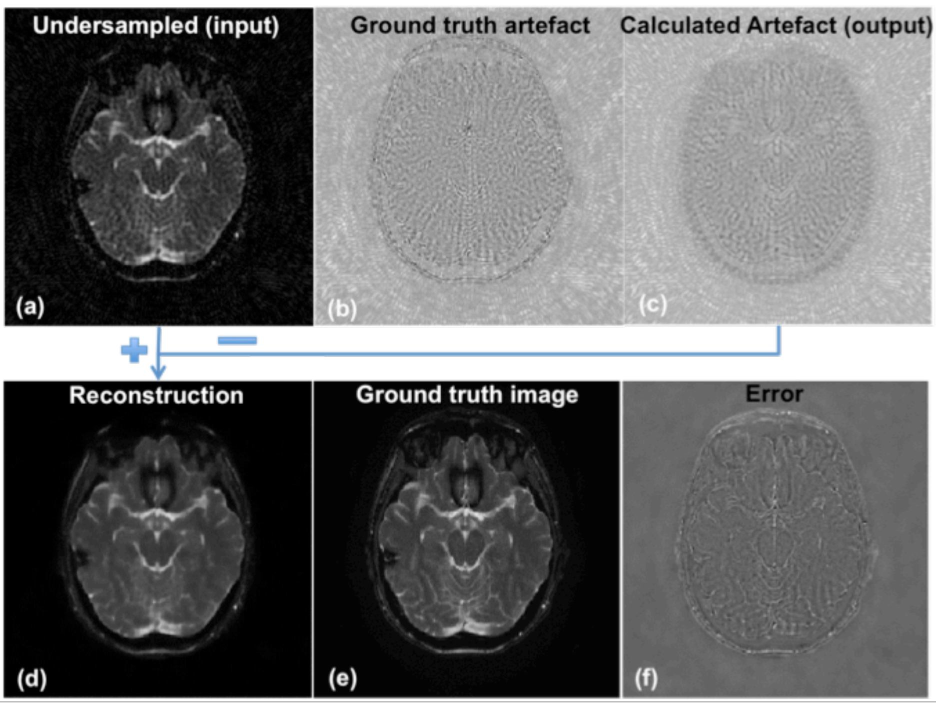

Figure 2 Example of reconstructed images. Input of the network is the undersampled image (a). The calculated output artefact (c) is compared with the ground truth artifact (b). An artifact-free image (d) can be calculated by subtracting (c) from (a). Comparing the ground truth (e) with (d) gives the error image (f).