Deep Learning-Based Contrast Transformation of High Resolution 3D Gradient Echo Images Trained Using Low Resolution 2D Turbo Spin Echo Images

Layman's summary

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Magnetic Resonance Imaging (MRI) is a widely used medical imaging technique offering many image contrasts, which can each highlight different anatomical features. These image contrasts are acquired using different sequences, which dictate e.g. when a radiofrequency pulse is sent out and when certain electromagnets in the machine are switched on or off. During most MRI examinations multiple of these image contrasts are acquired, because often no single image contrast is able to clearly show all of the clinically relevant information.

Each image contrast requires a certain sequence, with more sequences taking more time. A new trend is emerging in MRI in which computer algorithms are used to generate more useful images after scanning to reduce total scan time. One way to do this is using deep learning, which is a way of training a so-called neural network to learn complex patterns and connections between data. In the context of generating more images, this training is often done by presenting a neural network with an input image and a target image. The target image is the image that the neural network is supposed to reconstruct using the input image. By showing a neural network many of these paired examples, the network is able to learn the underlying connection between the image pairs. After training, you would only acquire the input image and use the neural network to generate the target image from it, which you no longer need to acquire using the MRI machine. The main motivation is that the computer time needed for the neural network to generate the images is much cheaper than the scan time required to acquire the images using a MRI machine. Moreover, as fewer images need to be produced by means of a MRI machine, more patients can be scanned in the same timeframe.

This idea is taken a step further in BoneMRI, which is a deep learning-based method that generates synthetic Computed Tomography (CT) images from Magnetic Resonance (MR) images—specifically, Gradient Echo (GE) images, a type of MR image—using a neural network that was trained on real MR and CT image pairs. CT images are normally acquired using harmful X-rays, but by generating the synthetic CT images from MR images, no harmful radiation is necessary. These synthetic images are useful, because they allow for much better investigation of the bone structures than on MR images.

The contrast of the GE images acquired for BoneMRI is mainly influenced by a physical property of the tissues called the T1, making the GE sequence a T1-weighted sequence. Multiple T1-weighted sequences exist, but the preferred T1-weighted sequence in the clinic is a Turbo Spin Echo (TSE), because it gives better contrast between soft tissues than e.g. a GE sequence. The TSE is therefore normally performed along with the BoneMRI GE in a standard examination of e.g. the neck along with other sequences. In this study we investigated the possibility of generating the TSE images from GE images using deep learning to replace the real TSE and thereby reduce the total scan time of an examination.

Another difference between the GE and TSE is that the TSE has much thicker slices of 3.3 mm than the GE, which has slices of 0.9 mm thick. The reason TSE images have thicker slices is because it allows for quicker coverage of a certain anatomical region and because it reduces the amount of noise in the images. Because the neural network has to learn a contrast transformation to go from the GE to the TSE this mismatch in dimensions is a problem, but this is normally fixed by interpolating the GE to the same resolution as the TSE, losing some of the information. We propose a new method, called the High-to-low approach, which does not require the interpolation to the TSE resolution and therefore does not lose as much information contained in the GE.

Our results showed that keeping this extra information in the GE created higher quality synthetic TSE images than interpolating to the TSE resolution, while also allowing us to generate synthetic TSE images (sTSEs) with a 4× higher resolution than the real TSE images that were used to train the neural network. Although the sTSEs were quite similar to the real TSE images, they were missing some essential features, which was a result of these features also missing from the GE images. We therefore conclude that the sTSEs are not able to replace the real TSE in their current form. However, we did show that using our training method a contrast transformation between two MR images is possible without sacrificing performance or image resolution.