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Deep Learning Reconstruction of Accelerated MRI: False-Positive Cartilage Delamination Inserted in MRI Arthrography Under Traction

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Abstract

Objectives: The radiological imaging industry is developing and starting to offer a range of novel artificial intelligence software solutions for clinical radiology. Deep learning reconstruction of magnetic resonance imaging data seems to allow for the acceleration and undersampling of imaging data. Resulting reduced acquisition times would lead to greater machine utility and to greater cost-efficiency of machine operations.

Materials and Methods: Our case shows images from magnetic resonance arthrography under traction of the right hip joint from a 30-year-old, otherwise healthy, male patient.

Results: The undersampled image data when reconstructed by a deep learning tool can contain false-positive cartilage delamination and false-positive diffuse cartilage defects.

Conclusions: In the future, precision of this novel technology will have to be put to thorough testing. Bias of systems, in particular created by the choice of training data, will have to be part of those assessments.

Keywords: accelerated MRI, MRI undersampling, deep learning MRI reconstruction, AI errors

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The radiological imaging industry is developing and starting to offer various artificial intelligence (AI) software solutions for clinical radiology. Examples include recommendation tools for interventional procedures,[1] automated image interpretation,[2,3] or also report drafting by language models.[4,5] Deep learning–based reconstruction of undersampled magnetic resonance imaging (MRI) data is another branch of that development.[6,7] MRI is the by far most cost-intensive modality of the clinical imaging modalities. Accelerated in-parallel image acquisition can reduce Acquisition Time (TA) substantially. However, it introduces to the undersampled MRI data-specific image artefacts. Resource efficiency is an increasingly relevant topic in medicine, not limited to radiology.[8] Limitation to MRI acquisition acceleration so far has been the noise increase. Novel deep learning–based reconstruction promises to provide adequate denoising. In an ideal case, undersampling will lead to time savings for greater machine utility and potentially on top to an increase of data quality.[6,7,9]

Deep Resolve Boost (DRB) is an AI tool since recently offered by Siemens Healthineers AG (Erlangen, DE); DRB performs the just described deep learning–based reconstruction of undersampled MRI raw data. Deep neural networks are applied multiple times to the input raw data to generate the image output which is used for diagnostics.[10] To the best of our knowledge, up to today, no study has been published on DRB; only one study has been published on the sister tool Deep Resolve Sharp.[11]

TECHNIQUE AND PROCEDURE

Reported case: A 30-year-old, otherwise healthy, male patient was referred for MRI arthrography under traction to our clinic by an orthopedic surgeon for right-sided hip joint pain.

Using fluoroscopy imaging, the right hip joint capsule was punctured without complications. Intra-articular position of the needle tip was confirmed by an injection of 2 mL iodine-based contrast enhancer (300 mg/ml, trade name: Iopamiro, Bracco Suisse SA, Cadempino, CH). In a second injection, 15 mL of MRI contrast enhancer (0.0025 mmol Gd/ml, trade name: Artirem, Guerbet AG, Zurich, CH) was injected into the joint capsule. A 3T scanner (VidaFit, Siemens Healthineers AG, Erlangen, DE) with a 36 channel body array (18 anterior and posterior elements each) acquired MRI data under 18 kg traction. The MRI scanner was equipped with the Syngo MR XA50A software package which contains DRB. As part of the study, coronary proton density (PD) turbo spin echo (TSE) images were acquired for a conventional protocol, Figure 1. An accelerated acquisition of TSE coronary images with DRB reconstruction was also part of the same MRI study, Figure 2. Table 1 summarizes a summary of the acquisition parameters. Parallel Acquisition Techniques (PAT) under Generalized Autocalibrating Partial Parallel Acquisition (GRAPPA) was increased for the accelerated protocol by 50%. Field of view (FOV) in both cases was (170 mm)^2. Averaging was lowered to 1 for DRB, allowing greater resolution. Undersampling lowered TA by ⅓, from 3:03 minutes to 2:03 minutes.

The conventionally acquired image in Figure 1 is considered the ground truth for this MRI arthrography under traction case. The hip joint is intact, and the capsule is distended by injected contrast enhancer. No distinct pathology or degenerative changes which would be considered atypical for the patient's age exist. The accelerated image in Figure 2 however has undergone amendments. The usage of DRB during image reconstruction has added false-positive cartilage delamination and a false-positive diffuse cartilage defect on the superolateral femur head.

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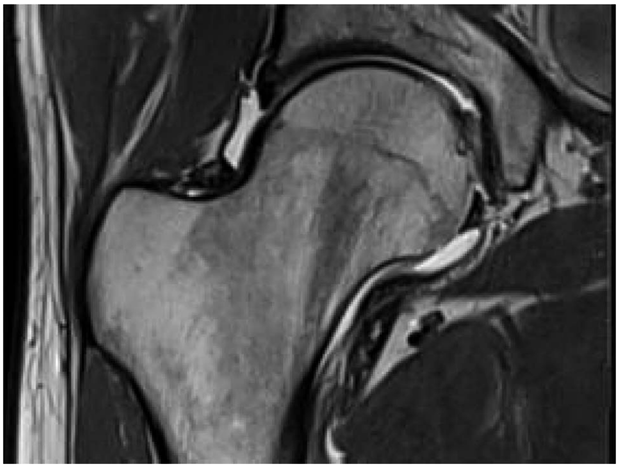

FIGURE 1. PD TSE coronary series, conventional without DRB reconstruction (series 36 image 10).

Those are visible on not only a single image but also start in series 35 at least on image 5 and are contained continuously without interruption till at least image 15, please see the study's open-access supplement below.

DISCUSSION

Until now, it has been argued that deep learning reconstruction of undersampled MRI data preserves natural appearance.[7] It was even hypothesized that deep learning reconstruction of an undersampled MRI data set might increase image quality to a level superior to that of conventional MRI imaging.[9]

The principle of deep learning reconstruction is however not to create additional information at source. Deep learning reconstruction only amends the undersampled data in the way it has been trained to do by the human programmers. This processing step is similar to the editing of smiles into a photography headshot.[12] Similarity estimates are applied in amending a data set.

FIGURE 2. PD TSE coronary series, undersampled with DRB reconstruction (series 35 image 10).

TABLE 1. PD TSE Protocols; Conventional Without DRB and Undersampled With DRB Reconstruction

	Conventional Coronary PD TSE	DRB Coronary PD TSE
Acquisition Time (TA) [min:s]	3:03	2:03
Repetition Time (TR) [ms]	3000	3000
Echo Time (TE) [ms]	26	28
Slice thickness [mm]	2	2
Averages	2	1
PAT (GRAPPA)	2	3, reconstruction by Siemens DRB
Resolution (acquired) [mm]	0.44 × 0.63	0.24 × 0.27
FOV [mm]	170 × 170	170 × 170

The core promise of the radiological imaging industry made for MRI undersampling and deep learning reconstruction is the increase of productivity of MRI machinery through shortened TA (reduction of ⅓ in this case study for purely the acquisition of images). In an ideal case, deep learning tools even promise to increase image quality at the same time.[9] Both are supposedly achievable by undersampling. Image quality however requires image data; this seems to be a certainty. One might doubt that the idea of increasing image quality through undersampling alone can work. Industry who wants to raise the economic potential of this novel AI technology will face that challenge.

Cartilage delamination and diffuse cartilage defects as shown in this case are not a matter of life or death. Nonetheless, patients expect correct diagnostic tools and they do so rightfully. The images of the presented case document that there are limitations to the ability of today's deep learning reconstruction tools. It seems logical that the share by which the measurement can be reduced during undersampling in a practical clinical setting is finite. Below this threshold, output data of the reconstruction have to be considered unreliable.

Future assessments will show if further shortcomings are discovered when this technology is put into clinical practice. A particular pressing question is what role the training data have. Access to the DRB training data would help researchers in their assessments and comparisons. Bias toward certain pathologies will be of great relevance. It is not clear whether a tool trained on adult scans can be used equally well in pediatric imaging. Regional differences between training scans might play a role as well. It is unclear how an AI will react in the hypothetical case of being exposed to a pathology which has been so far unknown to medical textbooks. What would be the appropriate similarity estimate in such a case?

Standards for content documentation and limitations of tool applicability do not yet exist. In the future, to ensure appropriate application of AI tools, those might become necessary to develop. AI components for image reconstruction might benefit in the future from regulation, similarly as already suggested in AI-based radiation protection.[13] Safety measures could include checks and balances through reviews by a human in the loop, or reviews by a second/third independent AI tool.

The radiological imaging industry has started providing AI software solutions. That they will come into clinical practice seems likely, if not certain, but they should reflect reality.

Open-Access Supplement

Both image series of Table 1 are deposited as open-access supplement under DOI: 10.6084/m9.figshare.25943740.

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