Clinical Implementation of Deep Learning-Accelerated HASTE and TSE

Judith Herrmann[1]; Andreas Lingg[1]; Matthias Kündel[1]; Sebastian Gassenmaier[1]; Saif Afat[1]; Haidara Al-Mansour[1]; Dominik Nickel[2]; Gregor Koerzdoerfer[2]; Ahmed Othman[1,3]

[1]Department of Diagnostic and Interventional Radiology, Tuebingen, Germany
[2]MR Applications Predevelopment, Siemens Healthineers, Erlangen, Germany
[3]Department of Neuroradiology, University Medical Center, Mainz, Germany

Introduction

Magnetic resonance imaging (MRI) has become a modality of choice for the diagnosis of several diseases and is currently indispensable in healthcare. One big disadvantage of MRI is the long duration of the examination, usually ranging between 20 and 60 minutes for body trunk imaging. Long acquisition times come with downsides, such as decreased image quality due to motion artifacts, increased costs, and reduced patient throughput [1]. In view of the limited availability of MRI scanners in general, MRI remains a scarce and more expensive resource than other imaging techniques with limited access to patients in need.

In order to improve this situation, over the past few decades, different acceleration strategies such as compressed sensing (CS) and parallel imaging (PI) have been proposed and established. Recently a revolutionary development based on artificial intelligence has been implemented to further accelerate the acquisition and improve the image quality at the same time: Deep Learning (DL) reconstruction has come to the fore and is gradually being implemented in clinical routine [2–4].

The aim of this report is to describe the first clinical implementation of DL-accelerated, T2-weighted (T2w) half-Fourier single-shot turbo spin echo (HASTE)[1] sequences of the upper abdomen as well as T2w and proton density (PD)-weighted turbo spin echo (TSE) sequences for musculoskeletal imaging in routine daily workflow. The novel DL-accelerated sequences are evaluated in terms of feasibility and image quality compared to standard sequences.

[1]*Work in progress. The application is currently under development and is not for sale in the U.S. and in other countries. Its future availability cannot be ensured.*

MRI technique

Acceleration strategies for Deep Learning-reconstructed TSE and HASTE[1]

To accelerate the image acquisition, a conventional undersampling pattern known from parallel imaging is used for both sequences [5, 6]. Besides the data acquisition for the actual image data, calibration data for the coil-sensitivity estimation need to be acquired. For the TSE sequence, these data are acquired as part of the imaging scan.
For the HASTE sequence, these are separately acquired using a second echo train covering only the region around the *k*-space center. In both sequences, a fraction of the *k*-space's periphery is not acquired to further reduce the acquisition time.

For TSE acquisitions, DL-reconstructed MRI can be used to improve on a combination of image resolution, acquisition time, and SNR, while maintaining the original contrast. In contrast to this, for the HASTE sequence, the improved DL reconstruction enables an improved image

Demographics	
Total (male/female), n	20 (8/12)
Age, mean ± SD (range), y	59 ± 13 (27–79)
Sequence and body region, n	HASTE, upper abdomen, 10 PD TSE, knee, 5 PD TSE, shoulder, 5

Table 1: Demographics of participating individuals
SD indicates standard deviation; y, years; n, number; HASTE, half-Fourier single-shot turbo spin echo; PD, proton density; TSE, turbo spin echo.

contrast. Specifically, with a higher acceleration factor the duration of the echo train can be shortened and therefore the effect of T2 decay can be reduced. As an additional benefit, the specific absorption rate (SAR) is reduced along with the number of refocusing pulses required. This allows for further sequence optimizations in the form of larger gaps between consecutively acquired slices and reduced repetition time.

Deep Learning image reconstruction

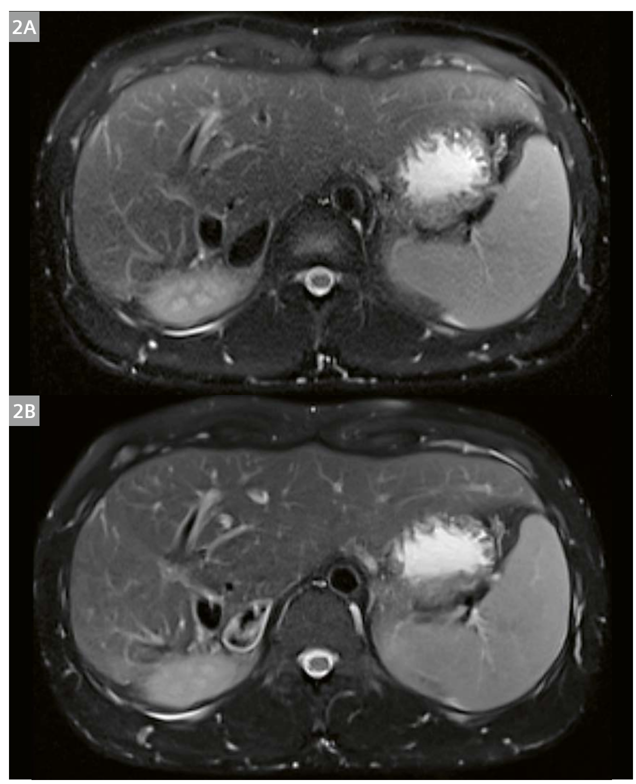
For both sequences, the image reconstruction comprises a fixed iterative reconstruction scheme or variational network [6, 7], alternating between data consistency and a Convolutional Neural Network (CNN)-based regularization. The regularization model's architecture is based on a novel hierarchical design of an iterative network that repeatedly decreases and increases the resolution of the feature maps, allowing for a more memory-efficient model than conventional CNNs. Coil sensitivity maps are estimated from the calibration data in advance as a pre-processing step. For the image reconstruction, undersampled *k*-space data, bias field correction, and coil sensitivity maps are inserted into the variational network.

The reconstruction was trained using volunteer acquisitions consisting of about 10,000 slices for each sequence type using conventional HASTE and TSE protocols acquired on various clinical 1.5T and 3T scanners (MAGNETOM scanners, Siemens Healthcare, Erlangen, Germany).

Implementation of DL image reconstruction in clinical workflow

To apply the DL reconstruction on clinically used MRI scanners, the network was converted to a C++ implemented inference framework. For the CPU-only reconstruction, inference needed about 2 seconds per slice for the protocol settings used. As the reconstruction was triggered after the end of the acquisition, the resulting perceived reconstruction time was 2–3 minutes including additional pre and post-processing. A GPU-based reconstruction is expected to reduce this duration to approximately 10 seconds, but was not available on the clinical scanners used.

1 31-year-old female participant with MRI of the knee in coronal (upper row) and sagittal (lower row) plane at 3T. Standard reconstructed PD-weighted TSE **(1A** and **1C)** show more noise compared to Deep Learning-reconstructed PD-weighted TSE **(1B** and **1D)**. The delineation and assessment of anatomic structures, such as the anterior cruciate ligament, is comparable in both reconstructions.



2 20-year-old male participant with MRI of the liver in axial plane at 1.5T. Image noise and edge sharpness of anatomical structures are improved in Deep Learning-reconstructed HASTE **(2B)** compared to standard reconstructed HASTE **(2A)**. Furthermore, the acquisition of the Deep Learning-reconstructed HASTE is possible within just one breath-hold.

Image quality analysis
Institutional review board approval was obtained for this prospective monocentric study. All study procedures were conducted in accordance with the ethical standards as laid down in the 1964 Declaration of Helsinki and its later amendments.

Accelerated MR images with DL reconstruction were prospectively acquired along with standard MR images on 1.5T and 3T MRI scanners (MAGNETOM Prisma^{fit}, MAGNETOM Vida, MAGNETOM Skyra, MAGNETOM Avanto, and MAGNETOM Aera, Siemens Healthcare, Erlangen, Germany) and an exemplary sample of 20 participants were included in this analysis (see Table 1). Two radiologists with three to ten years of experience in MRI who were blinded to participant information, acquisition parameters, and image reconstruction rated in consensus both standard MR images and accelerated MR images with DL reconstruction by using a random order. Overall image quality, artifacts, edge sharpness, and diagnostic confidence ratings were performed on an ordinal 5-point Likert scale ranging from one to five, with five being best. Reading scores were considered sufficient when reaching ≥ 3.

Image analysis was performed on a PACS workstation (GE Healthcare Centricity™ PACS RA1000, Milwaukee, WI, USA).

Statistical analysis was performed using SPSS version 26 (IBM Corp, Armonk, NY, USA). Besides descriptive statistics, comprising median and interquartile range (IQR), nonparametric paired Wilcoxon signed-rank tests were used to analyze Likert scores for image quality, artifacts, edge sharpness, and diagnostic confidence assessments. P-values less than 0.05 were considered statistically significant.

Results

The aim of this report was to describe the implementation of a DL image reconstruction in clinical workflow and evaluate its obtainable image quality in daily clinical routine. All sequences with DL image reconstruction were successfully implemented in clinical workflow and DL sequences were successfully acquired in all participants in all body parts. Fat suppression could be applied successfully for the TSE and HASTE sequences implemented with DL image reconstruction.

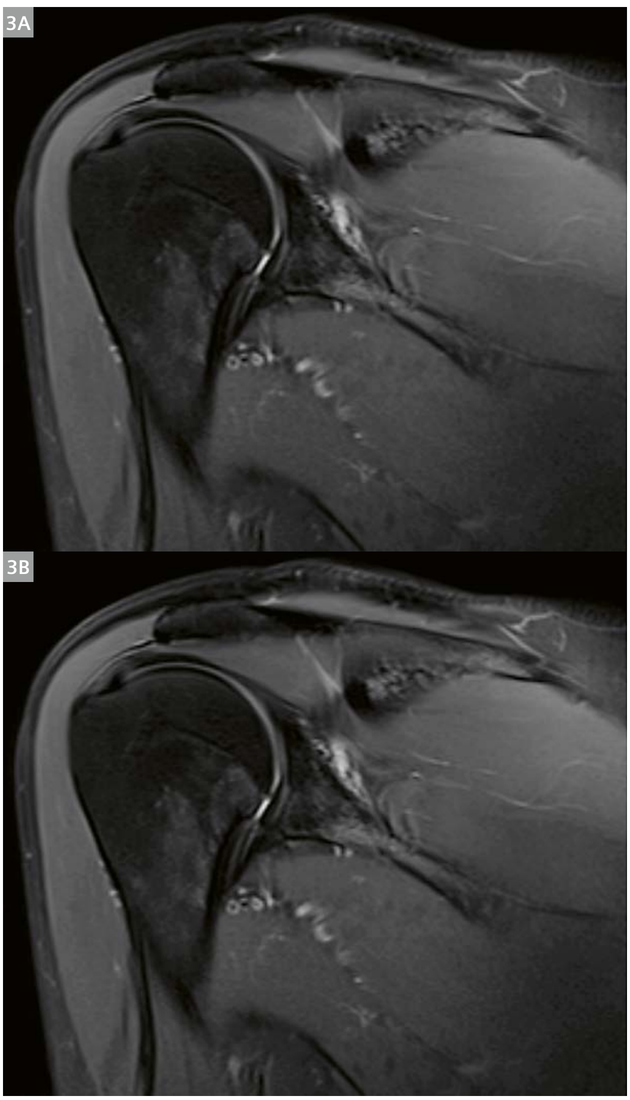
For TSE sequences, DL enabled a time saving of ≥ 50%. As expected, SAR did not exceed normal levels. For HASTE sequences, DL allowed for an acquisition time reduction of > 50%. As a single-shot sequence with a long train of refocusing pulses, HASTE is impaired by high power deposition, which limits its use at high resolutions and high field strengths, particularly if combined with acceleration techniques such as PI [8]. The DL algorithm used effectively reduced TA while staying within the SAR limitations. An overview of exemplary acquisition parameters is displayed in Table 2.

Radiologists rated the overall image quality of HASTE and PD TSE with DL reconstruction as excellent (median 5, IQR 4.25–5) and even superior to standard HASTE and

Sequence	HASTE		PD TSE FS	
	standard	DL	standard	DL
Body part	upper abdomen	upper abdomen	knee	knee
Tesla	1.5T	1.5T	3T	3T
Orientation	axial	axial	coronal	coronal
TA, min	1:28–1:44	0:16	3:11	1:33
FOV, mm	293 × 360	293 × 360	150	150
Voxel size, mm	1.13 × 1.13 × 6.0	1.13 × 1.13 × 6.0	0.2 × 0.2 × 3.0	0.2 × 0.2 × 3.0
TR, ms	1400	500	3790	3580
TE, ms	94	94	44	41
FA, degree	160	160	150	150

Table 2: Exemplary acquisition parameters of standard and vv sequences
HASTE indicates half-Fourier single-shot turbo spin echo; PD, Proton Density; TSE, turbo spin echo; FS, fat saturation; DL, deep learning; T, Tesla; TA, time of acquisition; FOV, field of view; TR, repetition time; TE, echo time; FA, flip angle.

PD TSE sequences (median 4, IQR 4–5, p<0.05). No severe artifacts occurred when using DL reconstruction as no difference was found in the extent of artifacts between standard (median 5, IQR 4–5) and DL-reconstructed sequences (median 5, IQR 4.25–5, p=0.157). Edge sharpness was improved with the DL reconstruction (median 5, IQR 5–5) compared to standard sequences (median 5, IQR 4–5, p<0.05). Diagnostic confidence was rated as comparable between the sequences (median 5, IQR 4.25–5. p=0.317). Image examples are given in Figures 1–3.



3 35-year-old female participant with MRI of the shoulder in coronal plane at 3T. Image noise and edge sharpness are improved in Deep Learning-reconstructed PD-weighted TSE **(3B)** compared to standard reconstructed PD-weighted TSE **(3A)**.

Discussion

Although MRI has evolved to become a modality of choice for the diagnosis of several diseases, its availability is still limited for reasons closely related to long examination times [1]. One promising approach to solve this shortcoming is to use novel techniques, including artificial intelligence (AI) and machine learning, to accelerate the acquisition of MR images. AI is in the public focus more than ever due to enormous innovations in the last decade, especially in the field of radiology. Novel AI techniques and new algorithms have not only been developed and trained to detect pathologies, but also to improve and accelerate image acquisition and reconstruction [9, 10]. Despite the rapid progress of all technological advances, especially in radiology, there is still a lack of widespread implementation in daily clinical routine. Therefore, the aim of this report was to describe the implementation of DL image reconstruction in daily routine and evaluate the obtainable image quality.

Our investigation demonstrates the successful implementation of DL reconstruction techniques in daily clinical workflow with a substantial reduction of TA and at the same time even higher image quality and improved edge sharpness compared to standard sequences. Effects of the implementation of these new techniques are primarily based on the reduction of TA without compromising regarding the extent of artifacts and diagnostic confidence. The reduction in TA of more than 50%, in particular, yields enormous potential for workflow optimization, increased availability of MRI, and improvement of healthcare.

One central issue in MRI has always been the shortage of scanners. Drastic acceleration and reduction of examination times might provide one piece of the big puzzle of how to enhance healthcare and balance the weight of supply and demand. This is of particular interest in low-income countries where there is only limited access to high-quality diagnostic MRI. DL reconstructions are mostly not very demanding regarding the technical specifications and can therefore also be applied in countries with less-developed technical infrastructures. Another issue that merits consideration is the increasing importance of MRI in standard of care diagnostic procedures. MRI has become increasingly important in many pathologies for diagnosis, biopsy planning, therapy surveillance, and follow-up [11-14].

One of the most challenging tasks in medicine has always been finding a compromise between best medical care and best economic outcome. As most healthcare systems worldwide are insurance based, they all face the same problem: shortage of money versus increase in demand due to development of new expensive therapies, increased life expectancy, and new diagnostic possibilities. Reduction in acquisition time might allow a higher number of examinations per day.

As we successfully implemented DL sequences in imaging of different body regions, this report is intended to motivate radiologists to establish new AI techniques in everyday clinical practice to further accelerate MRI and improve access to MRI for more patients. For this report we selected some illustrative examples of the DL examinations conducted to provide a brief introduction into how DL sequences are implemented in daily routine. Systematic analyses of the different body regions are in progress and will be outlined in separate studies.

To conclude, DL image reconstruction can be implemented in clinical workflow and enables accelerated image acquisition while maintaining excellent image quality.

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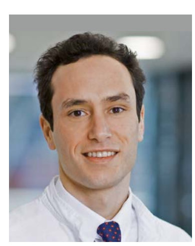
Contact

Judith Herrmann, M.D.
Eberhard Karls University Tuebingen
Department of Diagnostic and Interventional Radiology
Hoppe-Seyler-Strasse 3
72076 Tuebingen
Germany
judith.herrmann@med.uni-tuebingen.de



Ahmed Othman, M.D.
University Medical Center
Department of Neuroradiology
55131 Mainz
Germany
ahmed.e.othman@googlemail.com