Deep Learning-Based Reconstruction in Clinical MRI: How We Do it in Tübingen

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Introduction

MRI plays a critical role in everyday clinical practice. However, the acquisition of high-quality MRI images can be time-consuming depending on the anatomical region and the clinical scenario. This can cause patient discomfort, reduce the number of patients scanned within a given timeframe, and limit the availability of this crucial imaging modality.

To mitigate these obstacles, we have been investigating applying deep learning techniques to image reconstruction. Deep learning, a subset of artificial intelligence, is adept at learning from vast amounts of data and applying this knowledge in novel scenarios. By training deep learning models with extensive collections of MRI data, it has been possible to create innovative MRI sequences that shorten image acquisition times without compromising the quality necessary for diagnosis [1–3].

One of the first applications involved using deep learning-based reconstruction (DLR) with turbo spin-echo (TSE) sequences for musculoskeletal (MSK) imaging. In MSK cases, applying DLR to undersampled *k*-space data accelerates imaging without compromising image quality. The same effect is achieved when DLR is used in TSE sequences for oncologic staging of sarcoma patients, and in fast T2-weighted half-Fourier single-shot turbo spin-echo sequences for upper abdominal imaging.

In prostate imaging, where multiparametric MRI is important for identifying significant prostate cancer, using deep learning-based TSE sequences also appreciably shortens acquisition times while maintaining image quality.

Another remarkable use of this approach is in accelerated volumetric interpolated breath-hold examination (VIBE) sequences. Since the VIBE sequence has wide application in routine clinical practice, DLR has a broad impact[1], facilitating imaging of the liver, breast, thorax, and abdomen in both native and postcontrast sequences.

In addition to these morphological sequences, DLR has also been implemented in diffusion-weighted imaging (DWI).

The potential impact of deep learning-enhanced MRI sequences in the future is considerable. Shorter scan times can enhance the patient experience and allow for higher daily patient volumes, thus broadening access to MRI services. Furthermore, these advanced MRI sequences can also elevate image quality, potentially enabling more precise diagnosis and more effective treatment planning. This improvement in diagnostic accuracy and efficiency could lead to enhanced patient care and possibly lower healthcare expenditure [4]. Grasping the utility and advantages of deep learning in MRI, particularly in speeding up scans and elevating image quality, is therefore vital.

In the following, we provide a comprehensive overview of the daily applications that are already part of our clinical routine. We also address the promising results gained from DLR in a wide range of medical domains.

[1] *Deep Resolve VIBE is currently under development and is not for sale in the U.S. and in other countries. Its future availability cannot be ensured.*

Turbo spin-echo (TSE) sequences

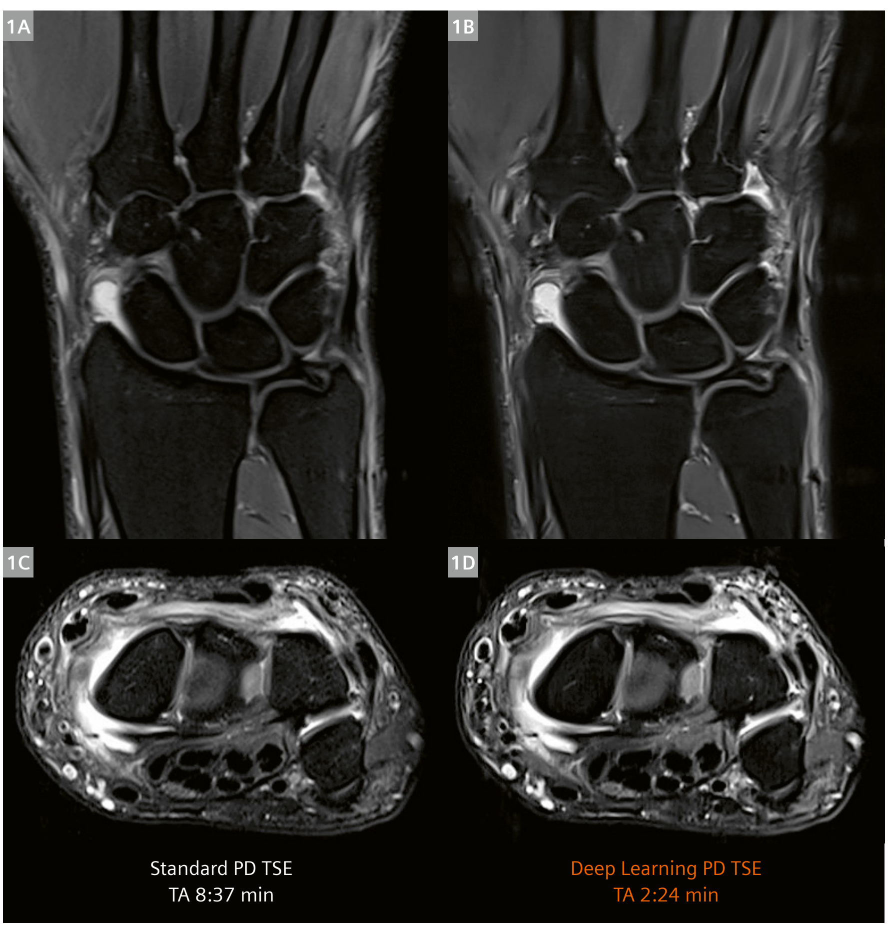
TSE in musculoskeletal imaging

MRI is an essential diagnostic tool for assessing the MSK system. TSE sequences are a key technique for imaging bones, joints, and soft tissues, offering the detailed visualizations that are crucial for diagnosis and treatment planning [5]. They provide high contrast resolution, can be optimized for fluid sensitivity and fat suppression, and can be adapted to produce different contrasts.

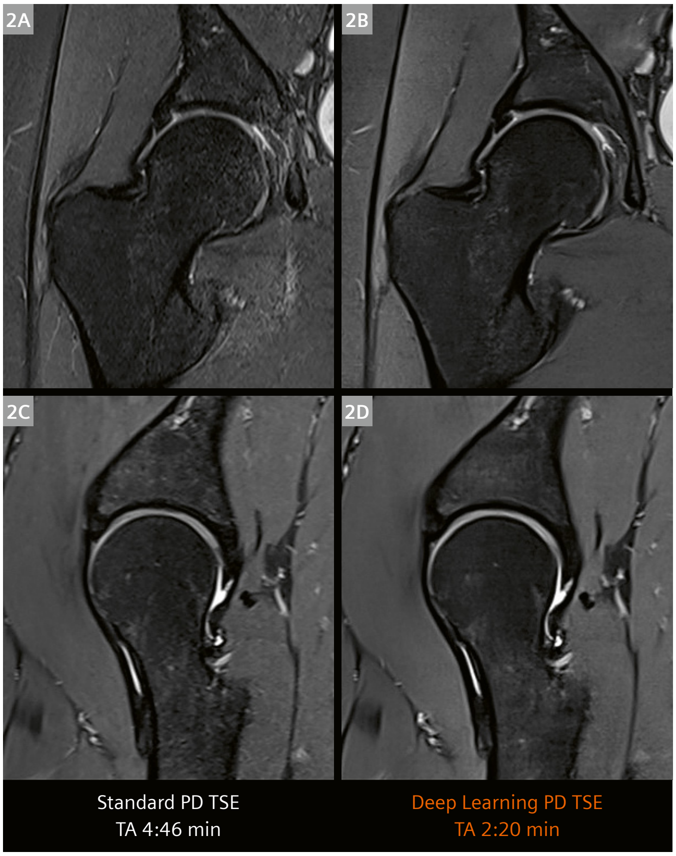
Looking ahead, implementing deep learning in the image reconstruction process can be leveraged to produce various possible benefits. On the one hand, it can reduce scan time, improving patient comfort and possibly leading to increased patient throughput and higher accessibility. On the other hand, it could enhance image quality when not focusing on scan time reduction.

To date, efforts have concentrated on speeding up acquisition while ensuring the images meet the required standards for diagnostic use. Using deep learning for image reconstruction has proven to be an effective way of achieving this. It involves a two-step process [6]: First, it increases the acceleration factor of the TSE sequences, which may result in images that are not optimal in terms of contrast, resolution, and signal-to-noise ratio (SNR). Second, a DLR algorithm is applied to create high-quality images expected to match or surpass the quality of traditional clinical imaging. This objective has been achieved, as evidenced by numerous published studies [2, 6–11]. The goal moving forward is to consistently produce superior images in shorter times, and to extend the application to three-dimensional isotropic TSE sequences such as SPACE[2]. In this section, we present several cases to demonstrate the capabilities of DLR in MSK imaging.

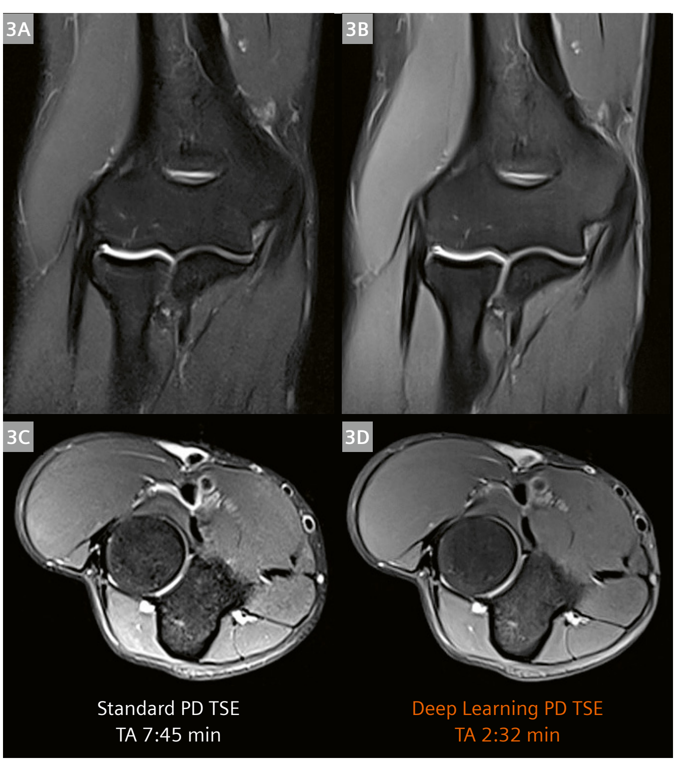
[2]Deep Resolve SPACE is currently under development and is not for sale in the U.S. and in other countries. Its future availability cannot be ensured.



1 A 3T wrist MRI of a 34-year-old male patient after hyperflexion trauma. Clinical suspicion of ligamentous injury. Proton density (PD)-weighted TSE images in the coronal (top row) and axial (bottom row) orientation. The coronal and axial images show a radiocarpal joint effusion. The axial images show swelling and edema of the dorsal extrinsic ligaments. Standard TSE images are displayed on the left, and DLR images are on the right. This example shows that despite a significantly reduced acquisition time, the image quality is well maintained and the deep learning image appears slightly sharper.



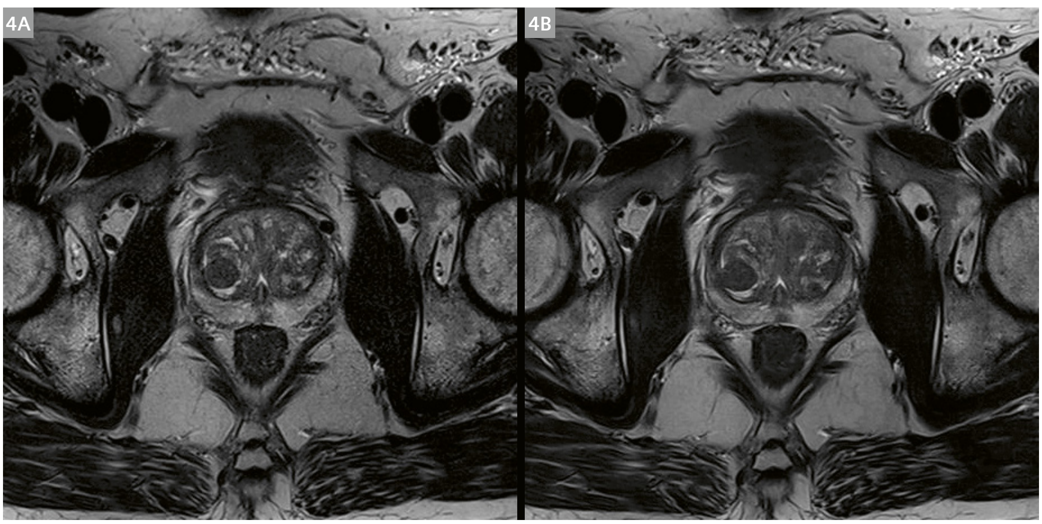
2 A 3T hip MRI of a 29-year-old male patient with suspected cam impingement and labral lesion. The coronal images show a cam morphology of the head/neck junction and a small lesion at the base of the superior labrum. Proton density (PD)-weighted TSE images in the coronal (top row) and sagittal (bottom row) orientation. The standard TSE images are on the left, and the DLR images are on the right. This comparison illustrates that even though the acquisition time is greatly decreased, the quality of the images remains high. Additionally, the images reconstructed with deep learning are slightly sharper and exhibit less noise.



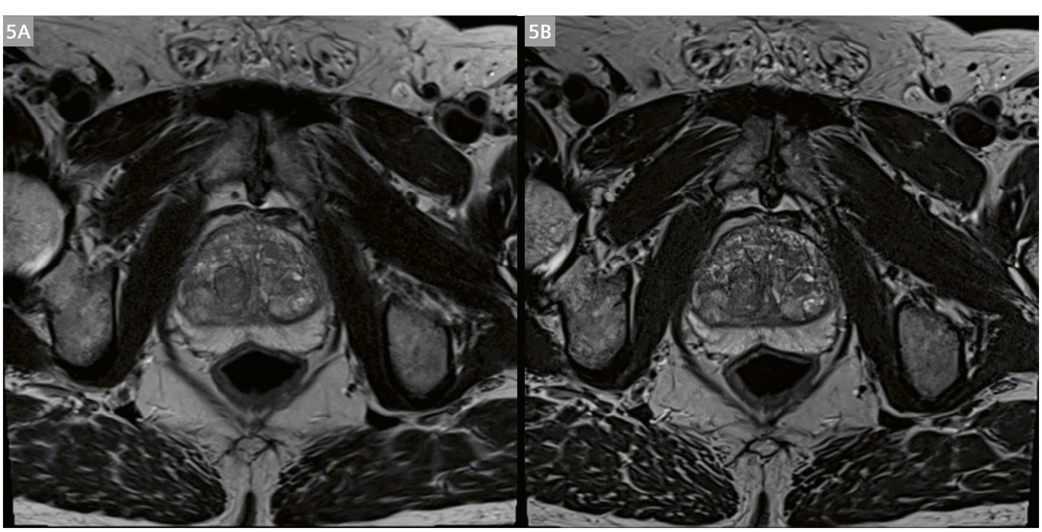
3 A 3T elbow MRI of a 28-year-old male volunteer without pathological findings. Proton density (PD)-weighted TSE images in the coronal (top row) and axial (bottom row) orientation. Standard TSE images are displayed on the left, and DLR images are on the right. The image quality is preserved even with a substantial reduction in acquisition time, and the DLR image also shows less noise.

TSE in prostate imaging

T2-weighted TSE imaging is essential in prostate MRI. It provides valuable information about the anatomy, structure, and pathology of the prostate. T2-weighted TSE imaging is therefore a key component for accurate diagnosis of prostate cancer according to the current PI-RADS classification. To ensure sufficient diagnostic image quality, the PI-RADS classification recommends specific sequence settings, e.g., regarding slice thickness and the acquisition of several planes. However, these settings result in prolonged acquisition times, which are problematic due to patient discomfort, reduced patient throughput, and increased energy consumption. DLR techniques have achieved promising and astonishing results regarding acquisition time reduction and image quality improvement: Several studies have demonstrated acquisition time reductions of over 50% in combination with improved image quality [12–14].



4 **(4A)** Standard T2-weighted imaging (acquisition time: 4:37 min) and **(4B)** DLR (acquisition time 1:38 min). The anatomical structures of the prostate are depicted sharper in deep learning imaging than standard imaging, despite the significant reduction in acquisition time.
However, as an alternative approach it is also possible to obtain higher morphological resolution using a thinner slice thickness without acquisition time prolongation in comparison with standard imaging. This improvement of spatial resolution might be helpful to more accurately predict capsule infiltration and extraprostatic growth.



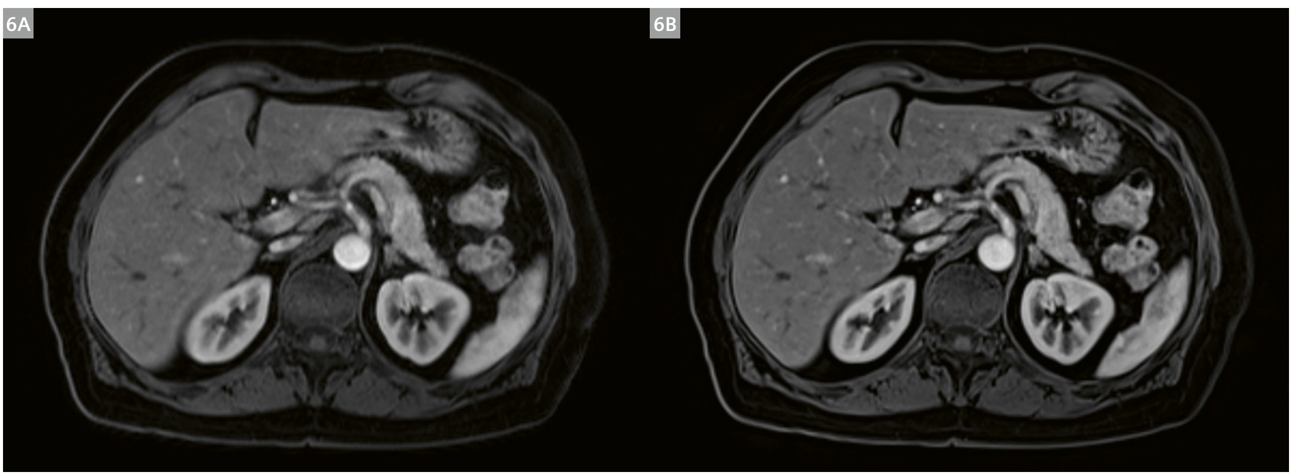
5 **(5A)** Standard T2-weighted imaging (acquisition time: 4:12 min) and **(5B)** high-resolution (2 mm slice thickness) DLR (acquisition time: 4:37 min). The anatomical structures are sharper on the high-resolution image with better delineation of the prostatic parenchyma.

Volumetric interpolated breath-hold examination (VIBE) sequences

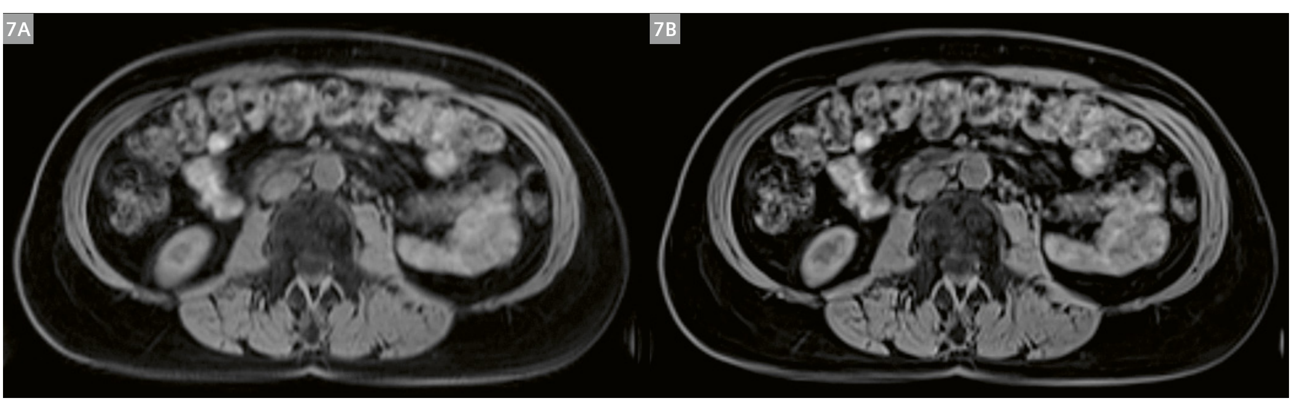
VIBE in liver and abdominopelvic imaging

Gradient echo (GRE) imaging is an important sequence in liver and abdominopelvic MRI, and is often used in dynamic contrast-enhanced imaging. By acquiring images at multiple time points after injecting a contrast agent, these sequences can help assess the vascular supply and perfusion of liver lesions. This information is crucial for diagnosing and staging liver diseases, including hepatocellular carcinoma. The major disadvantage of GRE imaging is the need for a breath-hold to avoid motion artifacts.

Furthermore, GRE imaging is prone to motion artifacts due to bowel movements. To shorten the breath-hold time, parallel imaging techniques are often used, with the downside of SNR loss. DLR is one method to further accelerate liver and abdominal GRE scans using more aggressive partial Fourier factors and compensation of SNR loss via super-resolution. Several studies have shown promising results in liver, pancreas, and abdominopelvic imaging [15–17].



6 Comparison of **(6A)** T1-weighted post-contrast VIBE imaging with standard reconstruction, and **(6B)** DLR with simulation of higher partial Fourier factors[1] (acquisition time reduced by approximately 2 seconds).



7 Follow-up examination of a 52-year-old woman who underwent MRI for staging after multicentric breast cancer. No metastatic lesions were found. **(7A)** The native VIBE with standard reconstruction shows a lower SNR and less sharpness of the intestine, organs, and lymph nodes compared to **(7B)** the deep learning-based super-resolution[1].

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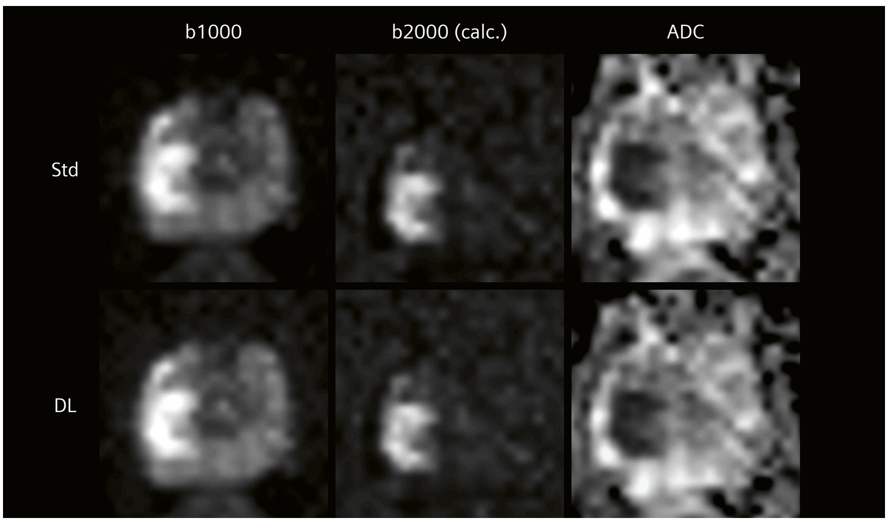
Diffusion-weighted imaging (DWI) sequences

DWI in prostate imaging

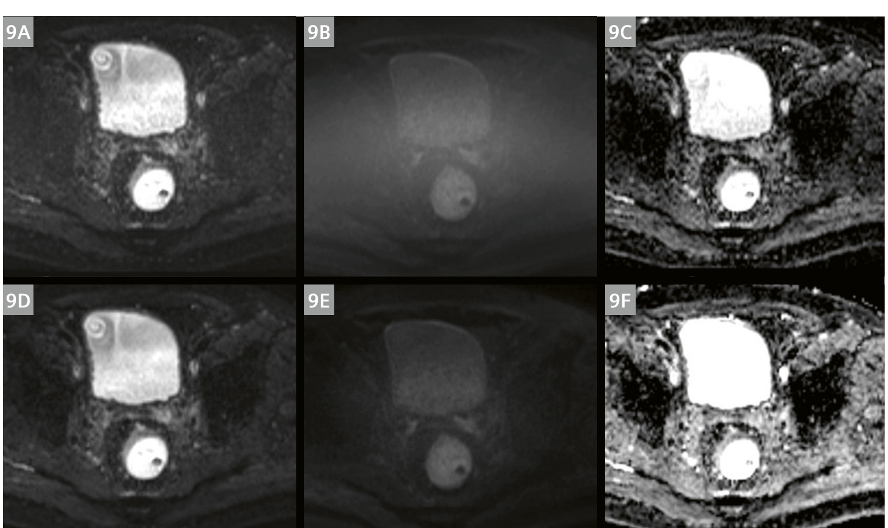
DWI is a key element of current state-of-the-art prostate MRI protocols. It is the most important sequence for assessing the peripheral zone, according to the PI-RADS classification system. Drawbacks of DWI are low SNR and long acquisition times. DLR has been shown to help to drastically reduce acquisition time without loss of image quality. However, if standard acquisition times are acceptable – in younger patients, for instance – it is also possible to obtain higher morphological resolution or images with higher SNR using DLR with similar acquisition times as standard imaging. This patient-centered approach could help to create a personalized MRI protocol.



8 Comparison of conventional ss-EPI diffusion and DLR diffusion with Deep Resolve in a patient with a marked diffusion restriction in the right peripheral zone of the prostate. DLR can reduce the number of averages and thereby help reduce the acquisition time from 4:30 to 2:46, corresponding to 38.5% faster acquisition, with no discernable impact on diagnostic quality.

DWI in pelvic imaging

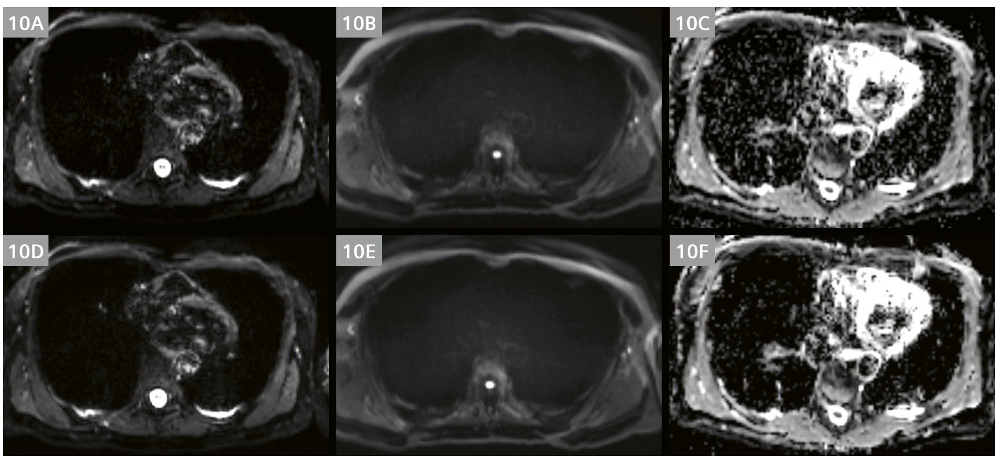
Pelvic tumors, affecting both sexes, necessitate accurate imaging. While DWI is crucial for tumor differentiation, it presents challenges such as low SNR and extended scan times. The common echoplanar imaging (EPI) technique also has limitations, such as susceptibility artifacts. Recently, DLR has also been introduced for DWI, promising enhanced image quality and reduced acquisition time. DLR for DWI shows excellent image quality and exhibits significantly less noise than standard DWI, while no differences were observed in artifacts, lesion detectability, organ sharpness, or diagnostic confidence. While standard DWI had an acquisition time of 2:06 minutes, simulated acquisition time for DLR DWI was 1:12 minutes, promising a significant reduction in acquisition time for pelvic DWI at 1.5T.



9 DWI with two different b-values (0 s/mm² and 800 s/mm²) and calculation of apparent diffusion coefficient (ADC) maps in a staging examination in a 76-year-old male patient with rectal carcinoma and condition after chemotherapy and radiation treatment. Note the reduced noise in the images with DLR (**9D–F**: b0 s/mm² DLR, b800 s/mm² DLR, and ADC DLR; bottom row) compared to the standard reconstruction (**9A–C**; b0 s/mm² S, b800 s/mm² S, and ADC S; top row).

DWI in whole-body imaging

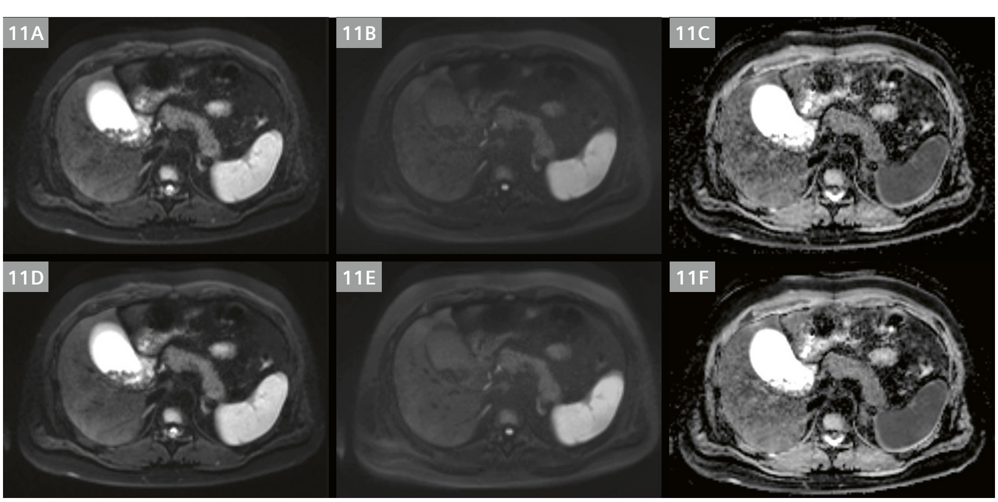
Especially in oncologic imaging, whole-body DWI plays a pivotal role in clinical routine, often serving as a screening sequence for pathological alterations. However, in comprehensive whole-body imaging, careful consideration must always be given to augmenting the protocol with additional sequences. This is particularly important because DWI is susceptible to artifacts and entails a relatively lengthy acquisition time, which is a notable challenge. The application of DLR in whole-body imaging has considerable promise, particularly in the context of DWI. Initial findings indicate that it enhances the image quality of DWI for whole-body MRI in the staging of patients with multiple myeloma at 3T, while significantly reducing the simulated acquisition time. This underscores the great potential of DLR in augmenting clinical efficiency.



10 DWI with two different b-values (0 s/mm² and 800 s/mm²) and calculation of apparent diffusion coefficient (ADC) maps in a staging examination in a 50-year-old female patient with multiple myeloma. Note the reduced noise in the images with DLR (**10D–F**: b0 s/mm² DLR, b800 s/mm² DLR, and ADC DLR; bottom row) compared to the standard reconstruction (**10A–C:** b0 s/mm² S, b800 s/mm² S, and ADC S; top row).

DWI in liver imaging

DWI is essential for appropriate liver assessment regarding metastatic disease. It is also helpful for the differentiation of focal liver lesions. Disadvantages of DWI in liver imaging are primarily related to the acquisition time. Mostly, a free-breathing DWI EPI sequence is used for acquisition. Via reduction of averages, it could be successfully demonstrated that application of DLR can prevent image quality loss.



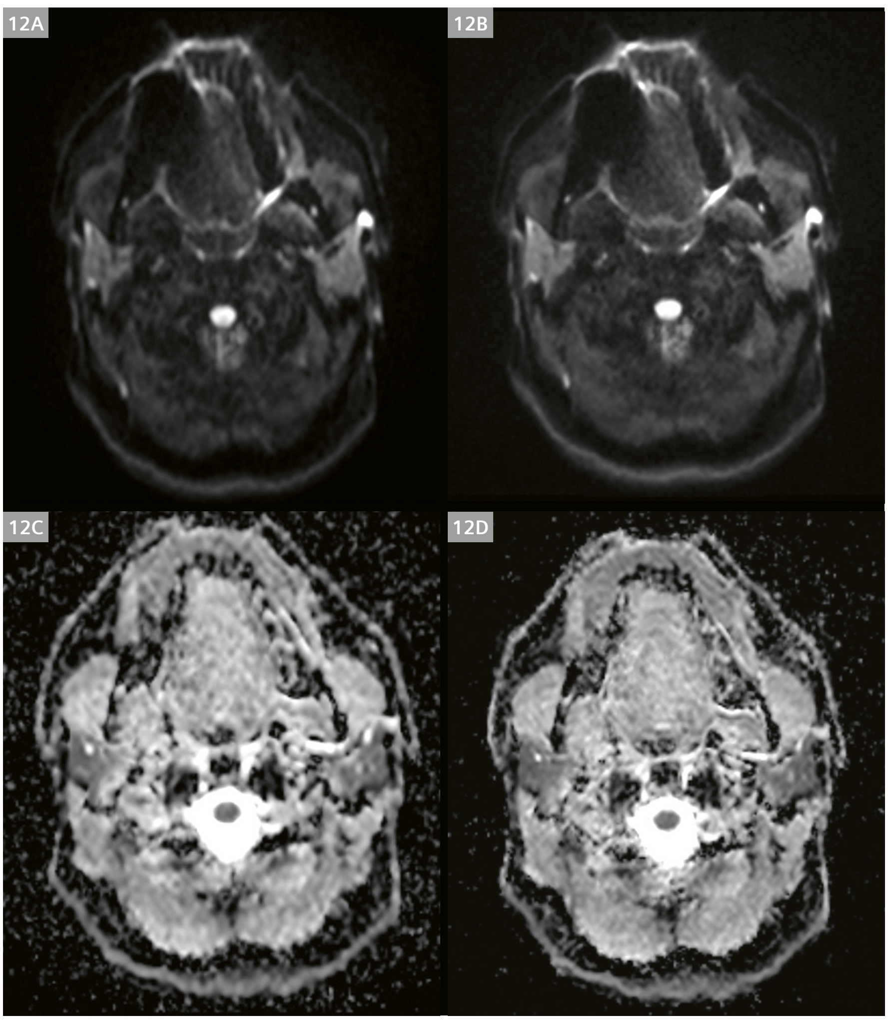
11 Standard DWI of the liver in the top row **(11A–C)** and DLR DWI in the bottom row **(11D–F)**. Despite decreased acquisition time, no loss in image quality is visible.

DWI in head and neck MRI

Diffusion-weighted MRI is employed in a broad spectrum of indications in head and neck radiology [18]. The most important indications include tissue characterization, oncologic staging, therapy monitoring, and differentiation between post-therapeutic changes and early recurrence [18]. As previously mentioned, a significant drawback of DWI lies in the time-consuming acquisition and the susceptibility artifacts.

One approach is to retrospectively implement a deep learning algorithm for reconstruction of DWI sequences. In the implemented sequence, the number of averages was reduced and image quality, among other variables, was systematically analyzed.

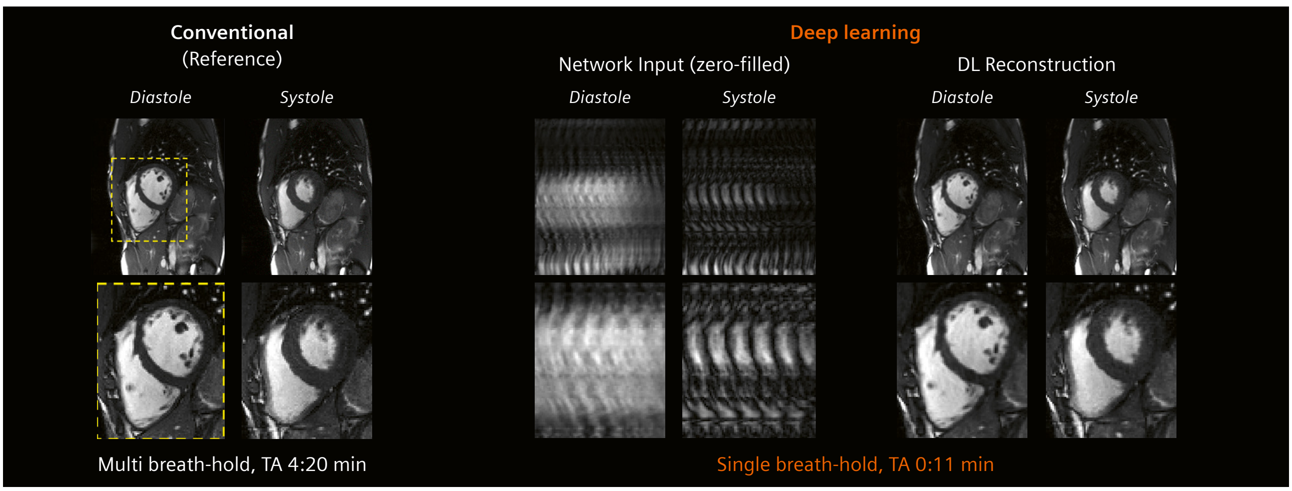
In summary, despite the significant reduction of acquisition time, image quality was not affected. These results could set the stage for ultra-fast DWI, which could reduce artifacts and enhance both the patient's and radiologist's experience.



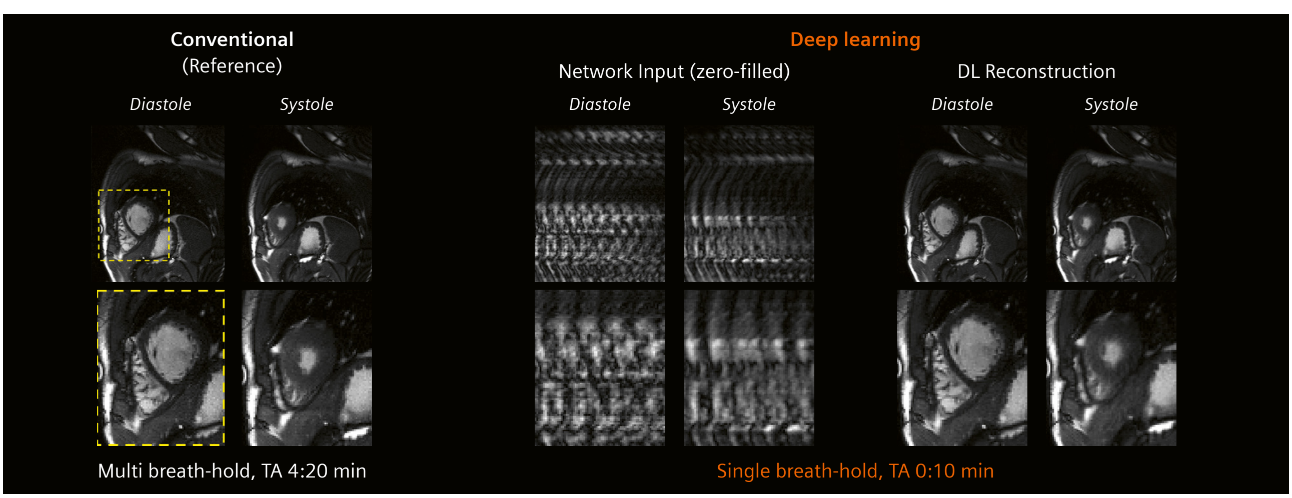
12 Neck MRI. The left column shows standard DWI images, **(12A)** b800 s/mm² and **(12C)** ADC map. The right column shows **(12B)** DLR b800 s/mm² and **(12D)** ADC images. Image quality was not compromised despite reducing acquisition time. Minimal reduction of noise was noted in the DLR ADC **(12D)**.

Cardiac cine

Cardiac cine MRI enables accurate and reproducible measurement of cardiac function. Conventionally, multislice 2D cine images are acquired under multiple breath-holds with retrospective cardiac gating, which causes patient discomfort and imprecise assessment (due to slice misalignments between breath-holds). The development of DLR methods has opened up new ways of accelerating cardiac imaging while keeping a high image quality. However, existing DLR methods face several challenges [19–23], such as limited and/or unweighted information-sharing across image and *k*-space domain, and between spatial and temporal samples. Thus, the limited generalizability may restrict the clinical adoption of these methods. To address these issues, we proposed A-LIKNet [24], which incorporates attention mechanisms and maximizes information sharing between low-rank, image, and *k*-space in an interleaved architecture. Results shown in Figure 13 and Figure 14 indicate that the proposed A-LIKNet allows cardiac cine imaging within a single breath-hold of ~10 seconds.



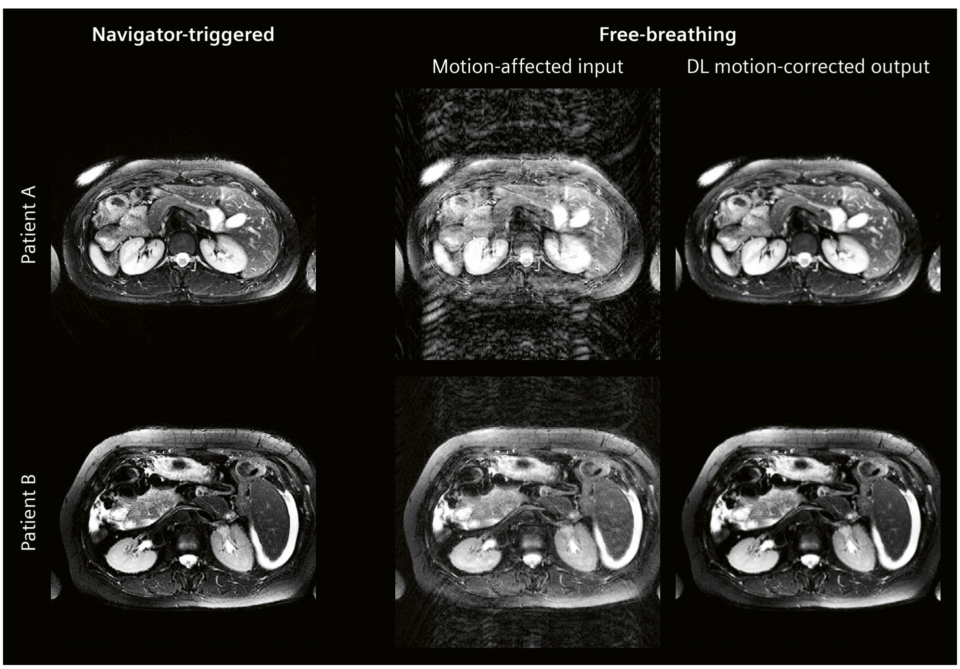
13 A healthy subject acquired with conventional cardiac cine (bSSFP, TE/TR = 1.06/2.12 ms, α = 52°, resolution = 1.9 x 1.9 mm^2, slice thickness = 8 mm, GRAPPA 2x, left ventricular coverage) on a 1.5T MRI system (MAGNETOM Aera, Siemens Healthineers, Erlangen, Germany) under multiple breath-holds, resulting in an acquisition time (TA) of 4:20 minutes. This is compared with a deep learning (DL)-accelerated sequence (24x acceleration, otherwise same imaging parameters) in a single breath-hold of 11 seconds. The network input (zero-filled) and reconstructed image of the deep learning reconstruction network (A-LIKNet) are depicted.



14 A patient with suspected myocarditis acquired with conventional cardiac cine (bSSFP, TE/TR = 1.06/2.12 ms, α = 52°, resolution = 1.9 x 1.9 mm^2, slice thickness = 8 mm, GRAPPA 2x, left ventricular coverage) on a 1.5T MRI system (MAGNETOM Aera, Siemens Healthineers, Erlangen, Germany) under multiple breath-holds, resulting in an acquisition time (TA) of 4:20 minutes. This is compared to a deep learning (DL)-accelerated sequence (24x acceleration, otherwise same imaging parameters) in a single breath-hold of 11 seconds. The network input (zero-filled) and reconstructed image of the deep learning reconstruction network (A-LIKNet) are depicted.

BLADE

Motion is one of the main extrinsic sources of MRI artifacts that can strongly deteriorate image quality and thus impair diagnostic accuracy. Numerous prospective and retrospective motion-correction strategies have been proposed to mitigate these artifacts [25–27]. Rigid motion artifacts result from translational or rotational movements of large parts of the patient's body and can be compensated for by special acquisition sequences such as BLADE MRI. The compensation of non-rigid motion artifacts arising from local deformations such as respiration are challenging to compensate, especially in a retrospective setting without any other prior knowledge about the motion (like navigators). Deep learning-based approaches currently show promising results in terms of compensating for non-rigid motion artifacts [28–30]. However, consistency of the acquired data often cannot be ensured with these approaches. Under the assumption of motion being represented as sparse outliers in *k*-space [31] and non-rigid motion being the superposition of local translational motions [32], we have reworked the non-rigid motion correction task as an image reconstruction. A deep learning network was trained, including data consistency, to recover a motion-free image from motion-corrupted scans. We can thus retrospectively correct for respiratory motion artifacts in cases when the navigator triggering fails, or even perform the BLADE sequence under free-breathing as demonstrated in Figure 15.



15 Deep learning (DL)-based retrospective motion correction of T2w BLADE imaging in the abdomen. A respiratory navigator-triggered sequence is compared to a free-breathing scan with subsequent deep learning motion correction, which provides similar image quality in a shorter scan time with 100% scan efficiency.

Excursus: Green MRI energy

Amidst the backdrop of rising energy costs, a feasibility study was undertaken to assess MRI scanner energy consumption and identify potential energy-saving techniques. The study demonstrated that optimizing protocols and integrating deep learning methodologies can lead to significant energy savings. The application of deep learning techniques even achieved substantial reductions in energy consumption. Despite the computational demands of deep learning in MRI sequences, the decrease in acquisition times offset any additional energy consumption.

The study's results underscore the profound benefits of technological advancements in reducing costs, energy consumption, and environmental impacts in healthcare. The results therefore provide valuable insights for radiology departments aiming to enhance their energy efficiency without sacrificing the quality of their services. Future research is aimed at refining these measurements and expanding the study to other high-energy devices in the healthcare sector.

Conclusion and outlook

The application of deep learning in image reconstruction for MRI is a rapidly evolving and promising field of research. One notable area of progress is the acceleration of MRI scans by reconstructing high-quality images from undersampled data, thereby reducing scan times and enhancing patient comfort.

Deep learning algorithms have demonstrated the ability to enhance image quality by providing better resolution, minimizing artifacts, and improving the overall image compared to traditional reconstruction methods. Importantly, these models exhibit increased robustness to the noise and artifacts commonly found in MRI data, contributing to the production of more reliable images, especially in challenging imaging conditions.

The adoption of deep learning techniques in clinical practice for MRI reconstruction requires rigorous validation and regulatory approval to ensure the reliability and safety of these models. Ongoing research focuses on improving existing models, developing new architectures, and addressing issues such as regularization, interpretability, and domain-specific adaptations.

The dynamic nature of the field implies that researchers and clinicians will continue exploring ways to leverage deep learning for MRI reconstruction, with the ultimate goal of enhancing diagnostic capabilities and improving patient care.

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