Deep Resolve – Mobilizing the Power of Networks

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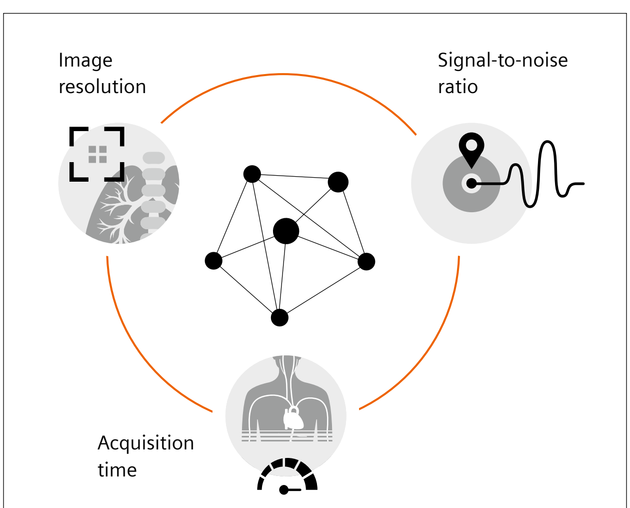
The limitations of conventional image reconstruction

MRI is established as one of the key modalities in diagnostic imaging. The absence of ionizing radiation and the unmatched soft tissue contrast distinguish MRI from other imaging modalities. While these features have helped to establish MRI as the method of choice for the diagnosis of many pathologies, the main limitation of MRI is the acquisition time.

With conventional reconstruction methods, the acceleration of an acquisition can only be achieved by accepting compromises with respect to image resolution or signal-to-noise ratio (SNR). In general, acquisition speed, image resolution, and SNR are tightly linked and increasing one of the three automatically has a negative effect on at least one of the two others (Fig. 1).

The use of receive arrays and parallel imaging has been an important breakthrough in MR image reconstruction and is an essential part of clinical routine in MRI [1, 2].

Parallel imaging, however, usually comes at the price of higher image noise, especially in regions further away from the receive coils. This results in inhomogeneous noise distribution, especially if high acceleration factors are used. Compressed Sensing was another major development when it comes to image acceleration [3]. Dynamic and non-cartesian 3D imaging are the key benefits but comes at the cost of a higher computational burden. 2D cartesian imaging, which is the core routine MR imaging, benefits less from Compressed Sensing.



1 Image resolution, SNR, and acquisition time are the three limiting factors of MRI. Using conventional methods, changing one of them directly affects at least one of the two others. Deep learning reconstruction has the potential to disrupt this convention.

Over the last years, artificial intelligence (AI) technologies have made their appearance in a various research publications [4, 5]. Especially the use of deep neural networks has proven to be helpful when trying to address the limitations of conventional MR image reconstruction, especially for routine 2D imaging. Deep learning image reconstruction has the potential to tackle all three limiting factors of MR imaging simultaneously: image resolution, SNR, and acquisition speed.

Deep Resolve Gain & Deep Resolve Sharp

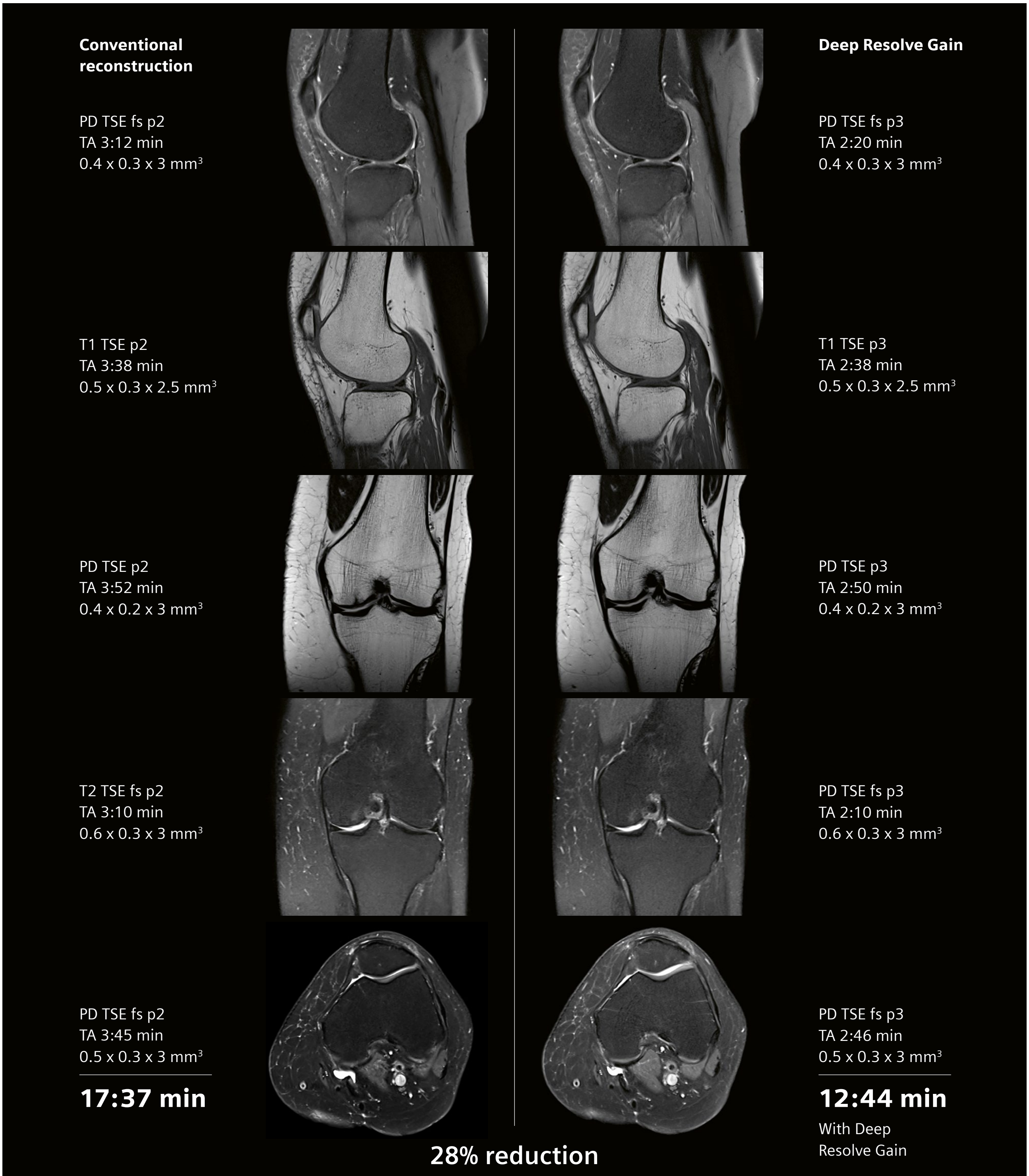
Deep Resolve brings deep learning and AI to the MR image reconstruction process. Deep Resolve is an advanced reconstruction technology, which in its first step brings denoising and deep-learning-based image reconstruction directly to the core of the imaging chain.

Deep Resolve Gain is a solution for targeted denoising. As mentioned above, in MRI, image noise is not uniformly distributed across the image. This can be due to coil array geometries since the SNR is usually higher closer to the receive coils. In addition, the use of parallel imaging reconstruction techniques can lead to varying noise levels in the reconstructed image. These local variations in image noise can not be addressed by conventional noise filters, as these operate globally on the entire reconstructed image. Deep Resolve Gain incorporates specific noise maps, which are acquired together with the original raw data, directly into the image reconstruction [6].

These noise maps are generated and extracted from the raw data without the need for additional scan time. The reconstruction algorithm takes local noise variations into account and enables stronger denoising where noise would be most dominant when reconstructing with conventional methods.

Deep Resolve Gain helps to mitigate noise that is introduced when accelerating the acquisition e.g. by reducing the number of averages or by increasing the acceleration factors in parallel imaging.

As the noise maps can be generated from the originally acquired raw data, no additional acquisition time is needed, and the results are available in real-time. Figure 2 shows how Deep Resolve Gain can be employed to accelerate an entire knee exam. Images acquired with increased acceleration and reconstructed with Deep



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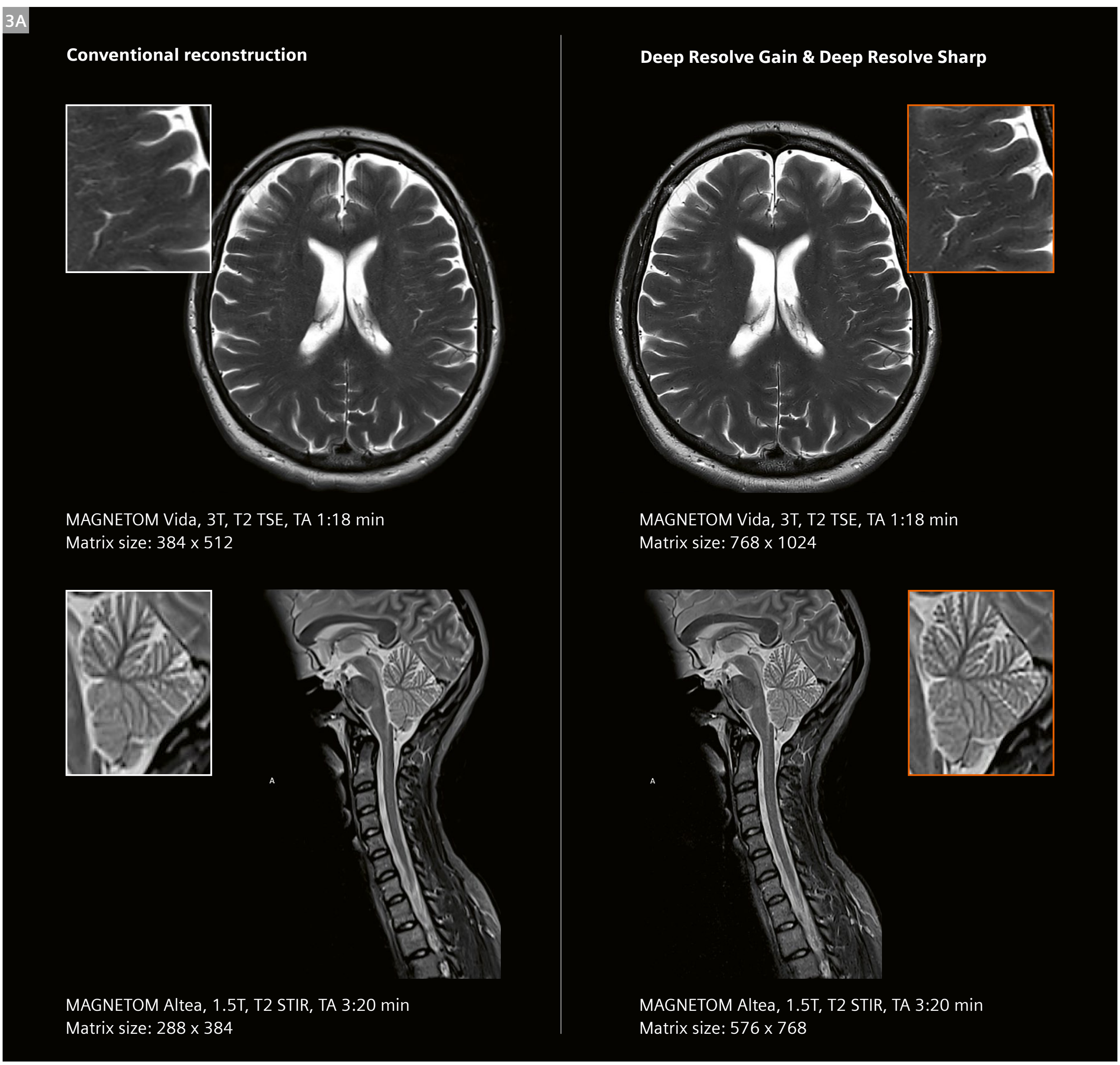
2 The increase in SNR achievable with Deep Resolve enables you to accelerate entire knee exams. The targeted reduction of image noise allows for the use of higher acceleration factors, without having to pay with increased image noise. Images are acquired on a MAGNETOM Vida 3T scanner.

Resolve Gain are similar in quality to the standard protocols which are conventionally reconstructed. In this example it results in an acceleration by 28% over the entire exam.

Deep Resolve Sharp is a novel image reconstruction technology to generate images with increased sharpness. The deep neural network at the core of Deep Resolve Sharp generates a high-resolution image from low resolution input data. The network was trained on a large number of pairs of low-resolution and high-resolution data.

As the training data for Deep Resolve Sharp covered a wide range of anatomies, the reconstruction network can be applied to all body regions. Deep Resolve Sharp can increase the matrix size by a factor of up to two along both in-plane axis, resulting in substantially increased image sharpness.

To ensure robust results, the acquired raw data is directly incorporated into the reconstruction and ensures consistency with the data from the scanner. The inclusion of the cross-check with the acquired raw data is essential for the robustness of the reconstruction and to ensure that contrasts are correctly represented in the final output. Figure 3 shows how Deep Resolve Sharp can be used to increase the sharpness of reconstructed images, without having to extend the acquisition time. Deep Resolve Sharp

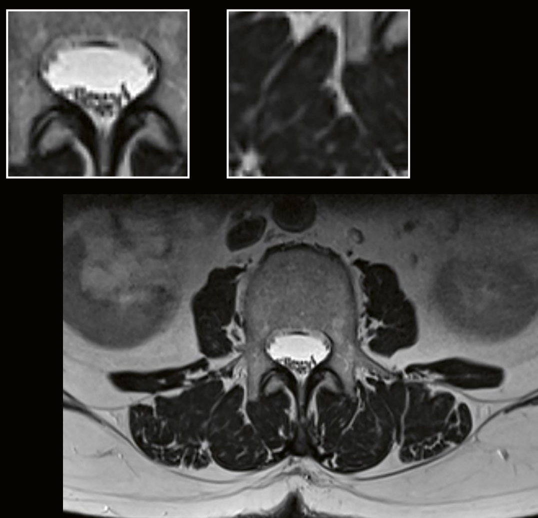


3 Deep Resolve Sharp uses a deep neural network to generate sharper images than ever before, enabling a clear depiction of fine structures and sharp edges. The use of raw data within the reconstruction process ensures robust results.

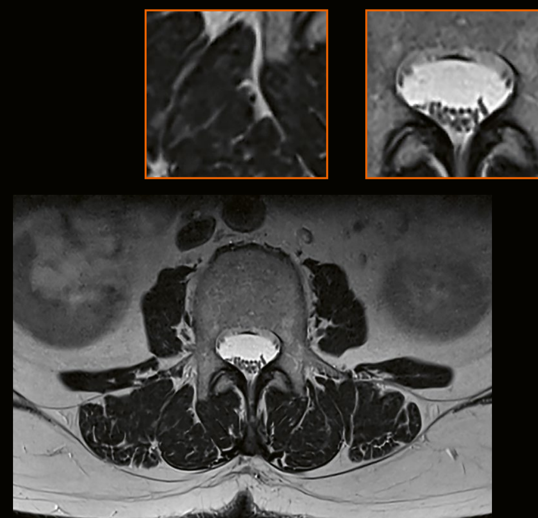
3B

Conventional reconstruction

Deep Resolve Gain & Deep Resolve Sharp



MAGNETOM Sola, 1.5T, T2 TSE, TA 3:45 min
Matrix size: 256 x 320



MAGNETOM Sola, 1.5T, T2 TSE, TA 3:45 min
Matrix size: 512 x 640

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MAGNETOM Sola, 1.5T, T2 TSE, TA 2:24 min
Matrix size 307 x 384

MAGNETOM Sola, 1.5T, T2 TSE, TA 2:24 min
Matrix size 614 x 768

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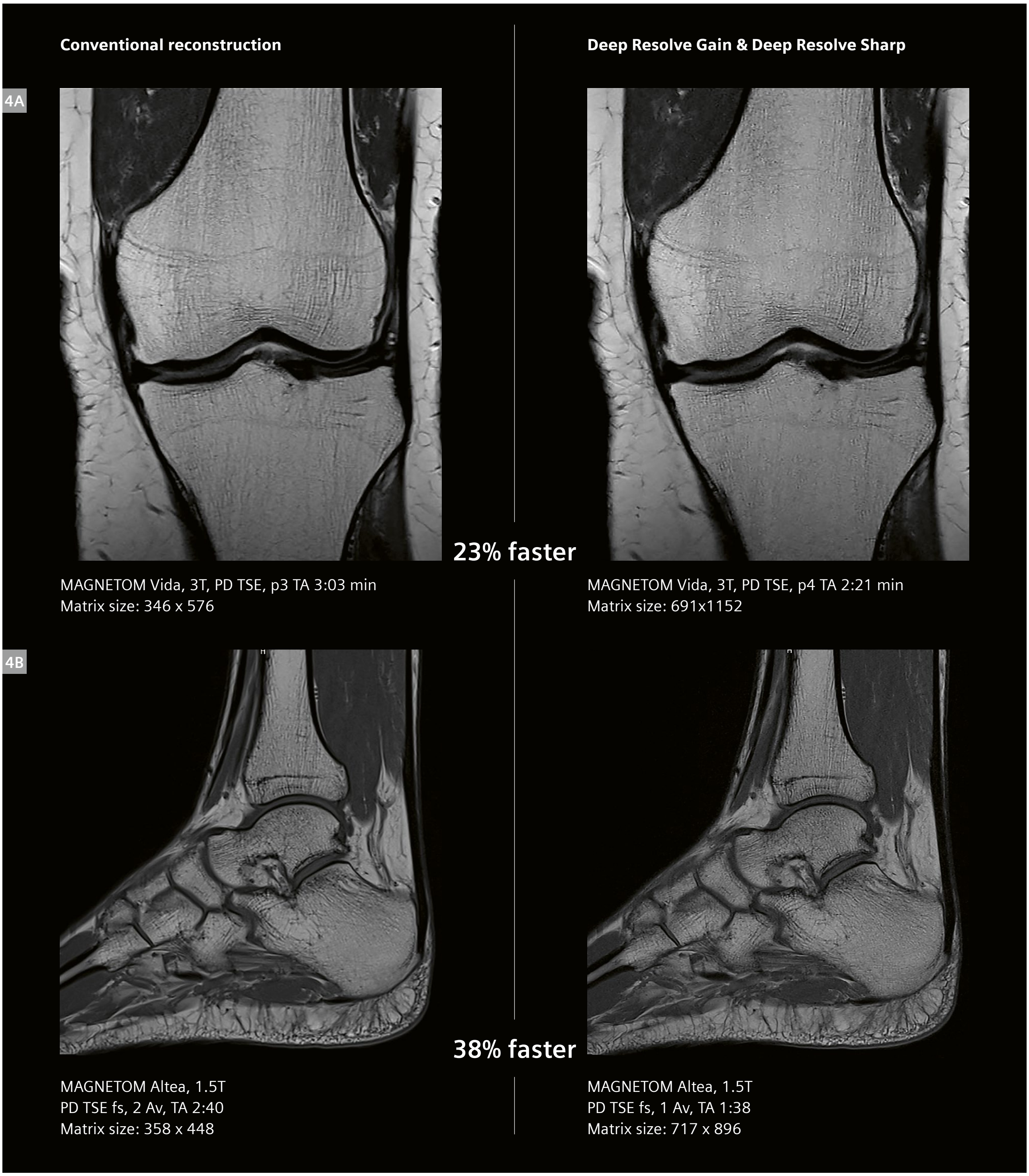
can also be used to enable quicker scans. The phase resolution can be reduced in the acquisition and Deep Resolve Sharp can be employed to recover the resolution in the reconstruction process.

In Figure 4 you can see how Deep Resolve enables accelerated acquisition while simultaneously increasing image quality and sharpness.



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4 Together, the Deep Resolve technologies enable faster acquisitions, while increasing the image sharpness simultaneously. The targeted denoising achieved with Deep Resolve Gain allows for the use of higher acceleration, while Deep Resolve Sharp increases the sharpness of the image by increasing the matrix size.

Technology corner

Deep Resolve Gain uses individual noise maps as input for an iterative reconstruction process. This iterative process, together with the noise maps as prior knowledge reflecting where more noise is to be expected in the image, enables an effective denoising in the reconstruction process. This is similar to the reconstruction process used in Compressed Sensing, extending it to cartesian 2D imaging. For Deep Resolve Gain, the denoising in every iteration step takes place in the wavelet-domain. Denoising in the wavelet domain is more efficient than denoising in image or frequency domain. It enables a better separation between noise and small structures that are part of the image to be reconstructed. The denoising strength of Deep Resolve Gain can be adjusted, depending on the amount of noise and personal preference.

Deep Resolve Sharp uses a deep neural network to increase the sharpness in reconstructed images. The convolutional neural network operates on complex data and enables a reduction of the voxel size by up to a factor of two along each in-plane axis compared to conventional reconstruction. During the reconstruction using Deep Resolve Sharp, the information content corresponding to the originally acquired raw data remains unaffected. Incorporating the acquired raw data along the reconstruction process ensures robust results and correct representation of image contrast. The deep neural network used in Deep Resolve Sharp is rather used to predict the contents of remote areas within *k*-space. Conventional reconstruction using interpolation expands *k*-space with zeros, therefore not adding any information or contributing to image sharpness. The deep neural network at the core of Deep Resolve Sharp, on the other hand, was trained with a large number of pairs of low- and high-resolution data. It can therefore enhance the image with meaningful information corresponding to the outer parts of *k*-space, beyond the originally acquired data.

Conclusion

Deep Resolve Gain and Deep Resolve Sharp introduce targeted, iterative denoising and deep learning reconstruction into clinical imaging. These technologies enable us to reduce acquisition times and improve image quality simultaneously. The unique inclusion of individual noise maps in an iterative reconstruction process enables intelligent, targeted denoising and Deep Resolve Sharp leverages the potential of deep learning reconstruction to achieve image resolutions beyond what is possible with conventional reconstruction methods. All this is done while including the acquired raw data along the entire reconstruction process, therefore ensuring robust and consistent results.

The potential of deep learning image reconstruction is immense, and current research is indicating a multitude of fascinating applications to come. Collaboration is key in MRI, so let us join our efforts in driving this exciting technology forward!

References

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