

The background of the advertisement features a stylized, glowing human head in profile, facing right. The head is composed of a series of vertical, wavy lines in shades of blue and green. The interior of the head is filled with a dense field of small, golden-yellow dots, which appear to be moving or pulsing, creating a sense of dynamic energy and data flow. The overall color palette is dominated by deep blues and greens, with the golden-yellow dots providing a strong contrast.

PHILIPS

SmartSpeed

Science brief

Philips SmartSpeed. No compromise.

Image quality and speed at your fingertips.

The need for speed and robustness

As the clinical utility of MR has increased, so has the pressure to efficiently scan more patients than ever. A reduction of scan time and examination time addresses to a large extent this need. Also from a patient, technologist, and radiologist perspective there is a big impact when scan and examination times are shortened. Solving this challenge while preserving diagnostic confidence for every patient

has been a key focus for Philips in the last decades. This path is continued with the introduction of Philips SmartSpeed. Its acceleration technology is applied not only to regular scanning, but covers a wide range of scans including diffusion weighted imaging, imaging near metallic implants and applications where motion often is hampering image quality. Hence, Philips SmartSpeed is designed to address the needs of every patient.

Philips SmartSpeed: the next generation in acceleration

Philips SmartSpeed builds upon Philips' track record in acceleration techniques. It leverages the strengths introduced with SENSE (coil sensitivity and background information) and Compressed SENSE (sparsity constraint) explained in figure 1. It brings them to the next level by expanding the proven Compressed SENSE technology, broadening its scope to previously untouched imaging protocols, and enhancing it with AI that is applied early on in the reconstruction process.

With the introduction of Philips SmartSpeed non-Cartesian sampling strategies can be combined with a reconstruction that take sparsity constraining into account. Furthermore, for 2D and 3D Cartesian acquisitions deep learning is integrated in the iterative reconstruction, namely during the coil element combination step.

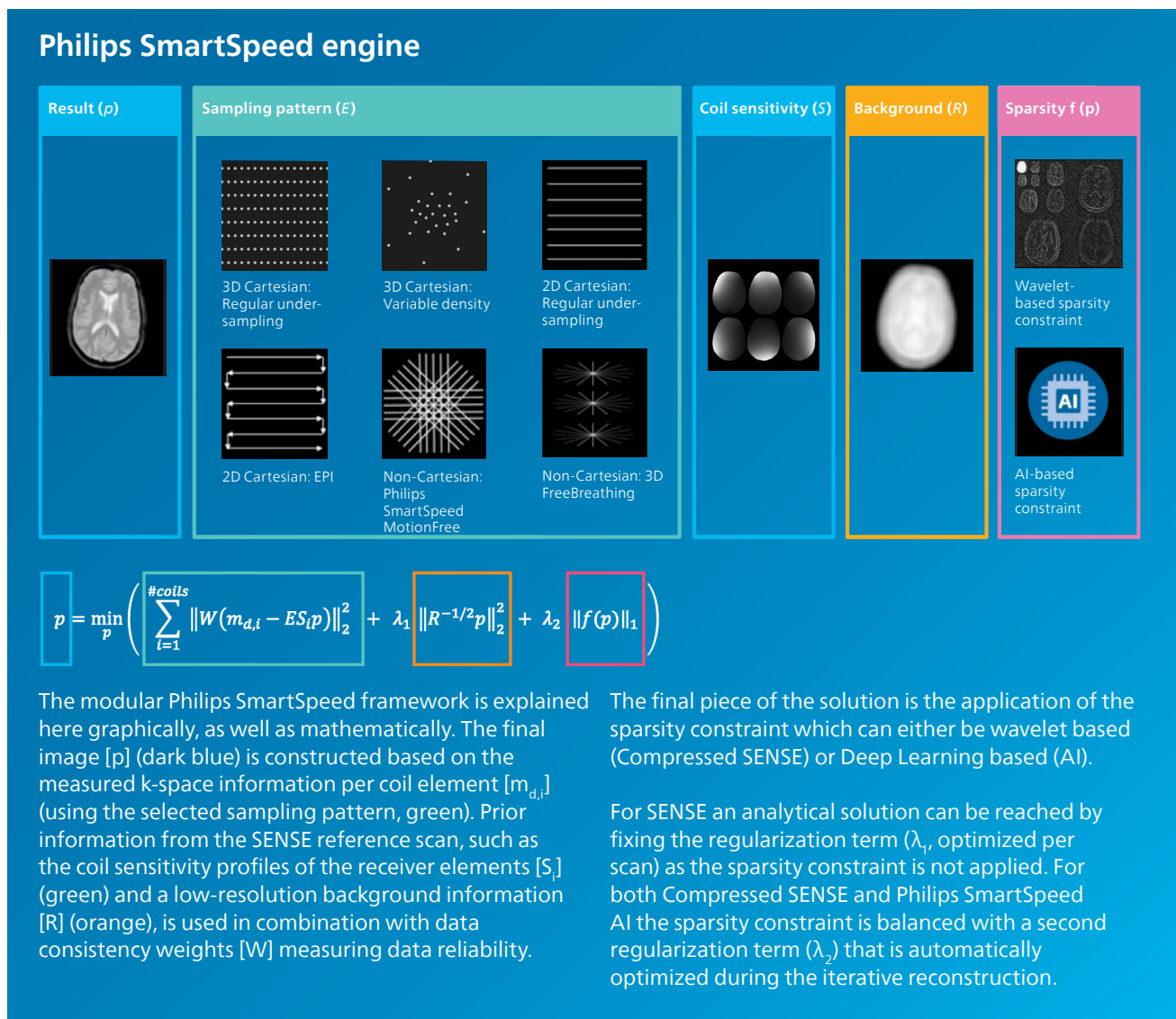
The Philips SmartSpeed engine has a modular framework with two key ingredients to accelerate:

- Acquisition of less data using dedicated data sampling patterns
- Smart reconstruction technology that allows the image quality from such a limited amount of data to be regained.

Using this technology, Philips SmartSpeed brings the following capabilities:

- **Philips SmartSpeed** integrates deep learning technology early on in the reconstruction pipeline for most of the commonly used sequences in all application domains
- **Philips SmartSpeed MotionFree** provides MultiVane multi-slice scanning for all contrasts across multiple anatomies
- **Philips SmartSpeed 3D FreeBreathing** applies to free breathing 3DT1w scans
- **Philips SmartSpeed Diffusion** implements sparsity constraining in diffusion-weighted imaging
- **Philips SmartSpeed Implant** enables imaging around metallic implants.

Figure 1



Adaptive-CS-Net deep learning technology applied at the beginning of the recon chain

Deep learning can be applied at multiple locations within the MR imaging chain ranging from calculating the sampling strategy and reconstructing the raw data, to post-processing of the images, see figure 2. The effectiveness of the deep learning algorithms depends on the goal and the location it is applied to:

1 Deep learning during post-processing:

AI applied at the end of the chain on the DICOM data has the advantage that it can be implemented as an additional post-processing step to any system having access to the images. However, information removed in the earlier steps of the reconstruction, e.g. phase information, is lost and can no longer be used.

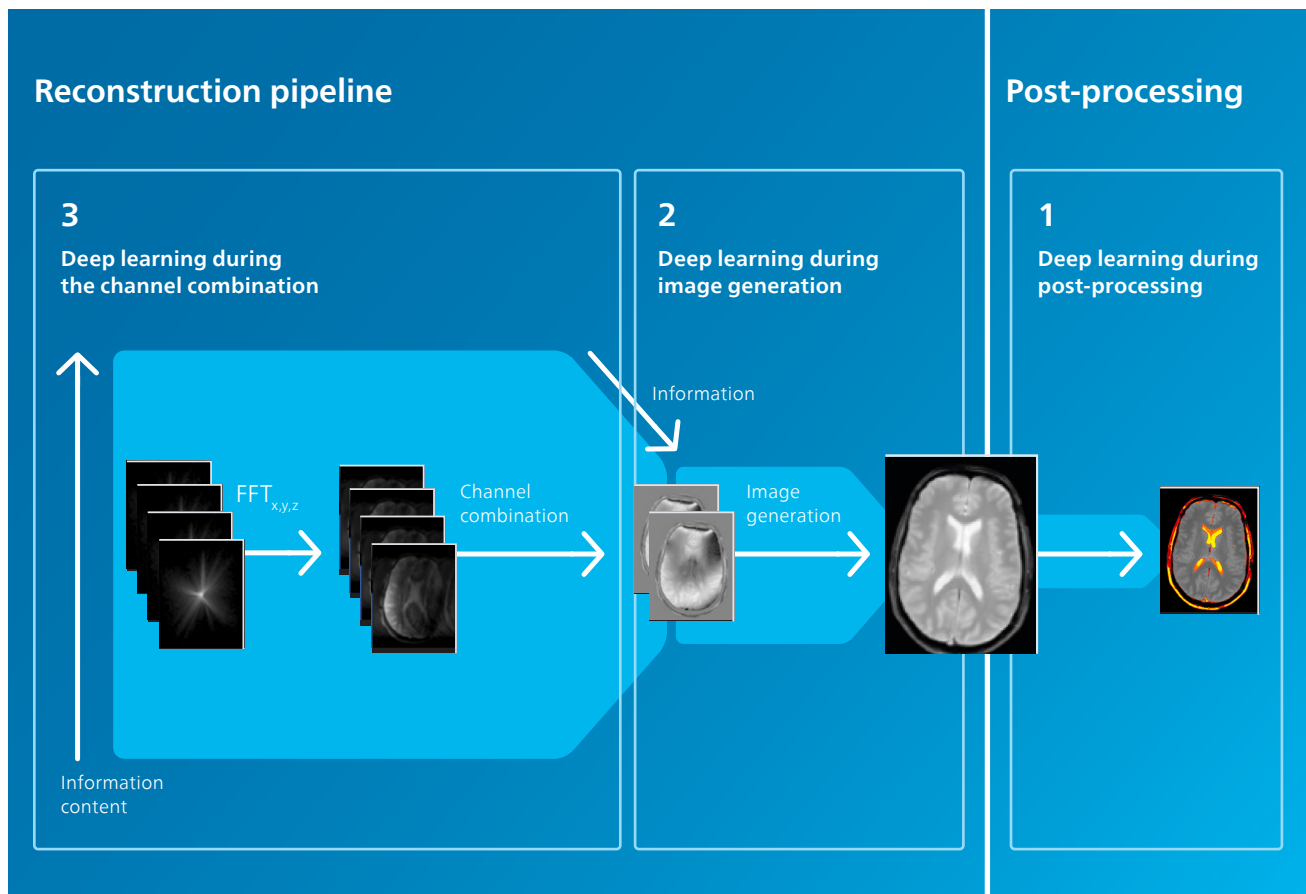
2 Deep learning during image generation:

AI algorithms that are applied to the complex imaging data do use the phase information, and allow iteration between the AI processed imaging data and the k-space data that is generated by the inverse Fourier transform of the coil element combined image. However, the raw k-space data of the individual coil elements is not available and can no longer be used in the optimization problem for e.g. data consistency checking in the iterative reconstruction.

3 Deep learning during the channel combination:

In Philips SmartSpeed, deep learning is applied during the coil element combination part of the reconstruction chain. This ensures the highest data consistency and signal fidelity. Deep learning used in Philips SmartSpeed is integrated into a proven acceleration framework of optimized sampling paradigms, multi-coil element input, and an iterative reconstruction with sparsity constraining. In its most basic view, the sparsity constraining step of the iterative reconstruction in Philips SmartSpeed is deep learning based. The applied convolutional neural network is trained for all contrasts and a wide range of acceleration factors. With the integration of the AI technology in the coil element combination step of the reconstruction, Philips SmartSpeed differs from the current industry norm, where deep learning technology is applied on complex imaging data or as a post-processing step.

Figure 2

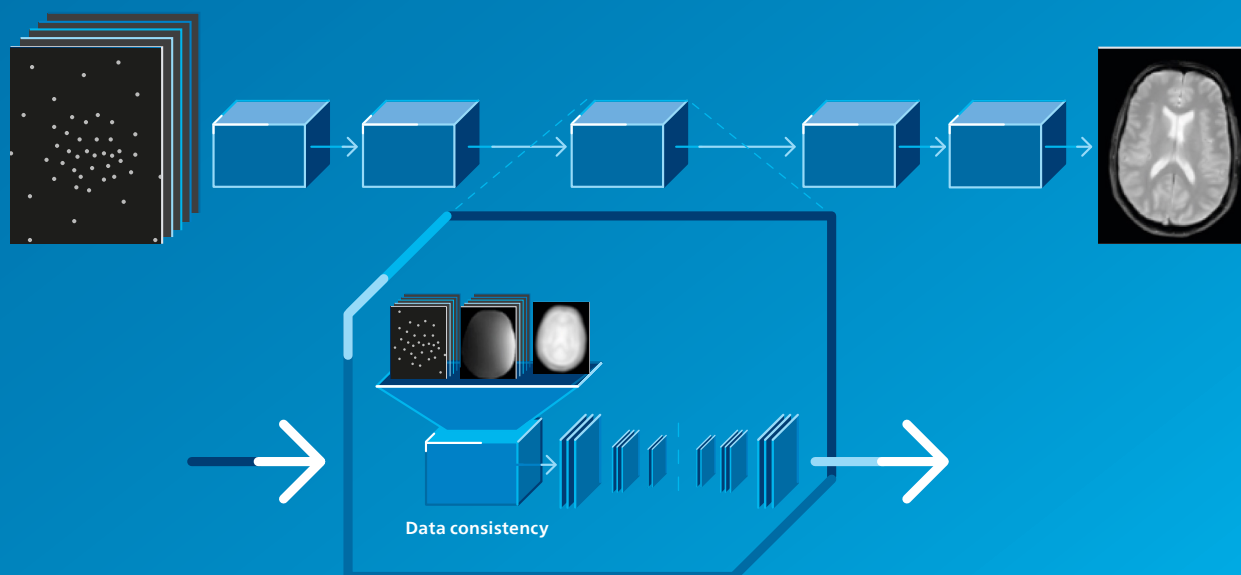


Adaptive-CS-Network topology

The Adaptive-CS-Net approach was first explored for the fastMRI knee challenge organized by New York Langone Health and Facebook AI Research. This network was scored best by a panel of seven independent readers in this challenge. It is a convolutional neural network that integrates and enhances the Compressed SENSE reconstruction by deploying a multi-scale network with integration of a data consistency term per coil element. This term is a key component to enforce that the reconstruction remains true to the acquired measurements. Furthermore, the network integrates priors like phase constraining and background information. Compared to the network implementation of the fastMRI challenge, which was focused on knee, the training is expanded to cover all application domains and contrasts for Cartesian 2D and 3D scans.

A diagram of the Adaptive-CS-Net is provided in Figure 3. The network is fed by raw k-space data, coil sensitivity data and coarse background information. All is rolled out over a set of connected, unique network blocks all consisting of a learned, multi-scale sparsifying transform on the residual. Data-consistency checking with the incoming raw k-space data is performed for each individual block. This was also done by all finalists of the challenge, demonstrating the importance of leveraging the data early in the reconstruction chain compared to techniques that rely solely on the reconstructed images or complex imaging data.

Figure 3



Johnson PM, Jeong G, Hammernik K, et al., Evaluation of the Robustness of Learned MR Image Reconstruction to Systematic Deviations Between Training and Test Data for the Models from the fastMRI Challenge. In: Machine Learning for Medical Image Reconstruction. 2021

