

AI for significantly lower dose and improved image quality

Precise Image

Overview

Philips Precise Image is a novel Philips approach that uses Artificial Intelligence (AI)* for images with an appearance that more closely resembles that of typical filtered back projection images while retaining the noise-reduction capabilities of advanced iterative reconstruction methods. This provides high-quality images with a familiar appearance, and at low dose.

Background

Filtered back projection (FBP) was the industry standard for CT image reconstruction for decades. While it is a very fast method, FBP is a suboptimal algorithm choice for poorly sampled data or for cases in which noise overwhelms the image signal, as is the case with low-dose or tube-power-limited acquisitions. Over time, incremental enhancements have been made to FBP to overcome some of its inherent limitations.

Philips previously introduced a hybrid approach (iDose⁴) and a model-based approach (IMR) to iterative reconstruction to help personalize image quality based on individual patient needs at low dose. When used



in combination with the advanced technologies of Philips CT systems, iterative reconstruction has provided a unique approach to managing important factors in patient care, such as imaging at low energy, low radiation

and low dose.

Traditional algorithms for iterative reconstruction typically penalize noisy images in some fashion, usually through a function of differences between neighboring voxels in the image. While effective in reducing noise, these penalty functions can produce an image appearance or noise texture that differs substantially from the appearance of traditional FBP images, which have been familiar to many radiologists over the years. This non-standard image appearance is a significant barrier to adoption of the technology for lowering dose across a range of clinical applications. While Philips IMR has addressed the computational burden of model-based reconstruction and its effects on reconstruction time, computational burden has

remained an issue for many manufacturers.

Now AI has provided the advances that make possible the next level of dose-reduction technologies, combining low dose with more familiar image appearance. AI deep-learning reconstruction is trained to quickly yield low-noise images from low-dose scans by comparing them to conventional-dose images in a supervised AI learning process. This supervised learning allows for an image with a noise texture that more closely resembles a typical FBP image, while retaining the noise-reduction capabilities of iterative reconstruction methods.

Precise Suite

Precise Image is one of the many AI-enabled tools of Philips Precise Suite, which includes AI that is deeply embedded into tools clinicians use every day to be able to apply their expertise to the patient, not the process.

How Precise Image **trains neural networks**

Precise Image follows a supervised learning process to train a convolutional neural network (CNN) in a specified manner.

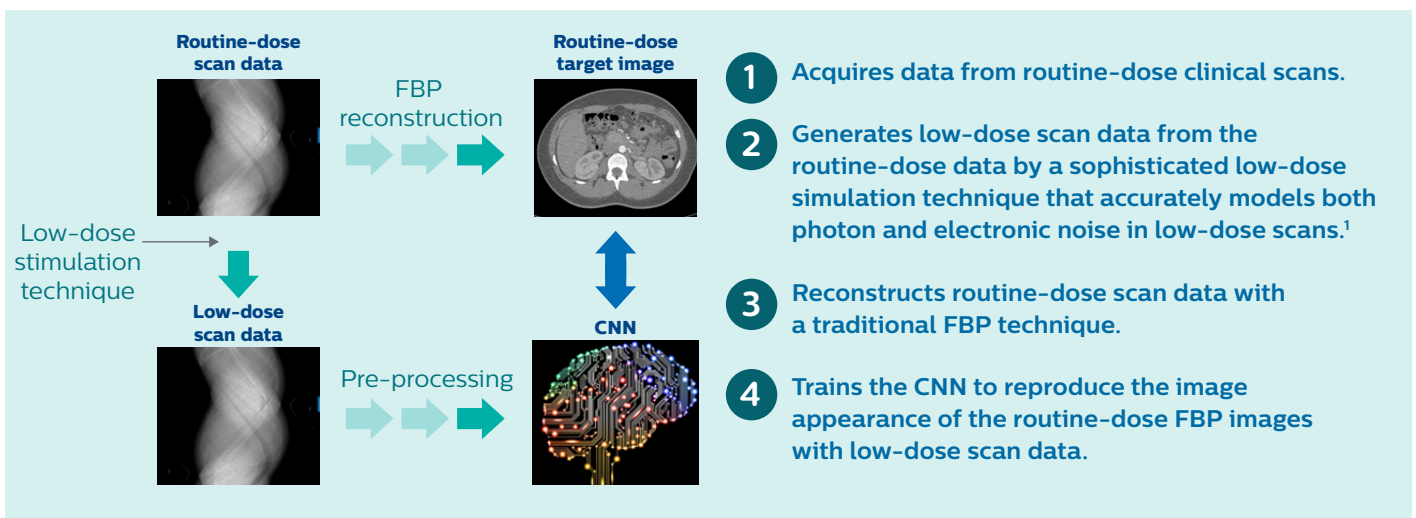


Figure 1 The training process for Precise Image AI reconstruction.

A closer look at deep learning

Deep Learning is a subcategory of machine learning and AI. A deep neural network (DNN) is an artificial neural network with artificial neurons or nodes arranged in multiple layers between the input and output layers of mathematical manipulation. Complex DNNs, such as those of Precise Image, have many layers and the ability to model complex non-linear relationships. The design of a DNN acts as the foundation that will allow the network to achieve its optimization target in an efficient manner. With Precise Image, the network was designed to address the specific challenges of image reconstruction and has optimized the number of nodes and layers within the network in a way that addresses the need for reduced latency and fast runtime while solving the complex optimization challenge.

Training the neural network

While a well-designed DNN presents a great deal of promise in solving complex optimization problems, it is important to realize that it is only as good as the training with which it has been provided. Correctly done, a supervised training strategy involves assembling a set of inputs and outputs that provide a sufficient sampling of the problem space to be solved. A well-reasoned and thorough approach at this point is critical for achieving robustness of the network. To train Precise Image neural networks, we begin with routine-dose scans with a clinically desired image appearance. From there, low-dose scan data is simulated in a way that accurately models both photon and electronic noise.

The network is then given the task of replicating the image appearance of the routine-dose images from the low-dose input. By training the networks in this way, they are more robust to the variety inherent in CT from factors such as applied radiation dose, patient size and patient anatomy.

Validating the neural network

Trained Precise Image neural networks are validated using patient data obtained with a variety of scan parameters from a diverse population. Philips begins by providing low-dose data simulated from routine-dose scans as input to the neural networks. The resulting low-dose images of Precise Image are compared to routine-dose images reconstructed using standard methods. When image quality of low-dose images of Precise Image meets or exceeds routine-dose standard reconstructions, sufficient training of the neural network is confirmed.

Inference allows for fast clinical workflows

Once networks have been trained, the weights of the nodes and layers of the DNN are fixed. This means new inputs in the form of patient data can be rapidly processed to support high-throughput clinical workflows with the improved diagnostic confidence delivered by Precise Image. With the smart design of the network as the foundation and the robust training complete, Precise Image delivers the fastest AI-based reconstruction in the industry.

AI-enabled image reconstruction

Philips Precise Image is the newest, most robust method of Philips CT image reconstruction, using recent technological leaps in AI. Precise Image is a reconstruction technique that uses a trained deep-learning neural network. Precise Image offers the industry's fastest reconstruction speed while maintaining the conventional appearance of FBP images.

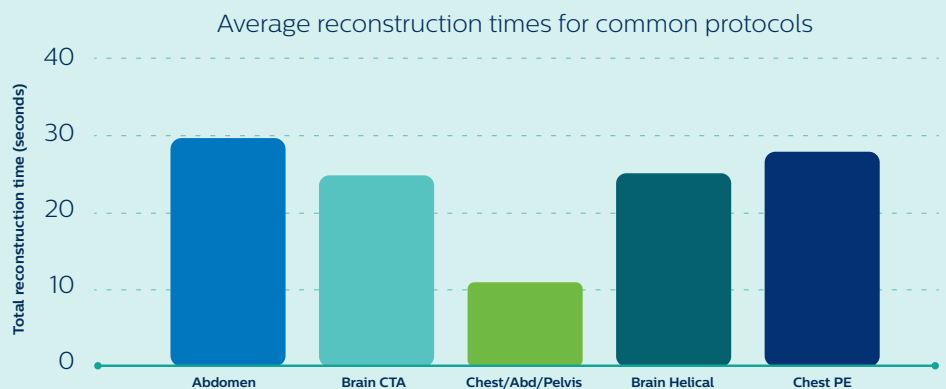


Figure 2 Precise Image allows for average reconstruction times of 30 seconds or less for common protocols.

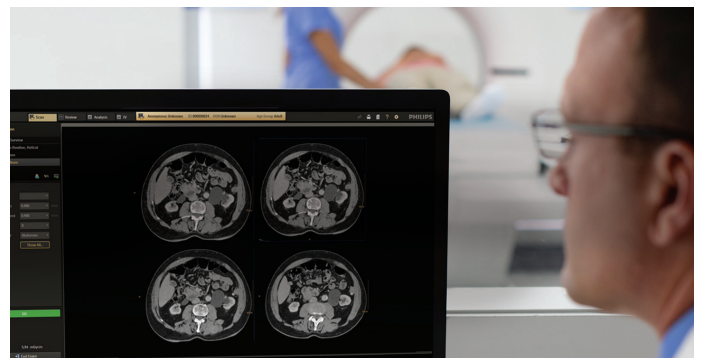
Going **beyond phantom studies** to clinical data

Philips Precise Image has been extensively tested on both phantom and clinical data. Many general image quality metrics are computed using phantom images. However, Precise Image uses primarily clinical images in the training procedure, rather than phantom images, to ensure that networks are not trained to simply give good results on performance phantoms, but to provide improved clinical images. Nevertheless, these clinical benefits can also be measured on traditional phantoms with excellent results, as shown in the following sections.

Noise-power spectrum

A common complaint with iterative reconstruction images is that the noise texture differs significantly from FBP images. Precise Image is trained to reproduce the noise texture of FBP, while at the same time delivering significant noise reductions. An established metric for quantifying noise texture is the noise-power spectrum (NPS). For this measurement, a 30 cm water phantom was scanned at 300 mAs, and again at 100 mAs. Images for Precise Image were generated from the 100 mAs scan with increasing noise reduction to create images with high image quality and reduced noise. A series of normalized NPS values were then computed for each of the images for Precise Image, as well as for the high-dose FBP image (**Figure 3**).

A nearly constant normalized NPS can be maintained with Precise Image – regardless of the magnitude of the noise reduction – that closely matches the NPS given by FBP reconstruction. Thus, image noise texture can be customized to closely match that of FBP images, even for low doses and strong levels of noise reduction (**Figure 4**).



NPS curve

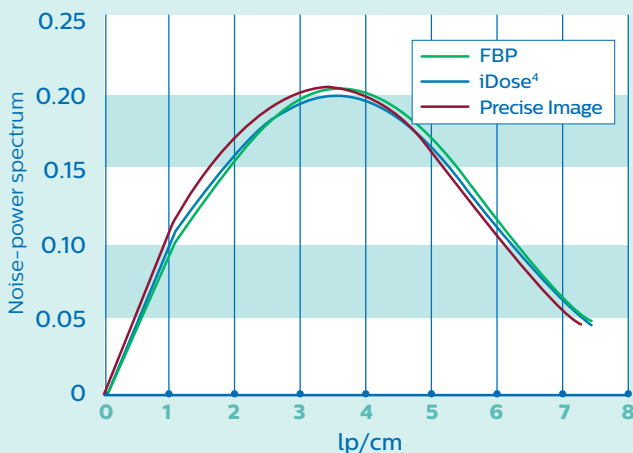


Figure 3 Normalized noise-power spectrum measurements from a 30 cm water phantom.

MTF curve

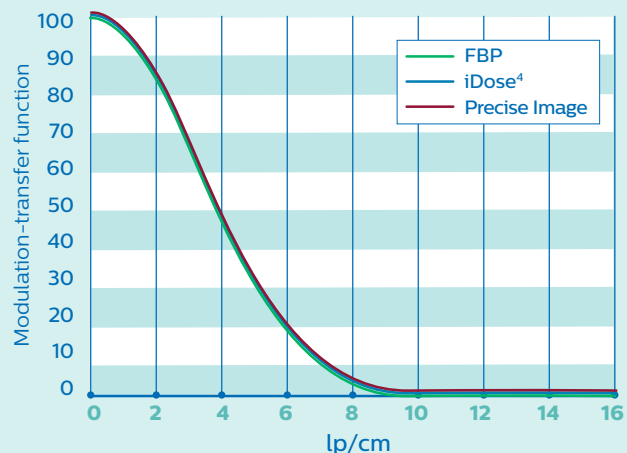


Figure 4 Resolution expressed as modulation-transfer function comparison of FBP and AI-enabled reconstruction.



Low-contrast detectability

A low-contrast detectability (LCD) test is an established method for measuring the dose reduction capabilities of reconstruction algorithms. A human or model observer is presented with many different noisy images, some containing a known low-contrast object and some with no object present, and for each image the observer must decide if the object is present or not. Success at making the correct determination for each noisy image is measured, and these scores can be used to derive a detectability index (d-prime) that reflects the statistical success of detecting the object with a given dose and reconstruction method. A d-prime = 0 corresponds to no better than random guessing (AUC = 0.5), while a d-prime = 4.38 corresponds to nearly perfect detectability (AUC = 0.999). "AUC" is the area under the receiver operating characteristic curve and is a measure of how well a system can discriminate between two categories.

The LCD test for Precise Image uses the MITA low-contrast phantom CT 189 and focuses on the 10 mm diameter, 3 HU contrast pin. The model observer is a channelized Hotelling observer (CHO) with 3-DOG channels, as described in the IQmodelo tool.² We use 200 image pairs (object present, object absent), and compare the d-prime of FBP at a dose of 10 mGy to Precise Image at 4 mGy and 2 mGy (60% and 80% dose reduction, respectively). Example images can be compared.

Results of the LCD test show detectability with Precise Image at 4 mGy is more than 80% better than FBP at 10 mGy. Detectability with Precise Image at 2 mGy is more than 43% better than FBP at 10 mGy. This test shows that with Precise Image, users can get both significant dose reduction and greatly improved low-contrast imaging at the same time, all while retaining a more traditional noise texture than with other recent reconstruction techniques.

Clinical studies and example images

A team of experienced radiologists reviewed images of the chest, abdomen and pelvis from 40 patients using iDose⁴ and Precise Image. Both image sets for each patient were rated for diagnostic confidence, sharpness, noise level, image texture and artifacts on a 5-point Likert scale, where 1 was the worst and 5 was the best. All scans were performed at routine dose levels, and iDose⁴ images were reconstructed at the acquired dose. Images using Precise Image were reconstructed at 50% of the routine acquired dose using low-dose simulation techniques.

For each attribute assessed, ratings from the two image sets were compared using a two-sample Welch's t-test ($\alpha=5\%$) to check for statistically significant differences in the ratings. Results showed an improvement in each attribute with images from Precise Image reconstructed at 50% of the acquired dose (**Figure 6**).

Precise Image improves diagnostic confidence at half the dose

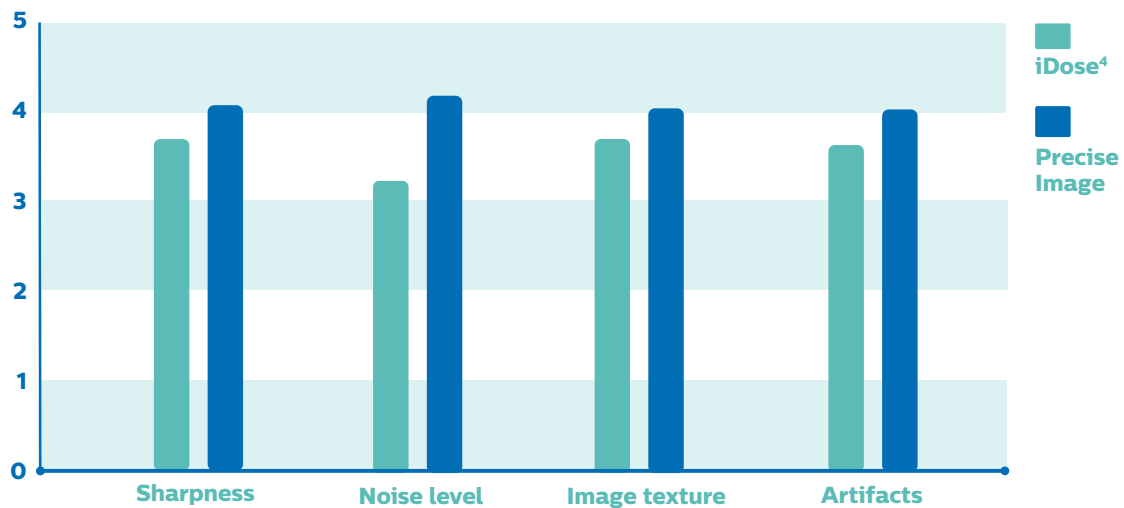


Figure 6 Image-quality ratings for Precise Image reconstructed at 50% of the routine dose were higher than those for iDose⁴ images reconstructed at 100% of the routine dose.

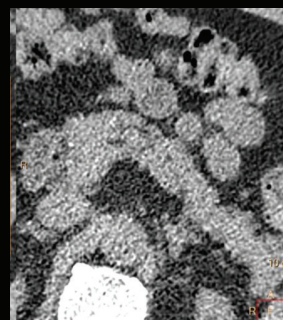
Clinical image comparisons



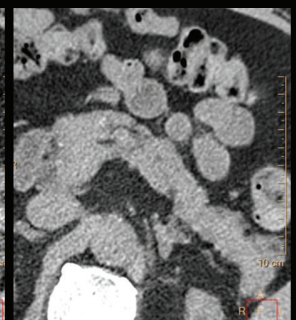
iDose⁴ 7.4 mSv



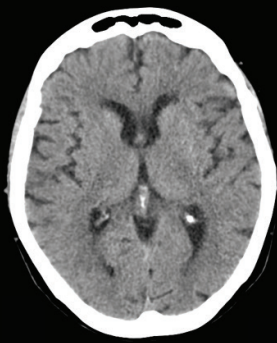
Precise Image 3.7 mSv



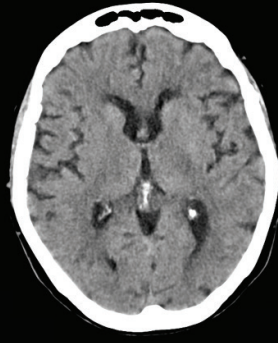
iDose⁴ 6.6 mSv



Precise Image 3.3 mSv



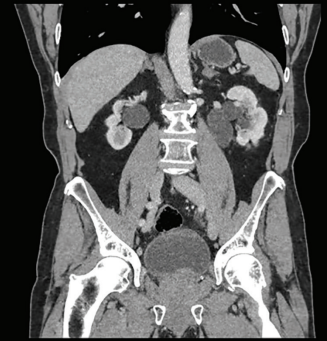
iDose⁴ 1.4 mSv



Precise Image 0.7 mSv



iDose⁴ 5.1 mSv

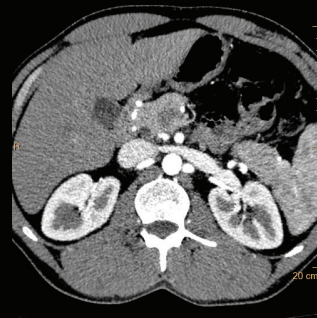


Precise Image 2.6 mSv

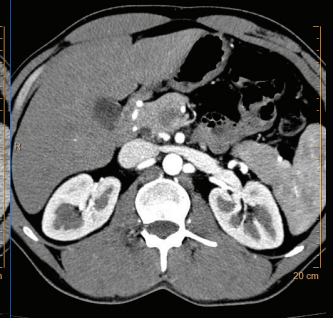


iDose⁴ 1.5 mSv

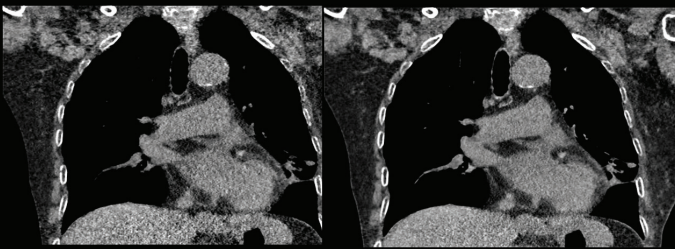
Precise Image 0.75 mSv



iDose⁴ 5.4 mSv



Precise Image 2.6 mSv



iDose⁴ 1.8 mSv



Precise Image 0.8 mSv



Precise Image CTA



Conclusion

Precise Image offers a significant advance in the speed of CT image reconstruction at low dose, producing images with a noise texture that more closely resembles a typical FBP image. Results of the clinical evaluation demonstrated that images reconstructed with Precise Image offer a significant advance in CT image reconstruction at half the dose, compared to iDose⁴ images.



*We embrace the following formal definition of AI (source: HLEG definition AI) Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal.

AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behavior by analyzing how the environment is affected by their previous actions. As a scientific discipline, AI includes several approaches and techniques, such as machine learning (of which deep learning and reinforcement learning are specific examples), machine reasoning (which includes planning, scheduling, knowledge representation and reasoning, search, and optimization), and robotics (which includes control, perception, sensors and actuators, as well as the integration of all other techniques into cyber-physical systems).

References

1. Žabic S, Wang E, Morton T, Brown KM. A low dose simulation tool for CT systems with energy integrating detectors. *Med Phys.* 2013;40(3):1–14. DOI: 10.1118/1.4789628.
2. Wunderlich A, et al. Exact confidence intervals for channelized Hotelling observer performance in image quality studies. *IEEE Trans Med Imaging.* 2015;34.2:453–464. DOI: 10.1109/TMI.2014.2360496. PMID: PMC5542023.

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