Advanced intelligent Clear-IQ Engine (AiCE) Deep Learning Reconstruction: Whole organ coverage with extraordinary image quality at the fast pace of medicine

Kirsten Boedeker, PhD, DABR
Senior Manager, Medical Physics
Canon Medical Systems Corporation

Introduction

A form of Artificial Intelligence (AI) called Deep Learning is the driving force behind the next leap forward in the evolution of Computed Tomography (CT) image reconstruction, creating extraordinary image quality to aid the clinician in diagnosis. The AiCE Deep Learning Reconstruction (DLR) algorithm brings together the best features of previous reconstruction approaches to quickly produce high quality anatomical images at low doses. The field of CT reconstruction began with simple Filtered Backprojection (FBP), in which the measured projection data from each position around the patient are first filtered and then backprojected, i.e. "smeared" back along a matrix, to form an image. The simple process yielded excellent noise texture but the noise magnitude levels required large patient doses. Hybrid iterative reconstruction algorithms, which act in both the image and raw data domains, reduced noise and associated dose but generally diminished noise texture and resolution. Fully iterative reconstruction methods, utilizing a forward projection step in each iteration, improved resolution to levels beyond even FBP but diminished image texture at low doses and the long reconstruction time hampered clinical workflow. Today, AiCE DLR combines the image quality benefits of fully iterative reconstruction approaches with the speed of earlier reconstruction methods to quickly produce images with superb low contrast detectability, low noise, excellent high contrast spatial resolution, and a noise texture more like FBP in comparison to FIRST (Forward projected model-based Iterative Reconstruction SoluTion).

AiCE achieves its results through Deep Learning, a subfield of machine learning that represents the state-of-the-art in the field of AI. Deep learning takes advantage of multi-layered artificial neural networks to produce results that have taken the AI world by storm—outperforming even humans at tasks such as object recognition. In fact, deep learning has opened the door to a host of applications that are solving complex problems in our daily lives, from the navigation systems in our cars, to near-instant language translation applications on our phones, to automatic photo recognition and labelling on social media and much more. Unlike conventional algorithms that are constrained by pre-programmed rules for performing a complex task, deep learning occurs when a neural network learns from its own intensive training process and develops its own logic structure. AiCE features a deep learning neural network that can differentiate signal from noise. AiCE retains and enhances signal, while reducing the noise, to create extraordinary, high quality images at a reconstruction speed fast enough to keep pace in a busy clinical setting. Together, AiCE and the Aquilion ONE GENESIS bring the power of Deep Learning and full organ, single rotation coverage to everyday use in the clinic, putting the future of CT in your hands.

Aquilion ONE / GENESIS Edition

The Aquilion ONE GENESIS CT system features 320 detector rows of 0.5 mm thickness. The resulting 16 cm of coverage permits whole organ coverage of the heart and brain in a single rotation, in addition to a host of advantages for pediatric imaging. The Aquilion ONE GENESIS was the first Canon Medical system to feature PUREViSION Optics (PVO) filtration and detection technology. PVO was designed to optimally handle low photon flux associated with both large patients as well as the reduced radiation doses made possible with improvements in reconstruction. The Aquilion ONE GENESIS sends 40% more light to the photodiode than its predecessor, the first-of-its kind 16 cm wide area detector Aquilion ONE CT system. The Aquilion ONE GENESIS with PUREViSION Optics demonstrates improved low contrast detectability, reduced streak artifacts, and reduced quantum and electronic noise for low dose acquisitions. In fact, PUREViSION Optics improves low contrast by 12-22% at the same radiation dose compared to the original Aquilion ONE system. In addition, the Aquilion ONE GENESIS reduces noise magnitude by 10-14% at the same dose compared to its predecessor. AiCE DLR is able to build on this efficient hardware foundation to further improve image quality, creating a system ideally suited for low flux at the detector.

Workflow efficiency: Achieving the speed you need in a busy clinical environment

During engineering development, the AiCE DLR algorithm is taught to produce high signal-to-noise ratio (SNR) images through an intense training process. AiCE learns to differentiate signal from noise by training on select, high quality patient data sets acquired with high tube current and reconstructed with all the benefits of Model-Based Iterative Reconstruction (MBIR) —including sophisticated system and noise models as well as a large number of iterations, a process too time intensive to be used clinically. Because this time-consuming training process is completed before leaving the factory, the fully-trained AiCE DLR is able to work quickly in the clinic, reconstructing 16 cm volume acquisition in about 35 seconds. This rapid reconstruction allows the clinician to take advantage of the benefits of Deep Learning, which by design incorporates the sophisticated modelling utilized in MBIR, in a time-efficient manner: working at three to five times the speed of MBIR reconstruction, AiCE is making the benefits of Deep Learning Reconstruction for whole organ coverage an everyday reality.

Like Canon Medical's iterative reconstruction algorithms, AiCE is also fully integrated into the SUREExposure mA modulation system. The system automatically adjusts each individual patient's mA profile based on the associated benefits and dose reduction abilities of AiCE reconstruction. AiCE DLR is available in three straightforward settings, Mild, Standard, and Strong, making the application of AiCE simple and easy-to-use.

Noise and low contrast detectability

AiCE DLR is able to dramatically decrease the magnitude of noise in an image, improving low contrast detectability. The most challenging test object in a standard Catphan® low contrast detectability module is a 2 mm diameter, 3 HU contrast object. However, in order to adequately challenge the AiCE DLR algorithm, Canon Medical needed to work with the phantom manufacturer to create a custom Catphan phantom that included a new, more challenging test object of 1.5 mm diameter and 3 HU contrast (Figure 1).

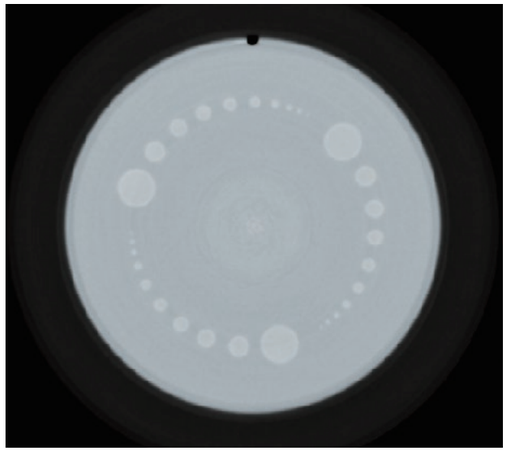

Figure 1 AiCE DLR has an LCD specification of 1.5 mm, 3 HU object detection at 22.6 mGy CTDI, an industry-first specification.

The low contrast detectability performance of AiCE is demonstrated in images shown in Figure 2 which shows a mixed lesion in the left anterior descending artery. The calcified and non-calcified components can be clearly identified.

In addition to low noise magnitude and excellent low contrast detectability, AiCE DLR images have a noise texture that is visually pleasing and more similar to traditional FBP. It is important to note that while AiCE DLR is trained with MBIR data to learn signal properties, AiCE DLR has its own distinct noise texture. The noise texture generated by AiCE DLR is improved relative FIRST, Canon Medical's fully iterative reconstruction algorithm, and through human observer studies has been shown to be closer in appearance to the gold standard, classic FBP noise texture. Compare the clinical images in Figure 3, which show improved, more visually appealing texture in the liver with AiCE relative to FIRST. Like FIRST, AiCE DLR is able to reduce radiation dose by up to 82.4% compared to FBP but does so while retaining better noise texture.

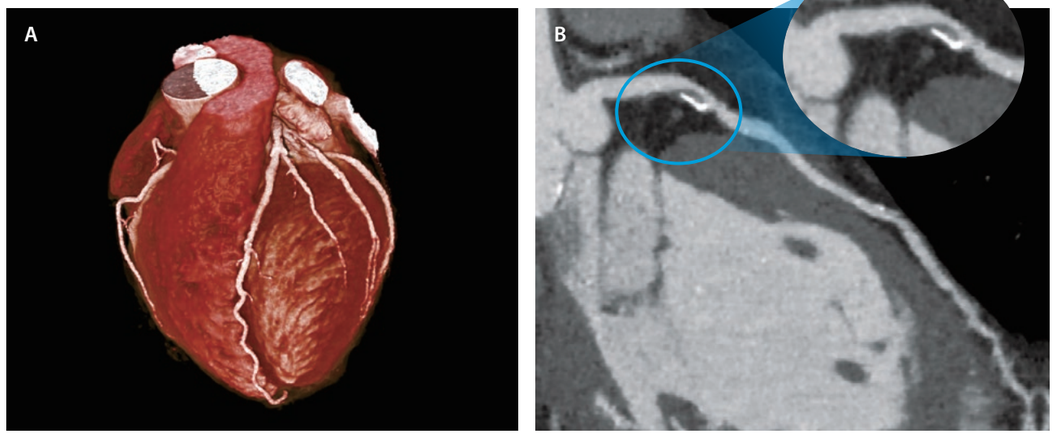

Figure 2 Cardiac CT Angiogram demonstrating a mixed lesion in the LAD. The calcified and non-calcified components can be clearly identified.

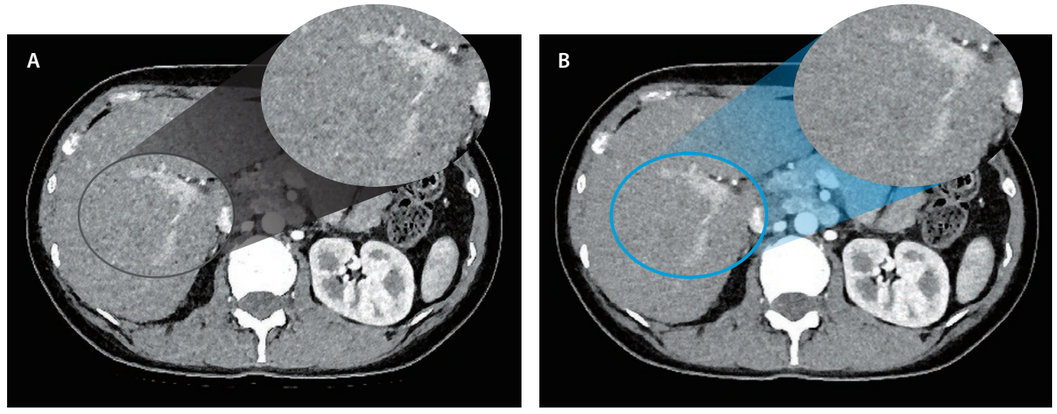

Figure 3 Clinical image comparison. (A: FIRST Image, B: AiCE Image)

Spatial resolution

Because AiCE is trained on images of the highest quality using MBIR reconstruction, AiCE DLR learns to preserve edge and maintain image detail, which is particularly important for lung and cardiac scanning.

Compare the MTF below for AiCE Cardiac Mode relative to its Adaptive Iterative Dose Reduction (AIDR) 3D for Cardiac Mode, achieved with an accompanying decrease in noise magnitude of 5% (Figure 4).

For Lung imaging, AiCE preserves high contrast spatial resolution in a manner similar to AIDR 3D for Lung, but with half the noise magnitude. Notice the detail preserved in the chest images below in Figure 5 and low noise compared to the corresponding AIDR 3D reconstruction.

Looking to the future with the Aquilion ONE / GENESIS Edition and AiCE DLR

Full organ coverage scanning combined with DLR will continue to expand the role of CT in the diagnosis of a wide assortment of clinical presentations. Clinical applications such as lung, cardiac, pediatric and adult abdominal scanning are all expected to benefit from AiCE DLR.

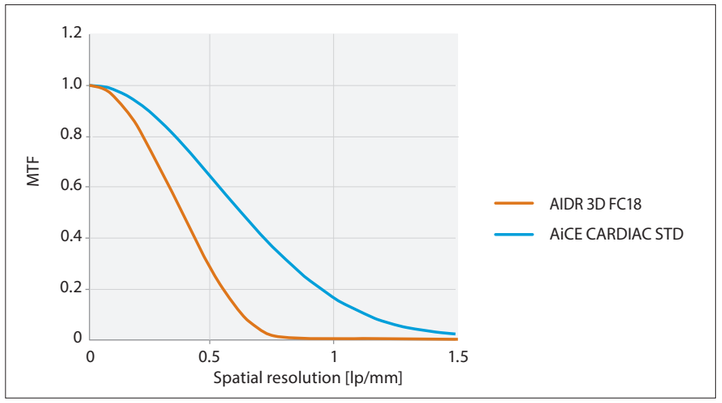

Figure 4 MTF

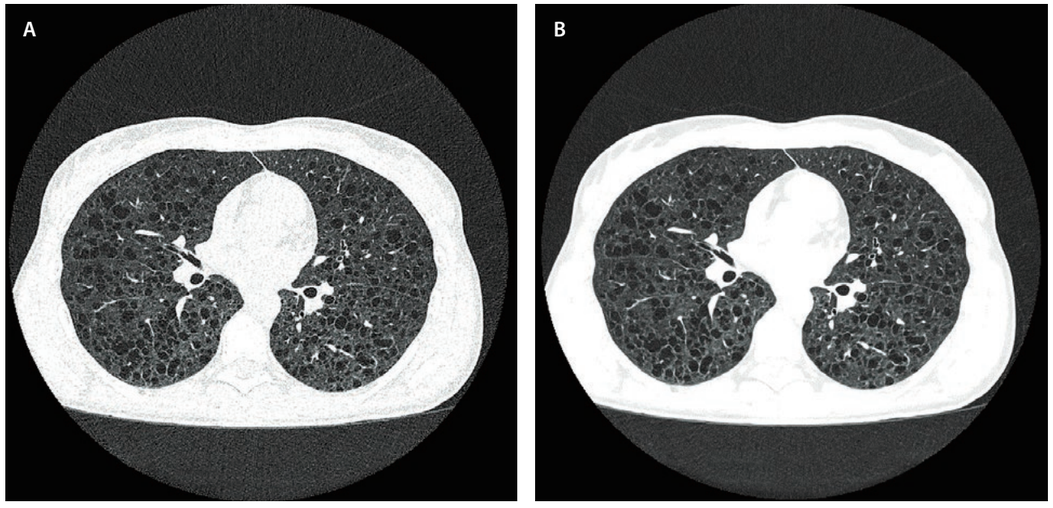

Figure 5 Chest image comparison. (A: AIDR Image, B: AiCE Image)

Advanced intelligent Clear-IQ Engine (AiCE) DLR: How does it all work?

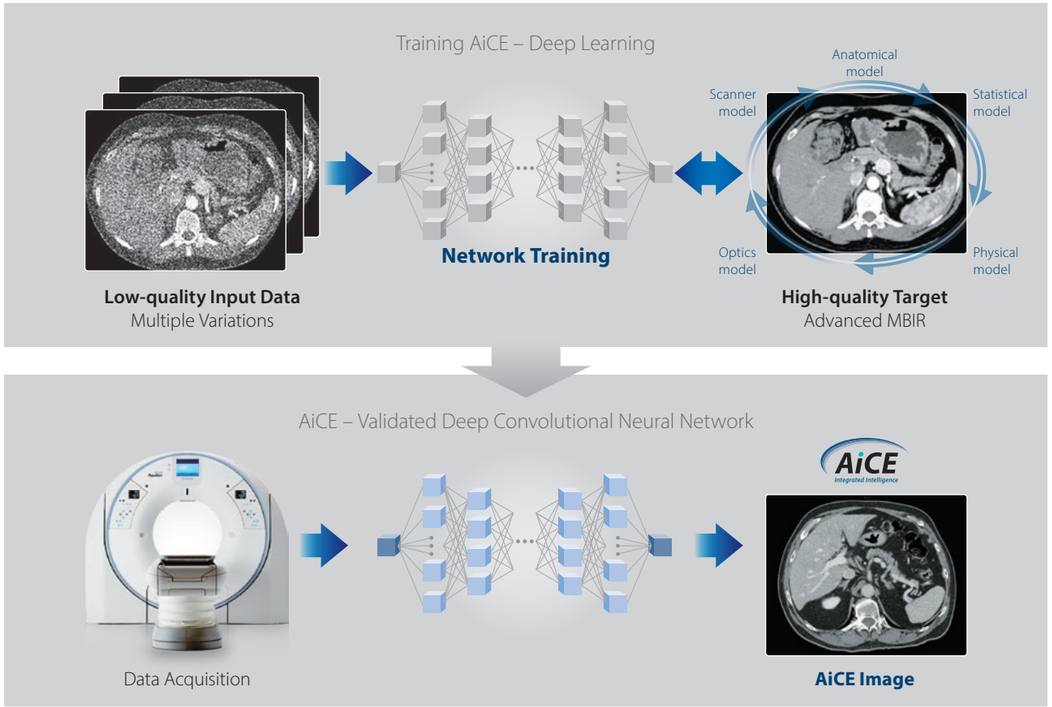

Figure 6 Overview of AiCE Deep Learning Reconstruction: The AiCE DLR is trained with high quality, advanced MBIR Target Images and learns to turn low quality input data into low noise images that are sharp and clear. In the clinic, AiCE DLR operates in the raw and image domain to efficiently reconstruct images.

Deep learning overview

Deep learning, the latest in AI, has been successfully applied to such tasks as image recognition, segmentation and classification. With deep learning, a Deep Convolutional Neural Network (DCNN) comprised of layers of neurons is trained in the performance of a complex task. A neuron is a node where a mathematical operation takes places, the output of which is connected with other neurons, forming a network. The neural network derives its name from the neuron-synapse paradigm found in biology and mimics how humans draw conclusions, based on learning from examples. This ability to learn via a deep neural network gives the deep learning algorithm the freedom to find the optimum way to perform the desired task. DCNNs have shown extraordinary performance at image classification tasks, erupting onto the artificial intelligence scene in 2012 by winning the ImageNet challenge--skillfully classifying one thousand object types from over one million images. A basic DCNN structure is illustrated in Figure 7.

Advanced intelligent Clear-IQ Engine (AiCE) DLR: Training

The key to a successful DCNN lies in its training, the process by which the DLR learns how to successfully perform its function. The network must compare its output image to a gold standard reference image in order to gauge its performance and learn, i.e. adjust the weights of its neurons. In order to do this the DCNN uses a mathematical loss function to determine the amount of error between its output and the reference datasets. In the case of AiCE, the gold standard clinical reference images are acquired with high tube current and reconstructed with true MBIR reconstruction, which takes into account modelling of the system optics, system physics, scanner statistical properties and human anatomy, and uses a greater number of iterations than could be otherwise used in a clinical setting due to time constraints. Using the estimation of error between the output of the DCNN and the gold standard, the DCNN backpropagates the error estimate through the network and adjustments are made to the neuron's weights in order to reduce the discrepancy. This input-forward, error-backpropagation process is iteratively repeated until the network is optimized. In order to ensure optimal results, millions of image patches were used in the training of AiCE DLR. This complex training process is completed in development with no off-site unsupervised training, which could alter algorithm performance, taking place.

In order to make sure AiCE DLR is robust in low dose situations AiCE's training included low quality data sets, used to teach AiCE how generate high quality images from low quality images while preserving signal and spatial resolution across the clinical spectrum. The algorithm was tested with independent validation datasets, to ensure wide applicability of the algorithm and avoid a phenomenon in machine learning known as overfitting, which occurs when an algorithm is too finely tuned to the training data to be robust against new inputs. Thousands of phantom and patient images were examined by medical physicists and radiologists in the development of the AiCE DLR reconstruction algorithm.

A question that is often asked by clinicians on the topic AiCE DLR training is "what happens when I scan a patient that has pathology not contained in the training set?" The answer is this scenario will not present a problem for AiCE DLR. The training that AiCE DLR undergoes teaches it simply to distinguish signal from noise, not to identify specific anatomy or pathology within the dataset. The features the neural network learns in order to recognize signal are generalizable, i.e., common to signal in general. To demonstrate this, a completely foreign signal—the face of gorilla—was artificially inserted into the raw data of an abdominal dataset. Figure 9-A shows the FBP reconstruction of this dataset while figure Figure 9-B shows the corresponding AiCE reconstruction of this dataset. AiCE DLR recognizes the gorilla face as signal and preserves it, while greatly reducing the noise in the image.

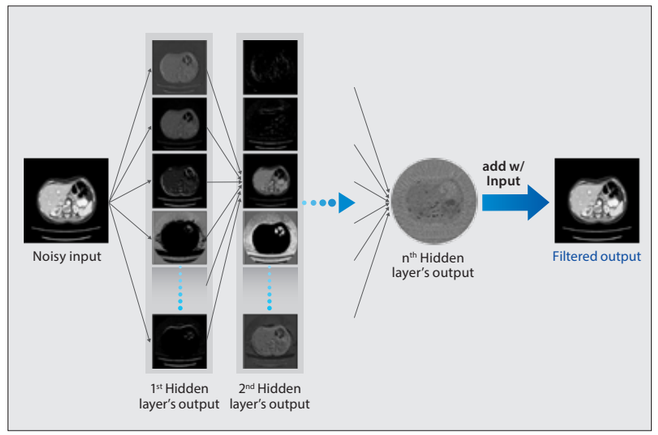

Figure 7 An illustration of a simple neural network consisting of layers of neurons working together to perform a task.

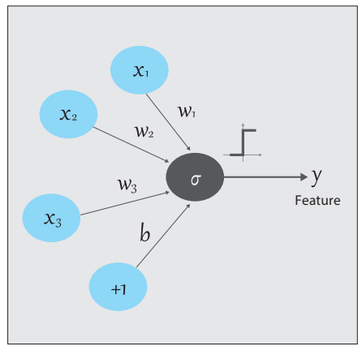

Figure 8 The structure of a basic neuron. A neuron will adjust the weighting factors (w) of its associated feature as it learns. The activation function (sigma) gauges the strength of the neuron response.

Inside AiCE DLR

The AiCE DLR applies the extraordinary classification abilities of a DCNN to the task of differentiating noise and signal in CT images to generate a high quality image for clinician interpretation. The AiCE reconstruction process begins in the raw data domain where AiCE analyzes the raw data and, armed with detailed scanner model information, makes modifications. These modifications in the projection domain improve output SNR and reduce artifacts, such as streaks. This raw data is then initially reconstructed to form a seed image, known as the "input layer", to the DCNN.

Once the input image is fed into the DCNN, it is analyzed by several network layers referred to as "hidden layers." The hidden layers of a DCNN contain convolutional layers, in which the component neurons act as feature selectors on small patches of data. In a traditional heuristic algorithm explicit image features, such as a curved edge, would be pre-selected by the programmer and "convolved," i.e., filtered, with the image data. During the deep learning process, each neuron in a convolutional layer learns what features to look for based on the training data. AiCE's DCNN has thousands of neurons, thoroughly sampling feature space. The network "learns" image features and their level of importance by adjusting the parameters, known as weight and bias, utilized by each neuron in the convolutional layer.

The output of the convolutional layer is the fed into an "activation layer." In biology, a neuron only fires when the input to it surpasses a threshold. Similarly, the activation layer in a DCNN serves an analogous purpose in that, based on the strength of a neuronal response to the input data, the activation layer determines which neuron responses will pass to the next layer in the DCNN. After passing through all the hidden layers of the AICE neural network, the signal and noise are separated and a signal image, known as the output layer, is generated for the user.

One key to a successful DCNN lies in its network structure design, which impacts both image quality and reconstruction speed. To achieve the best computational efficiency and improve output image quality, network structure factors such as number of network layers, number of neurons in each layer, convolution kernel sizes, etc, were fully optimized in the AiCE algorithm. Elegant acceleration strategies and memory management technologies were carefully designed and integrated in the system to fully utilize hardware capabilities and maximize reconstruction speed.

Putting the future in your hands

Integrated, effective, and easy-to-use, AiCE DLR brings the power of deep learning to wide volume CT. The raw data domain aspects of AiCE DLR combined with the ability of the deep convolutional neural network to differentiate signal and noise leads to improvements in noise, low contrast detectability, and spatial resolution preservation, generated with high speed reconstruction. AiCE DLR both improves routine imaging and provides new opportunities for advancement in patient diagnosis and clinical applications with whole organ coverage.

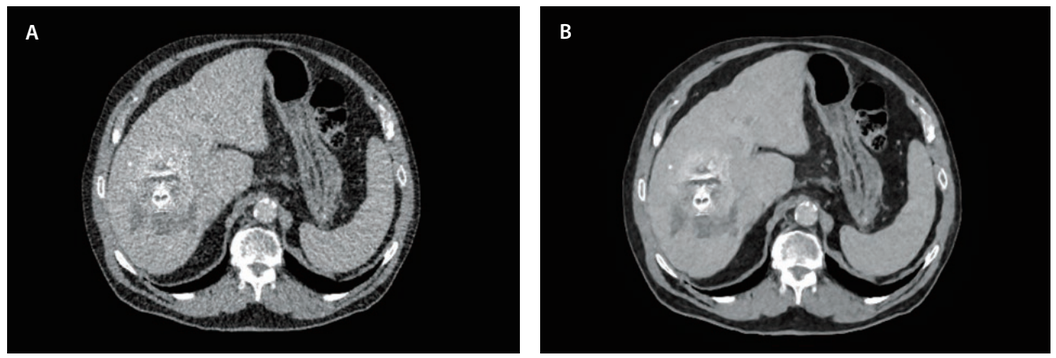

Figure 9 Filtered Backprojection reconstruction of an abdomen case with an artificial object inserted into the raw data (A) and corresponding AiCE reconstruction of the same data (B). Note that despite not having been exposed to this artificial signal during training, the AiCE DLR recognizes the unfamiliar object as signal, preserving it while reducing the noise.

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