Deep Learning Spectral CT
– Faster, easier and more intelligent

Kirsten Boedeker, PhD, DABR, Senior Manager, Medical Physics*1
Mariette Hayes, Global CT Education Specialist, Healthcare IT*1
Jian Zhou, Senior Principal Scientist*2
Ruoqiao Zhang, Scientist*2
Zhou Yu, Manager, CT Physics and Reconstruction*2

*1Canon Medical Systems Corporation
*2Canon Medical Research USA

Introduction

Canon Medical is infusing kV switching technology with the power of Artificial Intelligence (AI*) to transform Computed Tomography (CT) for both routine and advanced spectral CT applications. To obtain multi-energy projections, kV switching interleaves acquisition of high kV views and low kV views as the X-ray tube and detector rotate around the patient. By harnessing Canon Medical's position as the industry leader in Deep Learning Reconstruction (DLR), kV switching has now been brought to the next level with the introduction of rapid kV switching Spectral CT with Spectral Reconstruction.

Spectral Reconstruction is a raw data based, Deep Learning Reconstruction algorithm that allows for rapid kV switching Spectral CT with full anatomical coverage, up to 16 cm in the longitudinal direction and 50 cm in-plane. Spectral Reconstruction also makes possible the routine use of automatic exposure control with Spectral CT, ensuring both dose efficiency and uniform image quality. Rapid kV switching with Spectral Reconstruction has the further advantage of highly precise spatial and temporal alignment of the high and low kV views for robust material decomposition, conducted in the raw data domain, and minimal motion artifact.

Rapid kV switching Spectral CT, being launched with the Aquilion ONE / PRISM Edition wide volume CT system, offers automatically-generated monochromatic images, material specific reconstructions and iodine maps—requiring no additional effort or training for the technologist. Images are delivered directly to the reading station, making a rich array of information readily available to assist the radiologist with patient diagnosis. Interactive spectral analysis is also directly available through advanced applications developed on the Vitrea™ platform providing a scalable workflow solution that can be tailored to suit clinic-specific needs.

Single energy to Spectral CT

The limitations of single energy CT to distinguish between the elemental composition of various materials are well known. The fundamental challenge lies in that the Hounsfield Unit of a given voxel depends on both the physical density and effective atomic number (Z) of the anatomy imaged within the voxel. Traditional single energy CT is unable to distinguish between the effects of physical density and effective atomic number (Z), i.e., making materials such as calcium and iodine potentially difficult to distinguish from each other. However, the impact of effective atomic number (Z) on photon attenuation is energy dependent, making it possible to distinguish between materials when two energy levels are applied. In fact, the concept of using multi-energy CT for material classification was first introduced by Godfrey Hounsfield himself in 1973[1], but implementation of the idea was hindered by the limited technical capabilities of the CT scanners of that time period.

Today, Spectral CT takes advantage of the energy dependence of the effective atomic number (Z) to perform material classification, resulting in a wide variety of clinical outputs, including iodine maps for CTAs, bone identification and removal, virtual non-contrast images, beam hardening artifact reduction, material classification as well as electron density and atomic number determination. In addition, Spectral CT results in Virtual Monochromatic Images (VMI) that can be used in lieu of a traditional single energy image. There are a wide variety of approaches for achieving the benefits of Spectral CT, including two consecutive scans with different kVs, non-AI*-based fast kV switching, dual source acquisition, and acquisition with a dual layer detector. What sets Canon's rapid kV switching solution apart?

Rapid kV switching with artificial intelligence

In order to acquire views at more than one energy, rapid kV switching operates by quickly and repeatedly switching the energy of the beam from high to low as the tube and detector rotate around the patient. Rapid kV switching allows for the material decomposition process to take place in the raw data domain itself, rather than post-reconstruction in the image domain. Raw data based decomposition has been demonstrated to be less impacted by beam hardening and other biases that occur when material decomposition is performed in the image domain[2]. Previous implementations of kV switching have relied on brute force hardware approaches to acquire enough views at each kV to both preserve image quality and effectively perform material decomposition. Such systems, for example, must operate at a speed that prohibits the use of Automatic Exposure Control (AEC). These previous implementations of kV switching Spectral CT also suffer from a lack of full coverage in the longitudinal direction. Today, these challenges can be overcome with artificial intelligence.

Deep Learning, a subtype of machine learning, represents the state-of-the-art in artificial intelligence and is widely applied in many aspects of everyday life. Deep Learning powers navigational systems, language translation applications, facial recognition software—even your streaming service's next movie recommendation. In 2018, Canon Medical launched the first Deep Learning Reconstruction algorithm, Advanced intelligent Clear-IQ Engine (AiCE), designed to distinguish signal from noise, preserving and enhancing the signal while eliminating noise. AiCE improves noise texture and high contrast spatial resolution while reducing noise magnitude, leading to an industry-first 1.5 mm, 3 HU Catphan® low contrast detectability specification.

A Deep Convolutional Neural Network (DCNN) is comprised of multiple layers of neurons. A neuron, illustrated in Figure 1, is a node where a mathematical operation takes places, the output of which is connected with other neurons, forming a neural network. The ability to learn via a deep neural network gives Deep Learning algorithms the freedom to find the optimum way to perform the desired task. 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.

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 to a ground truth reference to gauge its performance and learn, i.e. adjust the weights of its neurons. In order to accomplish this the DCNN uses a mathematical loss function to determine the error between its output and the reference datasets. In the case of rapid kV switching, a DCNN can be trained to reconstruct spectral CT images such that data can be acquired without compromising wide volume coverage or automatic exposure control.

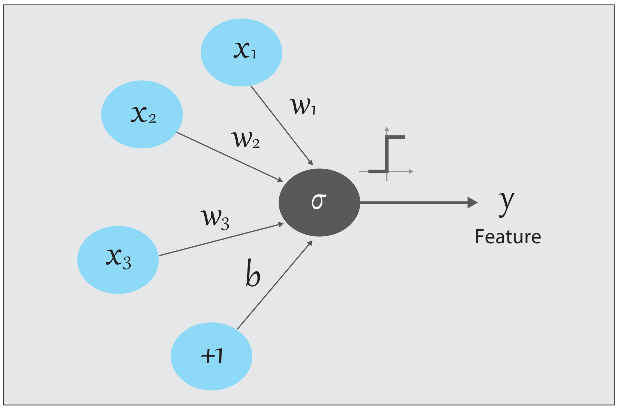

Figure 1 The structure of a basic neuron. A neuron will adjust the weighting factors (w) of its associated feature as it learns. The activation function (sigma) gauges the strength of the neuron response.

Deep Learning Spectral Reconstruction

Every multi-energy CT system needs to generate two complete sinograms worth of raw data, one at each energy, to perform material decomposition, i.e., the process of separating the data into two basis materials, such as iodine and water. Rather than compromise coverage or AEC by greatly increasing view rates, Spectral Reconstruction takes advantage of the fact that much of the anatomical information contained in a high kV view and a low kV view at a particular location is common to both views, such as the high spatial frequency information. The difference between the high and low energy views is the degree to which the X-ray beam is attenuated by the patient or object being scanned. Spectral Reconstruction works by transforming views of one energy into the other to create Deep Learning Views (DLVs). DLVs are generated by the trained neural network using measured data from both the opposite energy views as well as adjacent same-energy views. The DLVs then compliment the measured views at each energy to generate a complete sinogram for each kV. Spectral Reconstruction then completes the reconstruction process, taking advantage of the established noise reduction capabilities of Deep Learning to create low noise spectral CT image data (Figure 2). The noise reduction associated with Spectral Reconstruction helps ensure consistent image quality, coupled with mA modulation based on body size/composition and a user-specified IQ level (Figure 3).

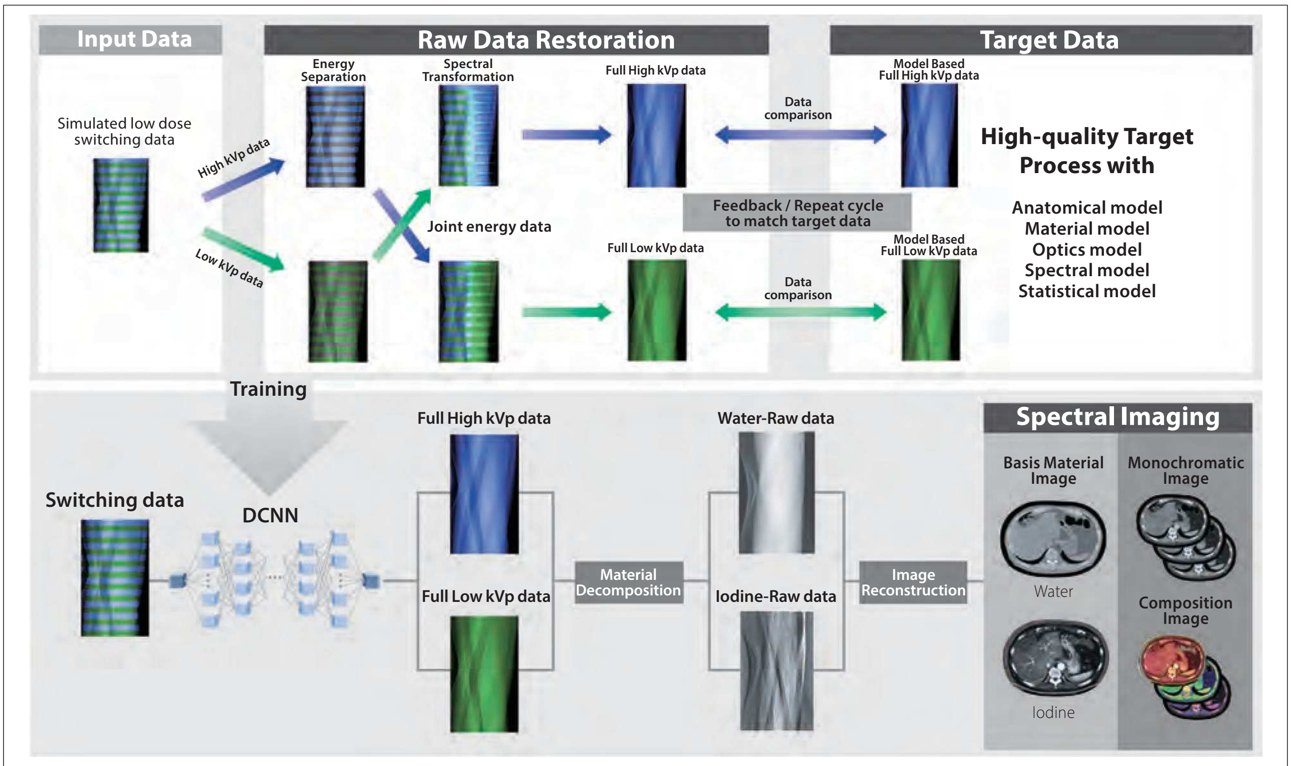

Figure 2 Deep Learning Spectral Reconstruction process.

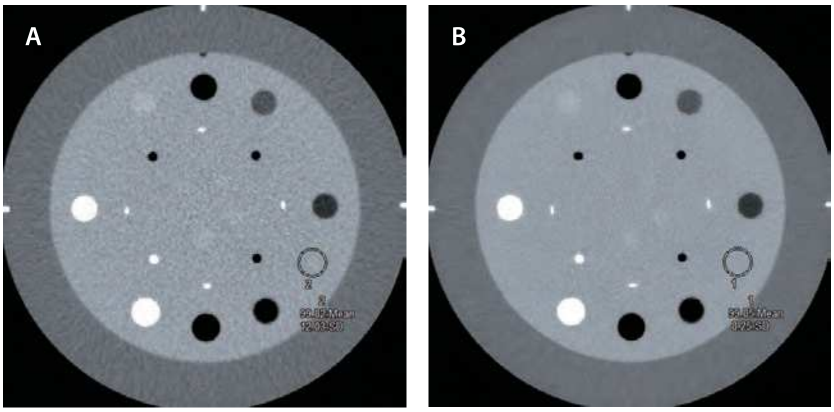

Figure 3 Phantom images demonstrating noise reduction with the Spectral Reconstruction (A: Adaptive Iterative Dose Reduction 3D (AIDR 3D), SD=12.03; B: Spectral Imaging 70 keV VMI, SD=8.25; 10 mGy)

As with all Deep Learning, the key to successful reconstruction lies in the training of the neural network. Spectral Reconstruction was trained on complete measured sinograms acquired at each energy for a wide variety of patient and phantom attenuation levels. The sinogram data used for training were processed with an array of sophisticated models, such as a Statistical Model for noise reduction. Other models utilized to ensure ultra-high quality training include Spectral, Anatomical, Material, and Optics models. Based on the resulting ultra-high quality sinograms, the DCNN is trained to generate DLVs from measured opposite energy views and adjacent same-energy views. After the extensive training process, Spectral Reconstruction was tested with independent validation datasets and hundreds of thousands of image results were reviewed extensively by engineers, medical physicists, and radiologists.

The use of Deep Learning Views, or DLVs, results in highly precise temporal and spatial alignment, helping to ensure accurate material classification and minimal temporal artifact. DLVs also permit Spectral CT to utilize the full range of coverage, including the 16 cm wide volume and 50 cm FOV. Performing Spectral CT on whole organs acquired in a single rotation, which further reduces motion artifact, offers increased diagnostic potential in applications such as Spectral cardiac CT.

Performance

The power of rapid kV switching with DLVs is best demonstrated through the diagnostic images and spectral data it produces. Canon's Spectral CT is designed to yield diagnostic VMIs. Because of the high sampling rate associated with DLVs, these VMI images have excellent high contrast spatial resolution, as demonstrated in the MTF in Figure 4. Like its counterpart AiCE DLR, Spectral Reconstruction produces low noise images that have improved noise texture compared to traditional iterative approaches. These spatial resolution and noise properties are illustrated in the 70 keV VMI of the liver (Figure 5).

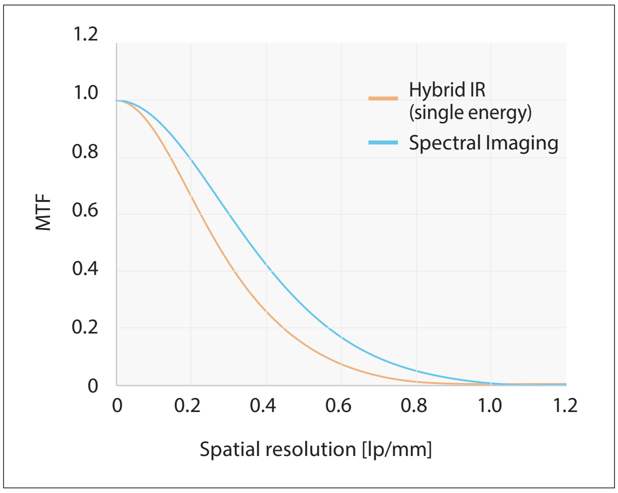

Figure 4 MTF of a Virtual Monochromatic Image

Figure 5 Virtual Monochromatic Image at 70 keV at the level of the hepatic vein.

Automated workflow

Automated workflow has been a key goal to empower sites to more readily adopt Spectral Imaging into their routine protocols. The Spectral Imaging solution offers automatically generated Monochromatic Images, material specific reconstructions and iodine maps, requiring no additional effort or training for the technologist. Images are delivered directly to the reading station, making a rich array of information readily available to assist the radiologist with patient diagnosis. Quantitative analysis is available on dedicated spectral applications in Vitrea.

The Vitrea spectral applications aim to provide clinicians with the appropriate tools for easy, fast and robust results to facilitate a diagnosis with increased clinical confidence. The entire workflow from spectral image analysis to saving and archiving results are integral design features of these applications. In combination with the automatic output from Spectral Imaging solution, full flexibility to support any user workflow preference is achieved. The spectral applications are available on a range of Vitrea deployments (Figure 6).

Spectral Image output: What are all these images?

The Spectral Imaging solution provides virtual monochromatic images, the ability to perform composition analysis and also optimize visualization of iodine contrast. Several of these images and features are briefly described below.

Basis material images: Iodine/Water and Water/Iodine

The Spectral Imaging System utilizes the power of raw data based material decomposition to produce a basis material Iodine/Water pair that is then used as the input data for all other spectral image analysis.

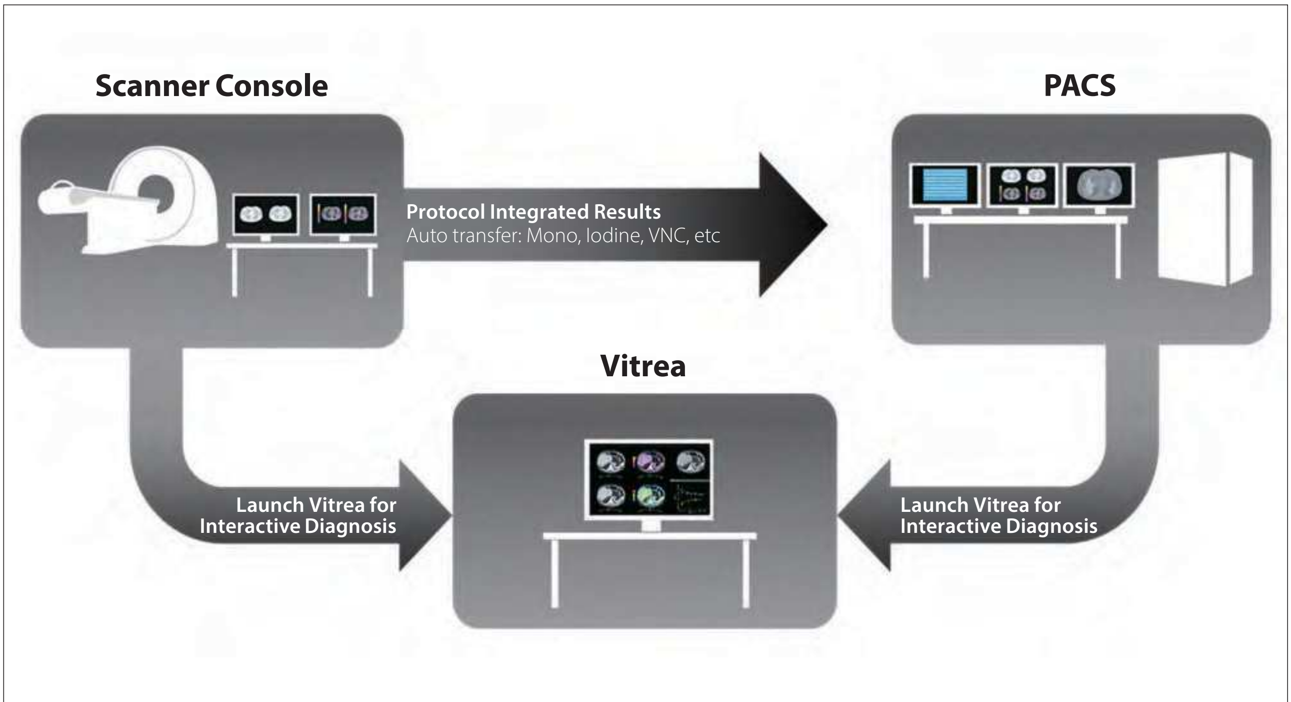

Figure 6 The combination of automatic transfer of images from the scanner to PACS with the interactive applications on Vitrea provide full flexibility to support any user workflow.

Virtual Monochromatic Images (VMI)

The VMI provide gray scale images in any of 101 energy levels ranging from 35 keV to 135 keV. Low keV images show increased density of iodinated contrast media and higher energy levels have less beam hardening effects which can help to reduce artifacts from metallic implants. The interaction with the VMI provides the clinician with an additional dimension for interpreting CT examinations (Figure 7).

Iodine Map

The iodine map is generated by 3 material decomposition providing a color map that enhances the conspicuity of iodine to provide the rapid evaluation of perfusion. Quantitative analysis of the concentration of iodine in mg/ml is available (Figure 8).

Composition analysis

3 material decomposition can be used in the evaluation of patients with tophi depositions for the presence of monosodium urate (MSU). An estimate of the MSU volume is provided (Figure 9).

Bone mapping

The bone map is generated by 3 material decomposition. In this case the bone is extracted and displayed as a map. The "Virtual Non Calcium" image allows evaluation of the bone marrow, for various conditions such as metastasis and bleed due to acute injury (Figure 10).

Effective Z images

These images allow clinicians to generate maps and histograms to assess the relative atomic number of a given object, or confirm the presence of a known material, for instance iodine. With sufficient accuracy, this would potentially provide the exact composition of any mass (Figure 11).

Stone analysis

The composition of urinary calculi can be characterized. Uric acid and other materials such as calcium oxalate can be identified. Determining the composition of stones aids in optimum treatment selection for patients with urinary calculi (Figure 12).

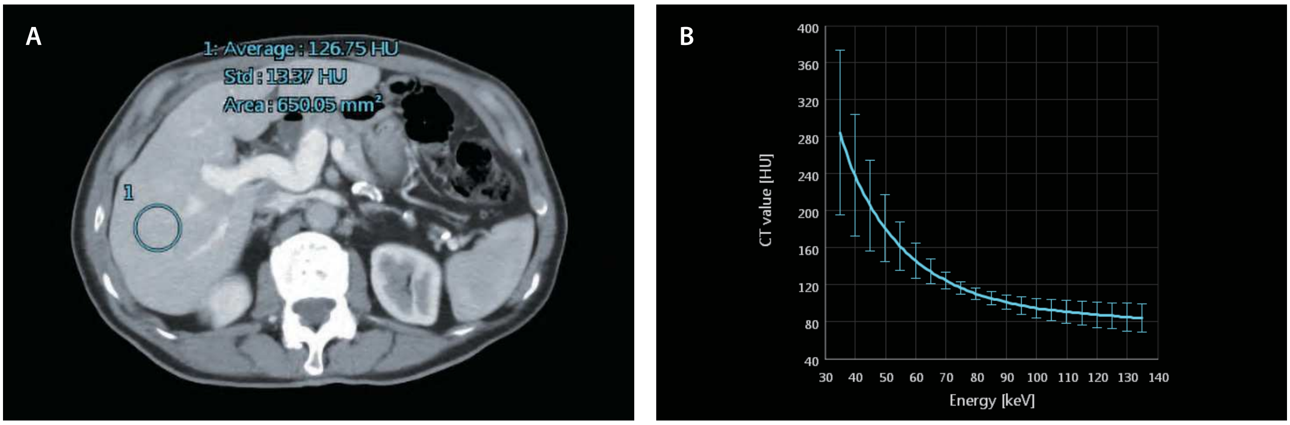

Figure 7 Virtual monochromatic image. The ROI is placed in the liver (A) and the curve for the liver tissue is displayed (B).

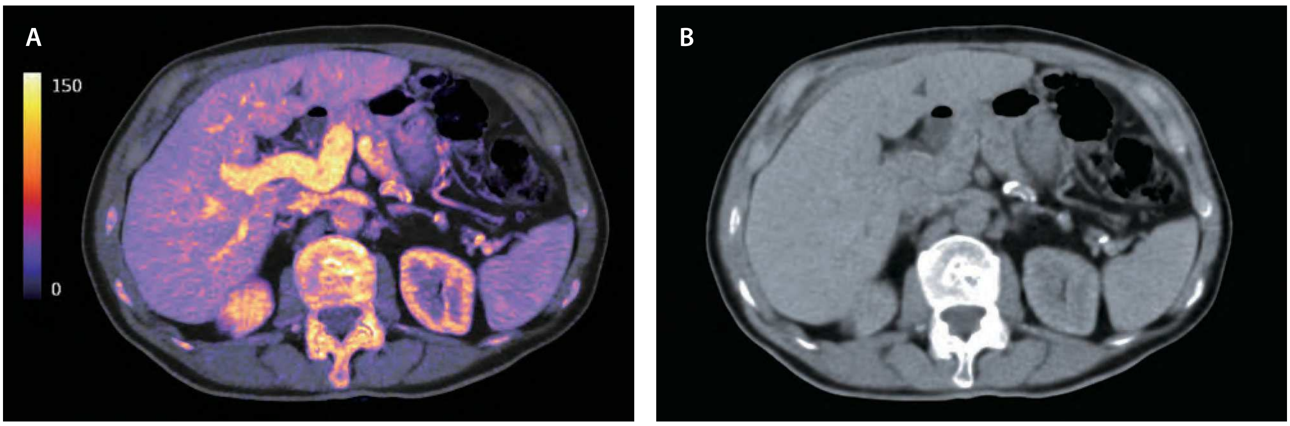

Figure 8 Iodine map of the upper abdomen with color fusion. (A) Iodine uptake of the liver in color can be evaluated. (B) The Virtual Non-Contrast image shows some calcifications in a splenic artery segment.

Figure 9 3D and MPR images of the foot demonstrate some tophi (green) indicating MSU associated with gout.

Figure 10 Bone map of the right wrist showing a fracture of the distal radius. (A) Spectral VMI, (B) Virtual Non-Calcium (VNCa) image. There is increased density of the distal radius bone marrow which may indicate a small trauma, associated bleed or edema.

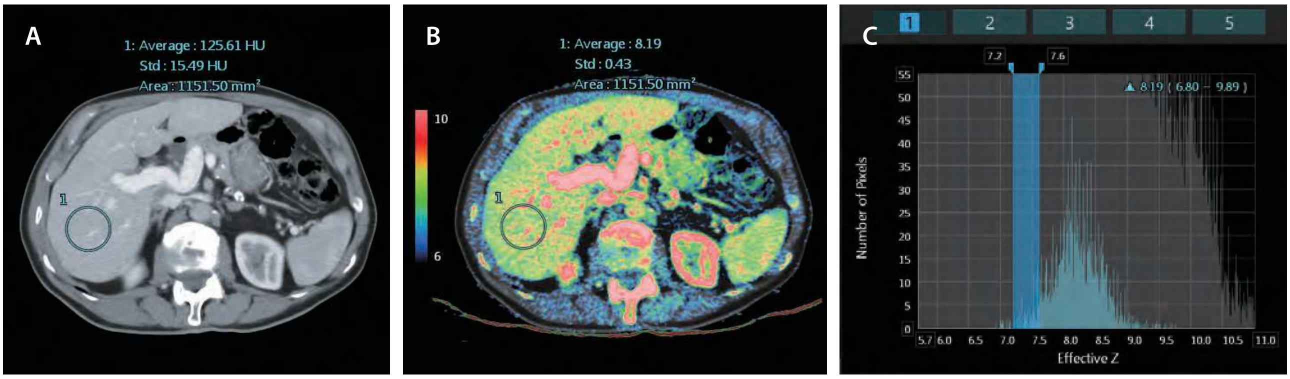

Figure 11 (A) An axial 70 keV VMI image of liver with a ROI in the right lobe. (B) The Eff. Z in the ROI is 8.19. (C) The effective Z histogram indicates Eff.Z of liver tissue relative to water. Water Eff. Z is approximately 7.4 and is indicated by the blue vertical bar. Up to five different materials with known Eff.Z can be preloaded in the Eff.Z histogram thereby providing a new comparative method for ROI analysis of tissue.

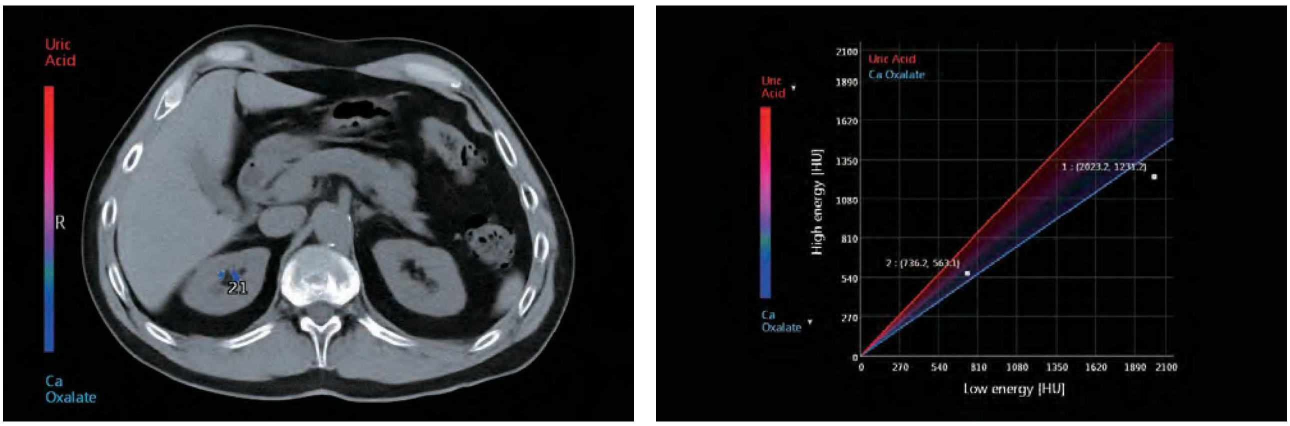

Figure 12 A Spectral Scan on a patient with multiple kidney stones. Each stone is segmented. The results show that both stones are Calcium Oxalate.

Electron density images

These images allow clinicians to generate maps and histograms to facilitate the assessment of the electron density of a given pixel. Histogram interrogation by ROI can be made interactively. An emerging application is the utilization of electron density for radiotherapy planning and treatment (Figure 13).

Summary

Canon Medical's Deep Learning Spectral CT system combines the temporal resolution benefits of rapid kV switching with patient-specific mA modulation and a Deep Learning Spectral Reconstruction algorithm that offers excellent energy separation for a low noise image reconstruction. In addition to acquisition and reconstruction advances, Canon's Spectral CT solution is rounded out by new advanced applications on the Vitrea platform for maximum workflow efficiency. This is Spectral Imaging without compromise.

References:

1. Hounsfield GN. Computerized transverse axial scanning (tomography). 1. Description of system. *Br J Radiol* 1973; 46:1016-1022
2. Li B, Yadava G, Hsieh J. Quantification of head and body CTDIvol of dual-energy X-ray CT with fast-kVp switching. *Med Phys* 2011; 38:2595-2601

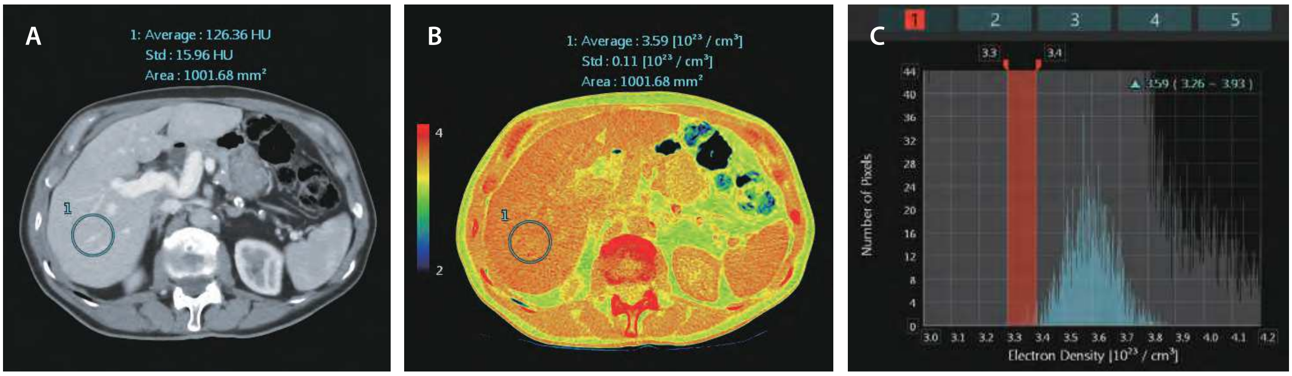

Figure 13 (A) An axial 70 keV VMI image of liver with a ROI in the right lobe. (B) The electron density in the ROI is 3.59. (C) The electron density histogram shows the electron density of liver tissue relative to water. Water electron density is approximately 3.34 and is indicated by the orange vertical bar. Up to five different materials with known electron density can be preloaded in the electron density histogram thereby providing a new comparative method for ROI analysis of tissue.

* The term Artificial Intelligence (AI) is defined here as technology using Deep Learning methods.

CANON MEDICAL SYSTEMS CORPORATION

https://global.medical.canon

MWPCT0002EA 2019-12 CMSC/SO/Printed in Japan