GE Healthcare

VUE Point HD™

Bringing accuracy to PET reconstruction

1 The clinical value problem

Iterative reconstruction techniques brought a dramatic improvement in image quality to PET and SPECT imaging and the quality of PET images continues to improve as more rigorous implementations are developed. A major dilemma in PET imaging is that there is rarely enough information. The amount of tracer in a patient and the imaging time are limited by practical considerations, and so the amount of information (number of detected positrons) is less than ideal. One result of the statistical limitation is that almost all clinical images are "filtered" after reconstruction to make the images more presentable. The filter results in the spatial resolution being degraded to a point much worse than that measured by NEMA tests. Generally, it is the image statistics, rather than the scanner's spatial resolution, that limits lesion detection in clinical images.

In clinical studies, the quality of diagnostic information is influenced by effective spatial resolution of the image, the accuracy with which relative changes in tracer concentration are mirrored in the image (e.g. if an organ has double the tracer concentration of surrounding tissue, the image should show double the concentration) and the "noise structure" of the image. Noise structure is the amount of variability among image elements representing the same tracer concentration. If there is significant noise, then resolution and accuracy are lost. The noise level is determined by the amount of information contributing to the image (quantity of tracer, imaging time, scanner sensitivity). The noise is usually increased by corrections involved in reconstruction. Image quality, and hence the quality of diagnostic information, is determined by our ability to select the best compromise between resolution, accuracy, and noise.

2 Addressing the challenge with VUE Point HD

The iterative algorithm cannot create a solution. Rather, it improves a proposed solution. As a starting condition, assume a uniform distribution of tracer throughout the patient; i.e. that every volume element of the patient contains exactly one unit of tracer. At the start, this is the "current estimate" of the solution. The algorithm then modifies the "current estimate" by repeating three simple steps:

Step 1 Compute "what we would expect to measure" if the "current estimate" of the tracer distribution is correct (the "modeling" step).

Step 2 Identify how "what we would expect to measure" differs from "what was measured" when this patient was scanned.

Step 3 Use the inconsistencies in Step 2, the ratio of the measured data to the "expected" data from Step 1, to modify the "current estimate".

By repeating these steps as often as necessary, the starting assumption of a uniform distribution can be transformed into a distribution that is close to the true distribution of the tracer.

Step 1 requires knowledge of how the tracer at a particular location in the patient leads to detected positron events in the scanner. It includes all the factors: attenuation, scatter, random coincidences, detector geometry and efficiency, which influence the likelihood of positron events being detected by the scanner. Step 3 requires a process to redistribute the tracer in the "current estimate" in a way that is likely to reduce the differences between "expected" and "detected" data.

Implementing the iterative algorithm is very complex and the computations take a long time. It is common to take "short-cuts" in the implementation to simplify and speed up the process. The most common short-cut is to "correct" the acquired data, to make the modeling step simpler. Typically, random events are subtracted, the non-uniformly spaced projections are interpolated to obtain evenly spaced projections (which are easier to deal with), and closely adjacent rays are combined (procedures called "mashing" and "spanning"). Each of these short-cuts degrades the result. Until recently, most 3D iterative PET reconstructions were performed in 2D. The 3D data was first converted to 2D by a process called Fourier Rebinning (FORE). The reason was that it took much longer to perform the more complex 3D reconstructions. A typical iterative reconstruction sequence is shown in Figure 1. VUE Point HD was the first algorithm to combine compute power, efficient projectors, and elimination of significant sources of error in the system model for a high quality, fully 3D iterative reconstruction with a clinically relevant time to completion.

As the tracer distribution is being altered, it is "converging" to the correct answer. In practice, the tracer distribution gradually gets better, but at the same time the noise in the image increases. There is never a point at which iteration produces no change. In practice, the images don't converge to "the truth", but to the "most likely" distribution that would give rise to the acquired data.

To get the correct result, it is important that the image converges before the noise increases to an unacceptable level. But the image must also converge uniformly; that is, all parts of the image must approach the best value together. Perhaps the biggest problem with iterative algorithms is that they did not converge uniformly. Most commonly, large volumes of tracer converge more rapidly than small volumes. The liver, for example, will converge before a small tumor. The result is that the contrast between large organs (such as the liver) and the average body background is accurate, but it will take many more iterations before the contrast between the small tumor and background is reached. Cold spots often converge more slowly than hot spots. Highly non-uniform convergence is largely due to pre-correcting data prior to iterative reconstruction. Uniformity of convergence is greatly improved with VUE Point HD since the corrections are included in the iterative loop.

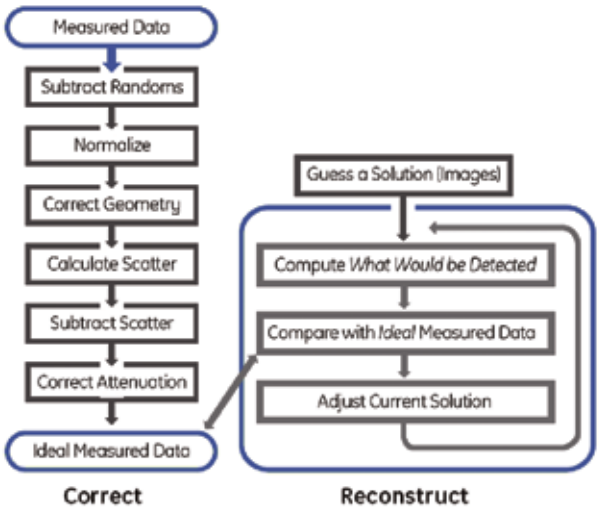

Figure 1. Typical FORE OSEM reconstruction scheme.

In addition, VUE Point HD includes normalization, dead time and system geometry into the system model. VUE Point HD utilizes a distance driven projector, which allows fast image reconstruction times and is particularly suited for accurately modeling both the detector curvature and the block-based distribution of crystals in PET scanners as shown in Figure 2.

PET data collected from a block-based detector have radially unevenly sampled projections due to the detector curvature and the block-based distribution of crystals in PET scanners. "Radial repositioning" is typically performed on clinical scanners in order to convert the projection data to an idealized, equally spaced set of projections prior to image reconstruction. This resampling of data results in a radially dependant degradation of resolution. In addition, this step necessitates the measured projection data be corrected for block dead time and normalization prior to image reconstruction.

In native geometry reconstruction, we perform forward and back-projections directly from image space to the projection geometry of the PET scanner. We have modified the distance-driven projectors to accurately model the uneven spacing of the projections due to the ring curvature of the scanner. A detailed description of this model was published by Manjeshwar et. al.

The impact of the native geometry reconstruction is two fold. First, it dramatically improves the radial resolution response of the reconstruction by removing the geometry correction. Second, it allows the normalization and dead time correction to be included within the iterative loop, so there is no pre-correction of the data as shown in Figure 3. This removes a significant source of error in the statistical modeling of the reconstruction.

As a result, VUE Point HD provides excellent spatial resolution, and correspondingly high contrast recovery coefficients, at activity concentrations and imaging times encountered in routine clinical imaging. This is particularly important for improved imaging of very small objects.

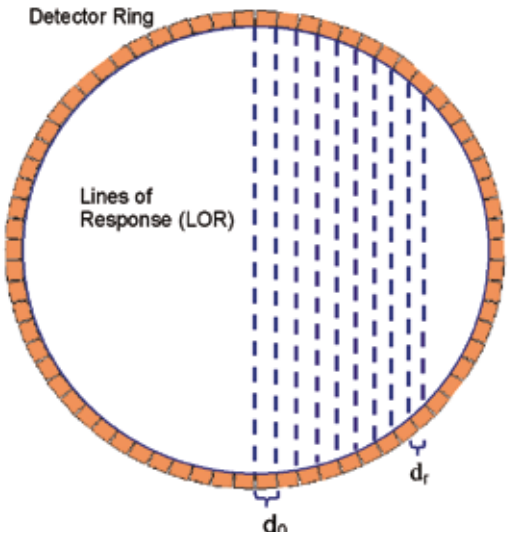

Figure 2. Ring-based detector geometry leads to an uneven line of response (LOR) width as a function of radius.

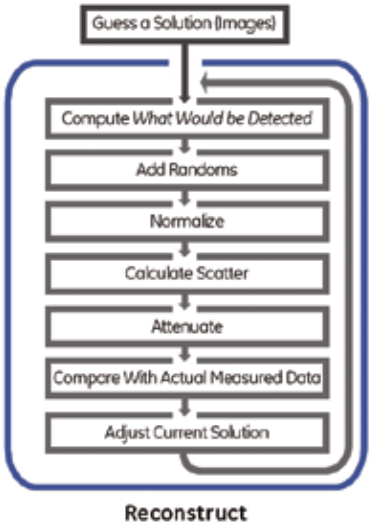

Figure 3. VUE Point HD Reconstruction sequence.

3 Performance evaluation

A major impact of VUE Point HD is improved image resolution. However there is a challenge in quantifying this since NEMA specifies that spatial resolution must be measured using Filtered Back-Projection reconstruction only. The reason is that measurements of a point source in air, with a large number of detected events, when reconstructed with an iterative algorithm, produce extremely small, but clinically unrealistic values. This is largely a result of the effects of the activity distribution and count density on convergence rate. Several investigators have shown that apparent spatial resolution values well below the true spatial resolution of the scanner (between 1 and 4 millimeters) are easily obtained with iterative techniques. However, these values have no relevance to clinical imaging. Clinical images published in the article references show that the practical resolution is in the range of 5 to 7 millimeters.

A much better method of assessing clinical resolution performance is to measure the signal-to-noise ratio, or contrast recovery as a function of background variability through successive iterations. The NEMA standard defines a procedure for measuring contrast recovery. To compare scanners and reconstruction methods, it is useful to plot graphs of contrast and background noise as a function of the noise across a number of iterations.

The NEMA IQ phantom was imaged as defined by the standard for a 4:1 background ratio. Data was reconstructed with FORE OSEM and VUE Point HD in a sequence of iterations. Contrast to noise analysis was conducted for each sphere at each iteration. Figure 4 show the FORE OSEM and VUE Point HD images. The contrast is plotted against the iteration noise in Figures 5 and 6 for FORE OSEM and VUE Point HD respectively.

The VUE Point HD phantom images demonstrate a visual improvement in sharpness and contrast as compared to FORE OSEM. The visual impression is supported by the quantitative contrast improvement achieved with VUE Point HD. From this data, it is demonstrated that the impact is larger for smaller objects with an improvement of approximately 60 percent in contrast for matched noise in the 13 mm sphere.

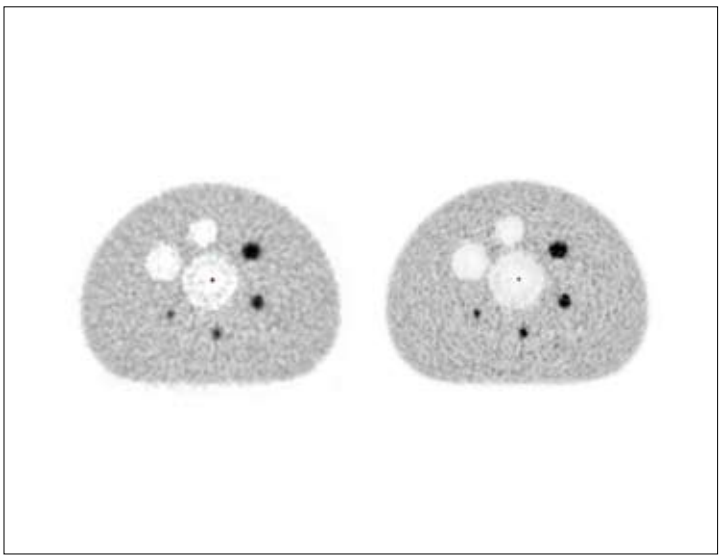

Figure 4. NEMA IQ phantom reconstructed with FORE OSEM (left) and VUE Point HD (right).

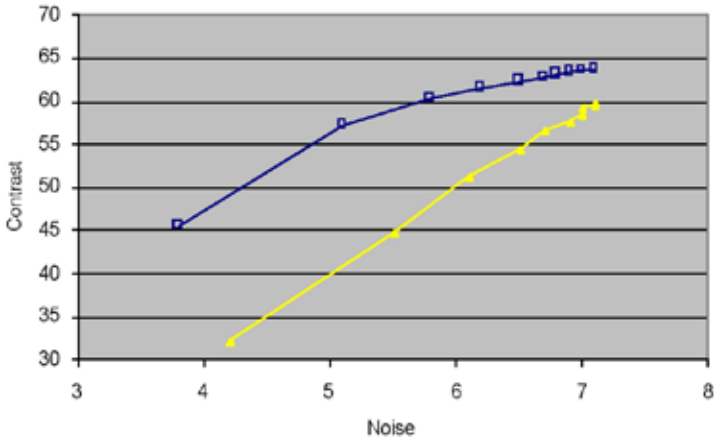

Figure 5. Contrast vs noise curves for 17 mm sphere.

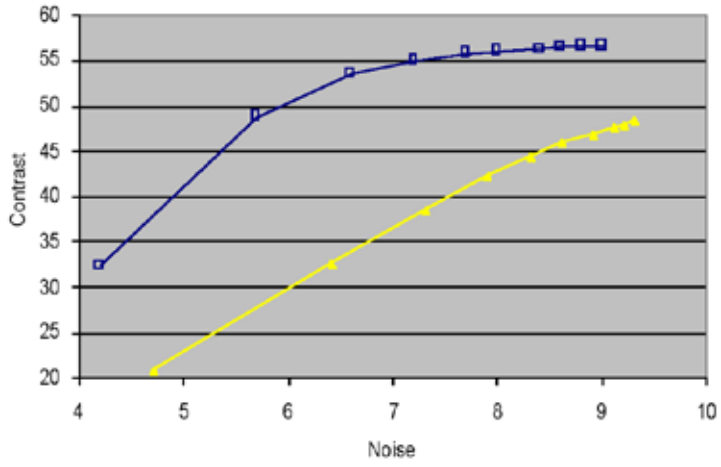

Figure 6. Contrast vs noise curves for 13 mm sphere.

Clinical brain and whole body examples are shown in Figures 7 and 8 respectively. Both data sets demonstrate a significant improvement in spatial resolution and contrast recovery with the VUE Point HD algorithm.

Quatitative comparison was conducted by calculating contrast to noise ratio (CNR) for four of the lesions in the whole body study. The lesion locations utilized are shown in Figure 9. Contrast was calculated as the ratio of the lesion to the surrounding background, and noise was measured using the pixel standard deviation within the liver. The CNR comparison between FORE OSEM and VUE Point HD is plotted in Figure 10. This data demonstrates a significant CNR improvement of approximately 70 percent for VUE Point HD.

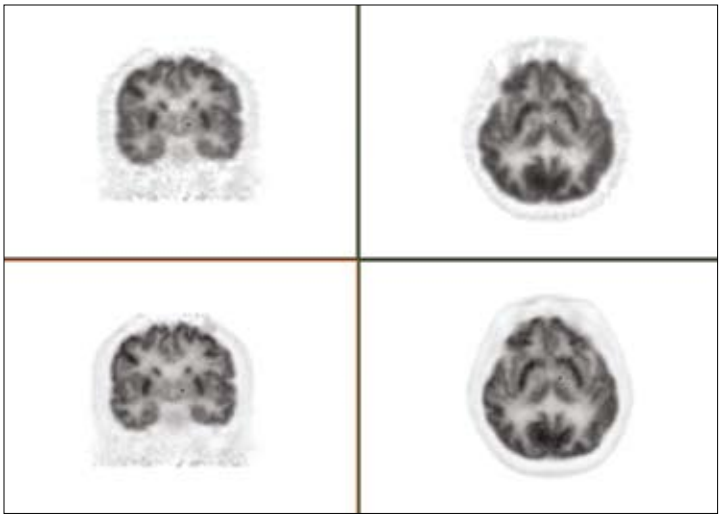

Figure 7. Brain imaging comparison between FORE OSEM (top row) and VUE Point HD (bottom row).

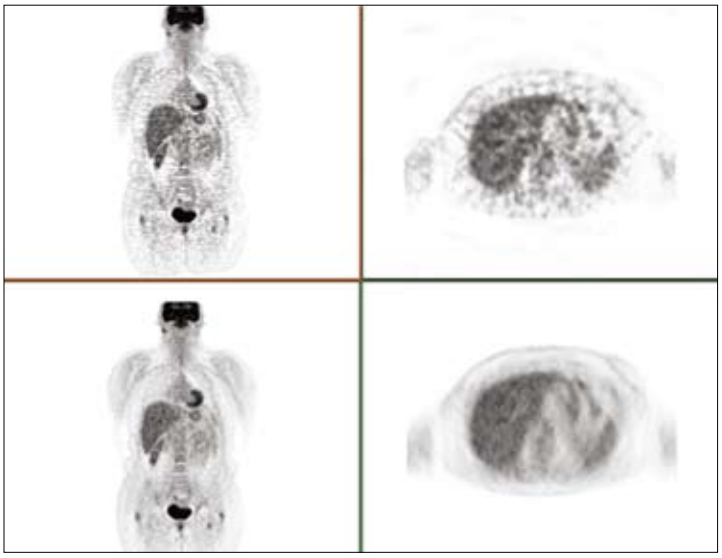

Figure 8. Clinical whole body comparison between FORE OSEM (top row) and VUE Point HD (bottom row).

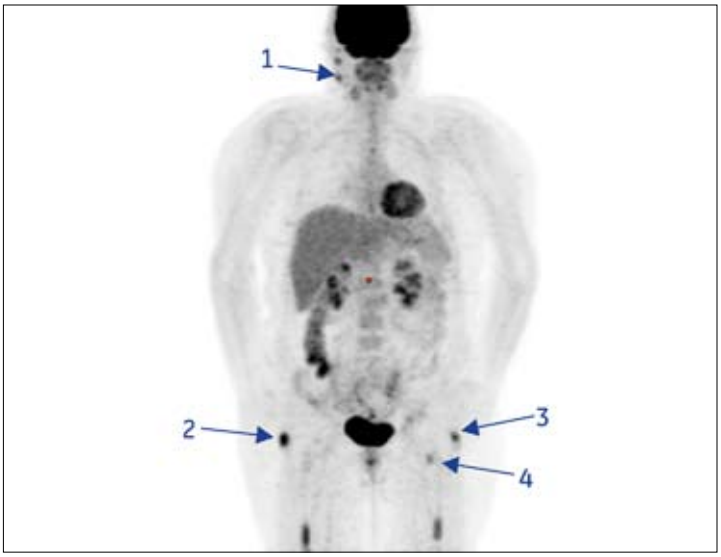

Figure 9. Location of lesions used for contrast to noise analysis.

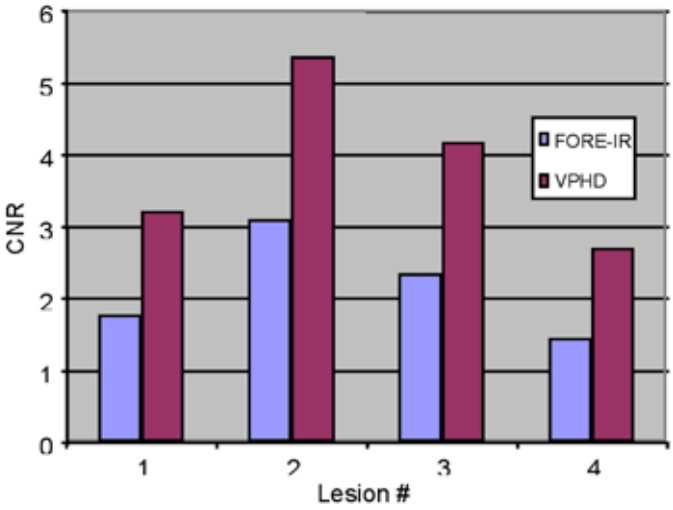

Figure 10. Lesion CNR comparison between FORE OSEM and VUE Point HD.

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GE Healthcare
3000 North Grandview Blvd
Waukesha, WI 53188
U.S.A.

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