Comparison of Energy Bin Compression Strategies for Photon Counting Detectors

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ABSTRACT

Photon counting detectors (PCDs) with energy discrimination capabilities allow us to perform quantitative material decomposition with high spatial resolution. Although PCDs provide more spectral information than conventional energy integrating detectors (EIDs), it is more challenging for the system to transmit projection data from the detectors across the slip ring to the processing computer and store the data, due to the increased amount of data with increasing number of energy bins. To address this problem, many approaches have been proposed to compress the bin data while maintaining the image quality. In this work, we compare the performance of strategies to reduce projection data and determine the optimal choice of bin compression strategies and the number of measurements for multiple tasks.

We first obtain the optimal thresholds for conventional energy bins, as determined by minimizing the Cramér–Rao lower bound (CRLB) for material decomposition tasks with a realistic silicon detector energy response. We then consider the case of reducing data from 8 native energy bins by forming weighted sums, either with binary weights or continuous weights, by minimizing the relative CRLB between the compressed measurements and the original 8 bins. We then evaluate their respective performance using Monte Carlo simulation for a head phantom. The results show that the continuous weights strategy is superior to others, with low bias and less than 10% variance penalty for 2 weighted sums, with a data reduction of 75% within a large material thickness space. The other strategies have up to 50% variance penalty compared with the original 8 bins and are less robust when there is photon starvation. With additional weighted measurements, the continuous weights method can achieve less than 1% variance penalty when reducing the 8 native energy bins to half the number of measurements. Overall, combining energy bins by forming weighted sums with continuous weights is an effective strategy for reducing data while preserving spectral information.

Keywords: photon counting detector, bin compression, Cramér–Rao lower bound

1. INTRODUCTION

Transmitting projection data from detector arrays on the rotating CT gantry through the slip ring to the data processing computer and storing them have always been challenging for CT systems. Photon counting detectors (PCDs) are advanced detectors that provide more spectral and spatial information than current dual-energy CT systems using energy integrating detectors (EIDs). For example, deep silicon PCDs with 8 native energy bins enable more precise material decomposition quantification by taking advantage of all the spectral information. However, the projection data transmission and storage become more challenging for PCDs due to the increased amount of data. There are several approaches to reducing the projection data by reducing the number of measurements. One direct approach is to reduce the number of native energy bins by setting fewer energy thresholds. Other strategies include splitting the native energy bins into N groups and summing them up based on a preset figure of merit [1]. Instead of transmitting and storing the native energy bins, the summed bins are then used for further processing so that the data is downsampled. A more generalized method is to combine the native energy bins into N measurements with binary weights. Wang *et al* had also proposed a weighting method to compress spectral information from infinite bins and an ideal detector energy response without information loss [2]–[4]. More recently, we proposed a generalized version of the continuous weights strategy for finite native energy bins under realistic non-ideal detector energy response and showed its potential in reducing projection data while maintaining material decomposition and virtual monoenergetic image quality [5].

In this work, we investigate the optimal strategy for bin compression that best preserves spectral information for specific

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tasks, such as material decomposition and virtual monoenergetic images, with high compression ratio. We compare the performance by assessing bias and noise in projection and image domains between four strategies – conventional bins, summed bins, binary weights, and continuous weights – with different compression ratios.

2. METHODS

2.1 Experiment Settings

We used a published deep silicon detector model with 0.5×0.5 mm^2 pixels and 30 mm thickness to simulate the detected binned counts [6]. We used an incident spectrum of 120 kVp with 0.4 mAs per projection. The energy thresholds of the 8 native energy bins were set to be 4, 14, 30, 37, 47, 58, 67, and 79 keV to maximize the spectral information contained in the native binned counts. Performance of material decomposition and virtual monoenergetic images (VMI) was evaluated for a basis material space that spans 0 to 40 cm water and 0 to 5 cm of calcium in cortical bone. These settings were used throughout our study.

2.2 Energy Bin Compression Strategies

2.2.1 Conventional Bins

We use conventional bins to refer to native energy bins obtained through selection of *N* energy thresholds. We fix the lowest energy threshold to be 4 keV, which is consistent with our 8 native energy bins. To obtain the optimal remaining thresholds, we used an exhaustive search to find the thresholds that give the lowest average relative Cramér–Rao lower bound (rCRLB) over the material space. The CRLB represents the minimum variance of a task, such as basis material decomposition or VMIs, for an unbiased estimator given the measurements. The rCRLB is defined as the ratio of CRLB between the proposed methods and the 8 native energy bins,

$$\mathrm{rCRLB}=\frac{\mathrm{CRLB_W}}{\mathrm{CRLB_8}}, \tag{1}$$

where we use subscript W to represent the proposed bin reduction method and the subscript 8 to represent the native 8 bins. Because each method reduces the amount of information, $\mathrm{rCRLB} \geq 1$, but should be minimized to reduce the increased variance. An average rCRLB for the tasks of material decomposition and VMI (at 60 keV) across a range of M material thicknesses can be expressed as:

$$\overline{\mathrm{rCRLB}}=\frac{1}{3M}\sum_A \left.\frac{\mathrm{CRLB_W(Ca)}}{\mathrm{CRLB_8(Ca)}}\right|_A + \left.\frac{\mathrm{CRLB_W(H_2O)}}{\mathrm{CRLB_8(H_2O)}}\right|_A + \left.\frac{\mathrm{CRLB_W(VMI,)}}{\mathrm{CRLB_8(VMI)}}\right|_A, \tag{2}$$

where A indexes the material thickness pairs.

2.2.2 Summed Bins

In this approach, we assume 8 native energy bins are acquired, and they each contribute once and only once to a summed bin. We used the same iterative method described in [1] to compress the 8 bins to different numbers of summed bins. In each iteration, the best combination of 2 bins is summed, using the average rCRLB as expressed in Eq. (2) as the figure of merit. The process and the results are shown in Figure 1.

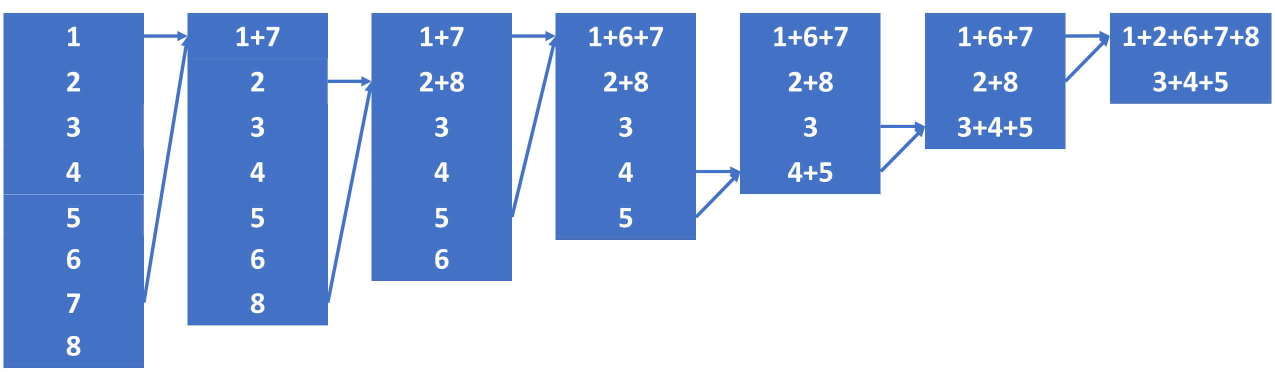

Figure 1: Optimization process of summed bins method.

Mathematically, we can use $W_{i,j}$ to represent N sets of weights, such that the jth summed bin can be written as $b_{W_j} =$

$\sum_i W_{i,j} b_i$, where b_i represents the original binned counts. For summed bins, we have $W_{i,j} \in \{0, 1\}$, and $\sum_j W_{i,j} = 1$ so that each native bin contributes once and only once to a summed bin.

2.2.3 Binary Weights

A more generalized bin compression strategy is to use binary weights, where the elements of energy weights matrix $W_{i,j} \in \{0, 1\}$, but no longer has the constraint $\sum_j W_{i,j} = 1$.

To obtain $W_{i,j}$, we start with the energy weight matrix of summed bins $W^{\mathrm{S}} = [\boldsymbol{w_1}, \dots, \boldsymbol{w_8}]^T$, which compressed the 8 native energy bins to N measurements, and update it row by row (bin by bin) to select the best binary combinations. The pseudocode is listed below.

$i \leftarrow 0$
$W = [\boldsymbol{w_1}, \dots, \boldsymbol{w_8}]^T = W^{\mathrm{S}}$
while $i < 8$ **do**
    $i \leftarrow i + 1$
    $y_{i,j} \in \{0,1\}, \sum_j y_{i,j} > 1$
    for all possible $\boldsymbol{y_i}$ **do**
        if $Y = [\boldsymbol{w_1}, \dots, \boldsymbol{y_i}, \dots, \boldsymbol{w_8}]^T$ is full rank **then**
            Compute $\overline{\mathrm{rCRLB}}(\mathbf{b}_Y = Y^{\boldsymbol{T}}\mathbf{b}, \mathbf{b}_W = W^{\boldsymbol{T}}\mathbf{b})$
            if $\overline{\mathrm{rCRLB}} < 1$ **then**
                $W \leftarrow Y$

2.2.4 Continuous Weights

For continuous weights, we fully generalize the elements of the bin weights matrix to $W_{i,j} \in \mathbb{R}$. In this case, we use Global-Search in MATLAB (R2021a) to minimize the objective function described in Eq. (2).

3. RESULTS

The optimal binary weights and continuous weights are presented in Figure 2 for 2 measurements. The binary weights are identical to summed bins, except bin 5 contributes to both measurements, which was found to slightly improve performance. The continuous weights are normalized to 1 and show that the optimal solution leverages the flexibility of real-valued weights, including negative weights.

3.1 rCRLB Vs Compressed Measurements

We first show our analytical results of the average rCRLB, defined in Eq. (1), over the basis material space of 0 to 32 cm water and 0 to 4 cm of calcium in cortical bone obtained from the four compression methods for different numbers of measurements (Figure 3).

The results show that with increasing number of measurements, the noise performance improves for all four compression strategies. Of all strategies, the continuous weights method is superior to the other three methods, while conventional bins perform the worst. The average rCRLB of 2 measurements generated from continuous weights (1.1294 and 1.0876 for calcium and water decomposition in projection domain) is less than that of 5 measurements from conventional bins (1.1675 and 1.1455 for calcium and water decomposition in projection domain), which indicates that with proper bin weighting combinations, spectral information from more native bins can be preserved better than simply reducing the number of native bins. Data reduction using summed bins and binary weights has less variance than conventional bins, but is substantially higher than continuous weights.

When we reach 4 measurements, the rCRLB obtained from continuous weights is 1.0061 for calcium decomposition, 1.0053 for water decomposition, and 1.0019 for VMI at 60 keV in the projection domain. The noise penalty of this strategy compared with the original data is less than 1% for all the tasks, while the amount of data is only half of the original. With continuous weights, the data from 4 compressed measurements performs essentially as well as the 8 native bins, which indicates that 4 measurements from continuous weights are sufficient to recover the information of 8 native energy bins across the full range of object sizes.

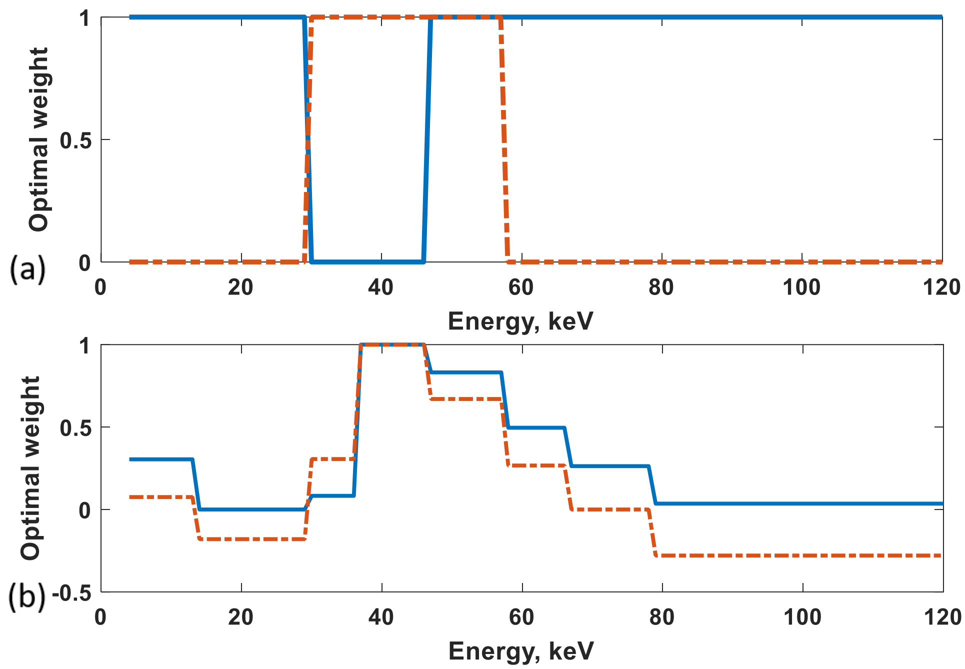

Figure 2: (a) Optimal binary weights and (b) optimal continuous weights for 2 measurements.

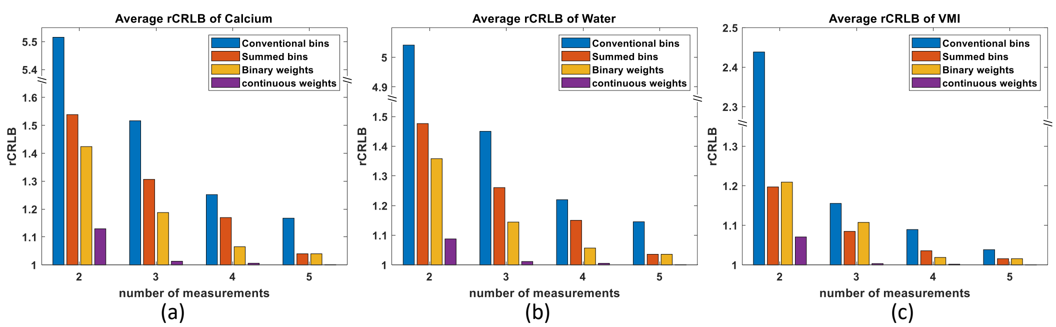

Figure 3: Average rCRLB of conventional bins, summed bins, binary weights, and continuous weights of (a) calcium and (b) water material decomposition and (c)VMI at 60 keV, with different number of measurements.

3.2 Projection Domain Monte Carlo Simulation

Monte Carlo simulation was conducted to validate the analytical results, using maximum likelihood estimation to perform material decomposition from the compressed measurements. 10^4 realizations were performed at each sample point of water and calcium thickness. The relative variance and bias of calcium thickness estimates are presented in Figures 4 and 5, respectively, for compressing to 2 measurements. The results of water thickness and VMI estimates are similar.

The variance penalty is defined as $\frac{\mathrm{Var}_W}{\mathrm{Var}_8} - 1$, where $\frac{\mathrm{Var}_W}{\mathrm{Var}_8}$ is the ratio between variances of basis material thicknesses estimated from the compressed data and the 8 native bins. We found that the variance penalties of 2 measurements with continuous weights for calcium decomposition in projection domain is less than 10% for most material thicknesses, with an average variance penalty of 5.55% in the central region, while that of the conventional bins is 499.67%, 55.14% for summed bins, and 54.29% for binary weights. The binary weights have lower variance penalty than summed bins for intermediate thicknesses, but higher variance penalty at greater thicknesses.

From Figure 5, we also observe that the bias of calcium material decomposition is small for compressing to 2 measurements with continuous weights, even for thicker material combinations. However, the other three strategies suffer increased bias when there are relatively few photons for thicker objects. The root mean squared deviation (RMSD) of the thickness bias is 0.0246 cm for continuous weights, which is a small increase from that of the 8 native energy bins (0.0153 cm). However, for summed bins, binary weights, and conventional bins, the number increases to 0.0457, 0.0640, and 0.1095 cm, respectively.

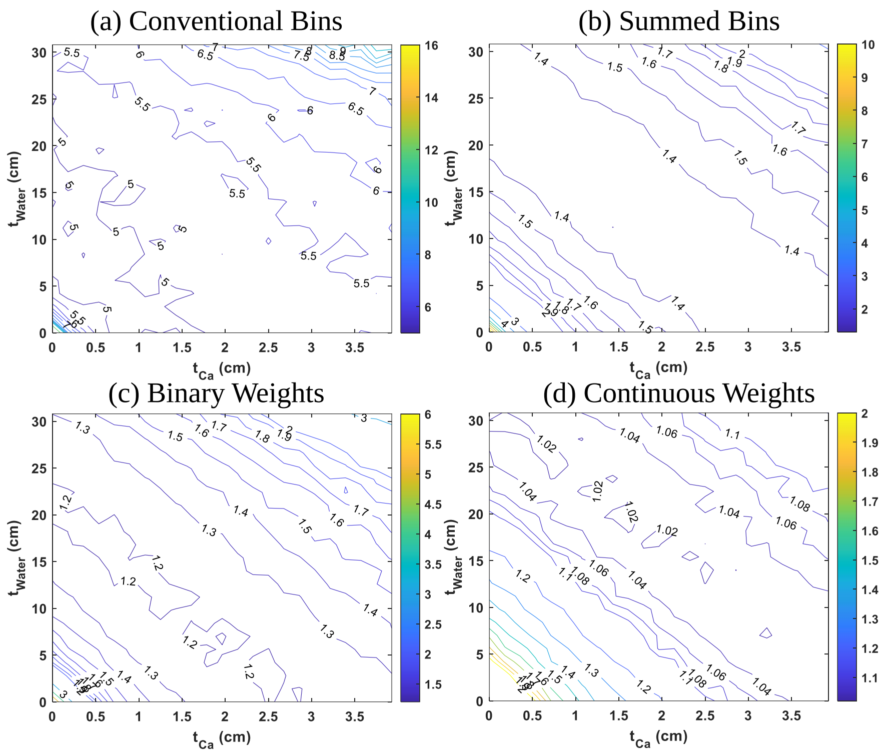

Figure 4: Relative variance between the bin compression strategies and 8 native bins for calcium decomposition.

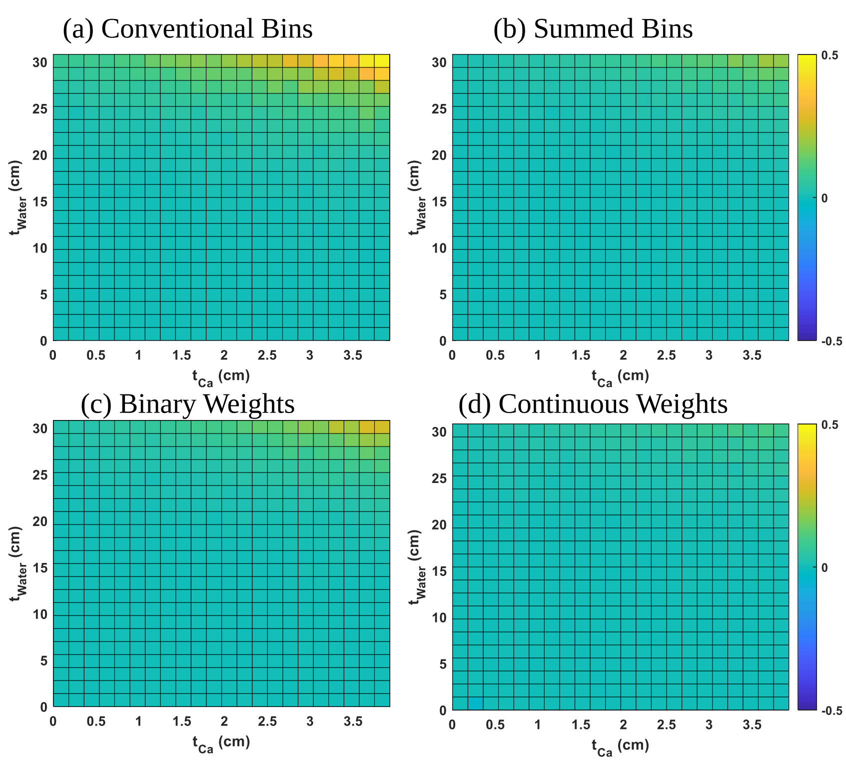

Figure 5: Bias of bin compression strategies for calcium decomposition.

3.3 Brain Phantom

We also applied these four strategies on a simulated brain phantom, and the resulting of water decomposition images for 2 measurements are shown in Figure 6. The average variance penalty of a region with uniform water is 352.35% for conventional bins, 33.54% for summed bins, 12.98% for binary weights, and 5.05% for continuous weights.

The increased noise due to bin compression is visibly obvious when we use conventional bins and summed bins. The image quality is the best when we use continuous weights and is comparable to that of 8 native bins (not shown). In addition, there is no structural bias observed between the images from compressed data and 8 native bins.

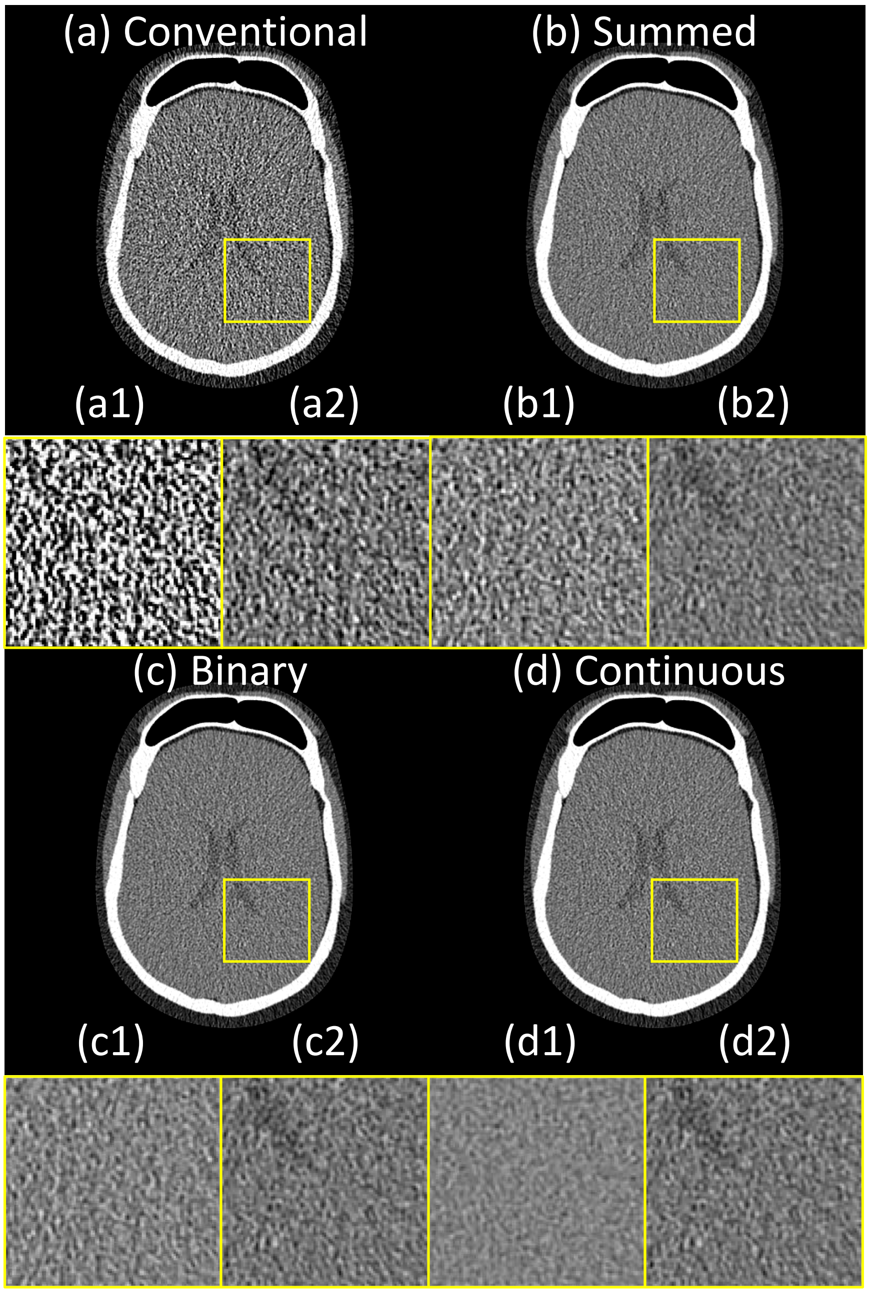

Figure 6: Phantom simulation results of water decomposition using data from two (a) conventional bins, (b) summed bins, (c) binary weights, and (d) continuous weights. (a2) - (d2) are the corresponding enlarged ROI. The display window is [0.9, 1.2] g/cc. The difference of the water decomposition between the proposed strategies and the 8 native bins is shown in (a1) - (d1), with display window [-0.05, 0.05] g/cc, showing the increased noise but no bias.

4. DISCUSSION

We have compared the bias and noise performance of 4 different energy bin compression methods in both projection and image domains. The results show that using continuous weights, the compressed 2 measurements can preserve almost as much spectral information as the original 8 native energy bins. It enables a 75% data reduction while preserving the native spectral information, with only a small increase of less than 10% in image variance over a large range of material thicknesses. Other strategies, such as conventional bins, summed bins, or binary weights, suffer from at least 50% increase in image variance when using 2 measurements. With 4 measurements using continuous weights, there is almost no image quality degradation.

The Monte Carlo simulation showed consistent results with the analytical CRLB predictions of noise performance. The bias of calcium thickness estimates is visibly higher at thicker material combinations when we use two conventional bins, summed bins, or binary weights, while the continuous weights and 8 native bins do not have this problem. From this observation, we infer that due to the lack of sufficient spectral information, if we use data from conventional bins, summed bins, and binary weights, the maximum likelihood estimator is no longer asymptotically unbiased when the detector collects fewer photon counts. We also conducted the same Monte Carlo simulation with 1 mAs per projection (not shown), which resulted in a smaller bias. This observation shows that the continuous weights method is more robust than the other three strategies in not only noise but also bias performance. It also indicates that extra calibration and higher exposures may be needed for large patients when only using 2 conventional bins. The silicon detector energy response is complex, with some high energy photons recorded in low energy bins due to Compton scattering. The 8 native bins and continuous weights with as few as 2 measurements contain the spectral information needed to account for the detector response, while other compression methods may struggle.

5. CONCLUSION

We found that compressing the binned data with continuous weights can best preserve the spectral information for material decomposition and virtual monoenergetic imaging from the original data of 8 native energy bins. Other bin compression strategies substantially increase image noise. With continuous weights, a compression ratio of 4 can be achieved with 2 measurements that mostly preserves the image quality of both basis materials and VMIs.

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