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Impacts of photon counting CT to maximum intensity projection (MIP) images of cerebral CT angiography: theoretical and experimental studies

Evan Cary Harvey¹, Mang Feng¹, Xu Ji¹, Ran Zhang¹, Yinsheng Li¹, Guang-Hong Chen^{1,2}, Ke Li^{1,2,3}

¹Department of Medical Physics, University of Wisconsin-Madison, 1111 Highland Avenue, Madison, WI 53705, United States of America

²Department of Radiology, University of Wisconsin-Madison, 600 Highland Avenue, Madison, WI 53792, United States of America

Abstract

While CTA is an established clinical gold standard for imaging large cerebral arteries and veins, an important challenge that currently remains for CTA is its limited performance in imaging small perforating arteries with diameters below 0.5 mm. The purpose of this work was to theoretically and experimentally study the potential benefits of using photon counting detector (PCD)-based CT (PCCT) to improve the performance of CTA in imaging these small arteries. In particular, the study focused on an important component of the CTA image package known as the maximum intensity projection (MIP) image. To help understand how the physical properties of a detector quantitatively influence the MIP image quality, a theoretical model on the statistical properties of MIP images was developed. After validating this model, it was used to explore the individual and joint contribution of the following detector properties to the MIP signal-to-noise ratio (SNR): inter-slice noise covariance, spatial resolution along the z direction, and native pixel pitch along z . The model demonstrated that superior slice sensitivity, reduced inter-slice noise correlation, and smaller native pixel pitch along z provided by PCDs lead to improved vessel SNR in MIP images. Finally, experiments were performed by scanning an anthropomorphic cerebral angiographic phantom using a benchtop PCCT system and a commercial MDCT system. The experimental MIP results consistently demonstrated that compared with MDCT, PCCT provides superior vessel conspicuity and reduced artifactual stenosis.

Keywords

photon counting CT; maximum intensity projection; CT angiography; autocovariance; partial volume effect

³Author to whom correspondence should be addressed. ke.li@wisc.edu.

1. Introduction

Cerebral CT Angiography (CTA) is an imaging technique that involves intravenous administration of an iodinated contrast bolus and rapid CT scan of the head and neck as the bolus reaches the cerebrovascular network (Rubin *et al* 2014). CTA is widely used for the diagnosis and management of various cerebrovascular diseases, including strokes, vasculitis, aneurysms, etc (Verro *et al* 2002, Tomandl *et al* 2004, Razek *et al* 2014). Taking stroke imaging as an example, the availability of high quality CTA images not only helps in identifying the presence and location of large vessel occlusion but also provides information about collateral circulation that is valuable for the clinical management of strokes (Bejer *et al* 2015). As another example, accurate rendering of the superficial temporal arteries is valuable in identifying vessel inflammation induced by giant cell arteritis (González-Gay 1999).

Despite the fact that CTA has become an established clinical gold standard for imaging large cerebral arteries and veins (ACR 2016), there is an important challenge that currently remains for MDCT-based CTA: its limited performance in imaging sub-millimeter perforating arteries (Tomandl *et al* 2004). As a consequence, the relatively invasive artery biopsy procedure remains the current clinical gold standard for the diagnosis of small vessel diseases such as giant cell arteritis (Chacko *et al* 2015). Among the major contributors to the poor performance of CTA in imaging small vessels is the physical performance of the MDCT detector. Conventional MDCT scanners use scintillator-based energy-integrating detectors (EIDs) that have excellent zero-frequency detective quantum efficiency (DQE) but poor high frequency DQE performance due to the isotropic spatial spreading of secondary quanta (light photons) (Youn *et al* 2015). To reduce spatial resolution loss and inter-pixel crosstalk, septa are usually placed in between detector pixels, which inevitably reduces the percent active area of the detector or the so-called geometric efficiency (Miess and Stefan 2011). For a given septum width, reducing the detector pixel size comes with a larger penalty in geometric efficiency (and radiation dose efficiency). Therefore, the physical size of a CT detector pixel is usually kept around 1 mm to maintain a balance between spatial resolution and dose efficiency. While this pixel size may be adequate in imaging large cerebral arteries, it can lead to several issues for small vessel imaging: besides limiting in-plane and through-plane spatial resolution, the relatively large pixel size often generates nonlinear partial volume averaging effects that lead to artifactual stenosis (Glover and Pelc 1980). Another major drawback of a scintillator-based EID is its highly sub-optimal detector response function that puts lower weightings on low energy x-ray photons carrying stronger iodine attenuation signal (Tapiovaara and Wagner 1985).

Photon counting detector-based CT (PCCT) offers potential technological solutions to these challenges MDCT systems face for CTA. When compared to EIDs used in conventional MDCT systems, the direct conversion mechanism employed by semiconductor photon counting detectors (PCDs) usually leads to better in-plane and through-plane spatial resolution (Yin *et al* 2000, Zhao *et al* 2001, Bellazzini *et al* 2013, Xu *et al* 2014). The reduced lateral spreading of secondary quanta in PCD also relaxes the need for inter-pixel septa and enables the use of a much smaller pixel size (e.g. 0.1 mm) without sacrificing geometry efficiency (Leng *et al* 2016, 2018). The relaxed tradeoff between spatial resolution

and dose efficiency can improve the CTA image quality (Willemink *et al* 2018). A smaller PCD pixel size also helps to reduce the blooming artifacts introduced by calcified plaques (Willemink *et al* 2018). Compared with the highly suboptimal weighting scheme used in EIDs, the inherent equal weighting of high and low energy photons in PCDs offers an improvement in the contrast-to-noise ratio (CNR) of iodinated vessels. In addition, by employing voltage comparators that compare the height of a pulse generated by each x-ray photon with pre-defined thresholds, the energy information of each x-ray photon can be estimated. This energy resolving capability of PCCT can be used to further improve the CNR of iodinated vessels (Tapiovaara and Wagner 1985, Roessl and Proksa 2007, Shikhaliev 2008, Schmidt 2009, Taguchi and Iwanczyk 2013) or to reduce beam hardening artifacts (Symons *et al* 2018). The energy resolving capability can also be used to generate virtual monoenergetic CT images that, upon optimization of the keV level, can improve the CNR of iodinated objects such as blood vessels (Zhou *et al* 2018).

Although previous studies have demonstrated potential benefits of PCCT to CTA source images, it is unclear whether and how PCCT may impact an important component of the CTA image package: the maximum intensity projection (MIP) image. A MIP image is formed by casting virtual 'rays' through a stack of CTA source images and selecting the maximal pixel value along each ray. This method is helpful for depicting high contrast objects such as contrast-enhanced vessels. As an example, figure 1 compares the CTA source and MIP images of an emergency room patient presenting acute ischemic stroke syndrome. Based on the CTA source image alone, it is very challenging to evaluate the vessel occlusion condition since the majority of the vessels extend to different *z* positions. In comparison, the MIP image that extracted vessel information from a broader *z* range (10 mm) provided clearer evidence for a middle cerebral artery occlusion. The MIP image also effectively enhanced the visibility of collateral blood vessels to facilitate physicians to choose the proper treatment method. However, as pointed out by the arrowhead in figure 1, the detectability of certain small vessels is still limited in the MIP image generated from a conventional MDCT system.

The purpose of this work was to study the potential impacts of PCCT technology to CTA MIP image quality. More specifically, the work aims at answering the following questions: Whether PCCT can improve the conspicuity of small cerebral vessels in CTA MIP images even without using the spectral imaging mode? If yes, how should the performance improvement be attributed to each physical property of the PCD system? To answer these research questions, a statistical model of the MIP image was developed and validated to connect the signal and noise properties of MIP image to the physical properties of the detector. Using this model, whether the benefits of PCCT to CTA source images (e.g. improved *z* resolution; reduced noise autocovariance along *z*) can cast a significant impact on the final MIP image was studied. Finally, experiments were performed using a benchtop PCCT system and an anthropomorphic phantom containing arteries of realistic size and orientation to directly demonstrate the impacts of PCCT to CTA MIP images.

2. Statistical model of MIP images

2.1 Model description

In clinical practice, a MIP operation can be taken along axial, coronal, sagittal, or even oblique directions. The following analysis uses an axial MIP as an example, but the analysis can be readily extended to other slice orientations. For a given axial spatial location (x, y) , the MIP operation seeks the maximal pixel value along the z direction within a specified range (e.g. $[0, 10]$ mm). This operation is performed for every (x, y) location so that a 2D MIP image can be generated for the given z range.

To derive the statistical model of MIP images, we first considered a simple case in which the z range is so narrow that it only includes two axial source slices. For a given (x, y) location, the MIP operator compares the pixel values at the two slice positions and extracts the maximal (max) value out of the two. If the max value is a number λ , there is only two possibilities: (case 1) the pixel value at slice 1 (denoted as f_1) equals λ , AND the pixel value at slice 2 (denoted as f_2) is no greater than λ ; (case 2) $f_2 = \lambda$, AND $f_1 \leq \lambda$. Therefore, the probability (Pr) of $\max[f_1, f_2] = \lambda$ is given by summing the probabilities of Case A and Case B:

$$\begin{aligned} \Pr_{\max[f_1, f_2]}(\lambda) &= \Pr(f_1 = \lambda \cap f_2 \leq \lambda) + \Pr(f_2 = \lambda \cap f_1 \leq \lambda) \\ &= \int_{-\infty}^{\lambda} \text{bPr}(f_1 = \lambda, f_2 = \lambda_2) d\lambda_2 + \int_{-\infty}^{\lambda} \text{bPr}(f_1 = \lambda_1, f_2 = \lambda) d\lambda_1, \end{aligned} \quad (1)$$

where $\text{bPr}(f_1, f_2)$ is a bivariate distribution function for variables f_1 and f_2 , and both λ_1 and λ_2 are dummy variables used in the integration.

The probability density function (PDF) of the bivariate max problem shown in equation (1) can be generalized to a multivariate max problem by replacing (f_1, f_2) with a $N \times 1$ vector $\vec{f}$ constructed from the pixel values from N slices. The MIP operation searches for the max value among the N elements in vector $\vec{f}$. By extending the 1D integration in equation (1) to $(N-1)$ dimensional integration and replacing the '+' operator by $\sum_{j=1}^N$, the probability density function of the multivariate max problem can be derived as

$$\Pr_{\max[\vec{f}]}(\lambda) = \sum_{j=1}^N \int_{-\infty}^{\lambda} \dots \int_{-\infty}^{\lambda} \text{mPr}_{\vec{f}}(\vec{f}_j) \prod_{k \in [1, N] \& k \neq j} d\lambda_k, \quad (2)$$

where the dummy integration variable λ_k is the k th element of the $N \times 1$ vector $\vec{f}_j$. In general, an arbitrary element of $\vec{f}_j$ is defined as:

$$f_j[k] \triangleq \begin{cases} \lambda & \text{when } k = j; \\ \lambda_k & \text{when } k \neq j. \end{cases} \quad (3)$$

In equation (2), $\text{mPr}_{\vec{f}}(\vec{f}_j)$ denotes the multivariate probability density function for $\vec{f}$ to be equal to an arbitrary vector of $\vec{f}_j$. This PDF is related to the autocovariance ($\mathbf{C}_f$) and expected signal value of $\vec{f}$ by

$$\text{mPr}_{\vec{f}}(\vec{f}_j) = \frac{1}{\sqrt{(2\pi)^N |\mathbf{C}_f|}} \exp \left[-\frac{1}{2} (\vec{f}_j - \langle \vec{f} \rangle)^T \mathbf{C}_f^{-1} (\vec{f}_j - \langle \vec{f} \rangle) \right]. \quad (4)$$

By definition, the n th statistical moment of $\max[\vec{f}]$, namely $\text{MIP}[\vec{f}]$, is related to the probability density function of $\max[\vec{f}]$ in equation (2) by

$$\langle \text{MIP}^n(x, y) \rangle = \int_{-\infty}^{\infty} \lambda^n \text{Pr}_{\max[\vec{f}(x, y)]}(\lambda) d\lambda \quad (5)$$

where the (x, y) dependence of vector $\vec{f}$ was put back in, and $\langle \cdot \rangle$ represents the expected value operator. Based on the statistical moment, several quantities that are closely related to the MIP image quality can be theoretically calculated. For example: the noise variance of the MIP image can be calculated from the first and second moments as

$$\sigma_{\text{MIP}}^2(x, y) = \langle \text{MIP}^2(x, y) \rangle - \langle \text{MIP}(x, y) \rangle^2. \quad (6)$$

The signal to noise ratio (SNR) of the MIP image value at a specific (x, y) location is given by

$$\langle \text{SNR} \rangle_{\text{MIP}}(x, y) = \langle \text{MIP}(x, y) \rangle / \sigma_{\text{MIP}}(x, y). \quad (7)$$

Based on equations (2)–(7), a detector property that influences either the source image signal ($\langle \vec{f} \rangle$) or autocovariance ($\mathbf{C}_f$) may influence MIP SNR through the multivariate probability density function of the source images, namely $\text{mPr}_{\vec{f}}$. The major remaining question is: how significant is the impact of each specific detector property? Section 3 will focus on addressing this question. Before answering this question, the statistical model of MIP images needs to be validated. The following section 2.2 presents the corresponding validation.

2.2. Model validation

To validate the statistical model of MIP images, the overall approach was to compare the MIP SNR predicted by the model with the SNR measured from MIP images. As shown in figure 2, the true profile of each simulated vessel object was blurred and sampled by the assumed CT system to generate $\langle \vec{f} \rangle$. Together with the autocovariance matrix of the same CT system ($\mathbf{C}_f$), $\langle \vec{f} \rangle$ was fed into equation (4) to calculate the multivariate PDF of the source images, $\text{Pr}_{\vec{f}}$. Next, equation (2) was used to obtain the PDF of the MIP image, $\text{Pr}_{\max}$, from which the theoretical SNR of MIP images was calculated based on equations (5)–(7).

Alternatively, the same set of object and CT system parameters was used to repeatedly simulate CTA source images, from which a MIP image ensemble was produced and MIP SNR was measured.

To be more specific, three vessel-simulating digital phantoms with different sizes were used to test the robustness of the theoretical model. As shown in figure 3, each object consists of a vertical vessel with a connected branch containing an oblique and horizontal region. The largest object had a diameter of 3 mm, height of 8 mm, and a nominal signal level of 600 HU; the medium object had a diameter of 1.5 mm, a height of 6 mm, and a nominal signal level of 400 HU; and the smallest object had a diameter of 0.5 mm, a height of 4 mm, and a nominal signal level of 200 HU. The three objects were emerged in a brain tissue-simulating background (40 HU). Although the ground truth profiles of the phantoms were voxelized, the size of the native voxel ($25 \times 25 \times 25 \mu\text{m}^3$) was kept much smaller than the detector sampling interval (1.1 mm, or 0.625 mm at iso-center) of the CT system used in the validation study. The ground truth profile of each phantom was blurred along both the axial and z directions using the aperture function of a typical CT detector pixel ($0.625 \times 0.625 \text{ mm}^2$). Discrete sampling was then imposed to the blurred profile to obtain the final $\langle \vec{f} \rangle$.

The validation study used realistic autocovariance matrices ($\mathbf{C}_f$) measured from two CT systems: one is a diagnostic MDCT system (GE Discovery CT750 HD), and the other one is an experimental PCCT system in the authors' lab. More description about the two systems is provided in section 4. Using the measured $\mathbf{C}_f$ shown in figure 4, noise-only images were generated by filtering white noise images with a Gaussian kernel; the width of the kernel was determined based on the criterion that the autocovariance measured from the filtered images matched $\mathbf{C}_f$ in figure 4. For each $\mathbf{C}_f$ and phantom, 10 000 sets of noise images were generated and added to the noise-free CTA source images of the phantom. From the 10 000 sets of noisy source images, an ensemble of noisy MIP images were produced and MIP SNR was measured at the following regions of each phantom: a vertical vessel region, an oblique vessel region, and a horizontal vessel region.

3. Application of the statistical model

As shown by the experimental $\mathbf{C}_f$ and slice sensitivity profile (SSP) in figures 4 and 5, the PCCT technology can effectively reduce noise covariance and improve spatial resolution along the z direction. In addition, due to the use of a much smaller native PCD pixel size (e.g. 0.1 mm), partial volume effect (PVE) and noise aliasing could potentially be reduced by PCCT. Using the statistical model presented in the previous section as a tool, how the improved z spatial resolution, reduced PVE and noise aliasing impact the MIP SNR was theoretically studied. The imaging task is the detection of a 0.5 mm diameter vessel parallel to the axial plane. For each of the two CT scanners (MDCT and PCCT), the system-filtered profile, $\langle \vec{f} \rangle$, of the vessel and the corresponding autocovariance matrix, $\mathbf{C}_f$, were fed into the theoretical model to theoretically calculate the MIP SNR. This process was repeated for a range of nominal vessel signal levels (200–800 HU, with 80 HU increments). This reference vessel signal range was chosen based on what's observed in clinical CTA source images. At each vessel signal level, five sub-studies were performed to investigate the separate and joint

contribution of the following factors to MIP images: noise aliasing, PVE, noise covariance, and z spatial resolution:

Study 0: Isolating the impact of noise aliasing

In this study, discrete sampling (0.1 mm sampling interval for PCCT; 1.1 mm for MDCT) was only applied to the noise component of the projection data, so that the impact of noise aliasing can be isolated from other factors such as PVE. Prior to sampling, both the noise magnitude and noise correlation condition were matched for the two CT systems. The sampled noise was processed by the designated reconstruction pipeline, and the resulting noise-only source images were used to measure the autocovariance matrix C_f . Depending on whether the two CT systems undergoing different noise sampling rates generate the same C_f , the influence of noise aliasing was evaluated.

Study 1: Isolating the impact of PVE

In this study, a comparison of MIP SNR was performed between two CT systems that have identical autocovariance and SSP; the only difference between them was the native (unbinned) detector pixel size, which determines how the pre-log raw projection data was sampled. System 1 used the native detector pixel size of the MDCT system (1.1 mm); System 2 used the detector pixel size of the PCCT system (0.1 mm). The post-logarithmic transform projection data of System 2 was rebinned and filtered along the z direction so that the SSP of the reconstructed image matched that of System 1. The purpose of this study design was to isolate the impact of PVE on MIP SNR.

Study 2: Isolating the impact of noise covariance

In this study, comparison was made between two CT systems that have identical native detector pixel size (1.1 mm) and SSP; the only difference between them was the autocovariance along the z direction: one system used the realistic autocovariance matrix of MDCT, while the other one used the realistic autocovariance matrix of PCCT shown in figure 4.

Study 3: Isolating the impact of through plane resolution

In this study, comparison was made between two CT systems that have identical native detector pixel size (1.1 mm) and autocovariance; the only difference between them was the SSP: one system used the SSP of MDCT, while the other one used the SSP of PCCT shown in figure 5(a).

Study 4: Combining all factors

After studying the individual impact of PVE, autocovariance matrix, and z spatial resolution to MIP SNR, their combined effect was studied. In Study 4, comparison was made between CT systems that have different detector pixel sizes, SSPs and autocovariances. One CT system simulated the MDCT scanner shown in figure 6(a), while the other one simulated the PCCT system shown in figure 6(b).

For each study, by using the PCCT system the MIP signal enhancement factor (γ), noise reduction factor (β), and SNR improvement factor (κ) were respectively calculated using the following equations:

$$\gamma = \frac{\langle \text{MIP} \rangle^{\text{PCCT}} - \langle \text{MIP} \rangle^{\text{MDCT}}}{\langle \text{MIP} \rangle^{\text{MDCT}}} \times 100\%, \quad (8)$$

$$\beta = \frac{\sigma_{\text{MIP}}^{\text{MDCT}} - \sigma_{\text{MIP}}^{\text{PCCT}}}{\sigma_{\text{MIP}}^{\text{MDCT}}} \times 100\%, \quad (9)$$

$$\kappa = \frac{\langle \text{SNR} \rangle_{\text{MIP}}^{\text{PCCT}} - \langle \text{SNR} \rangle_{\text{MIP}}^{\text{MDCT}}}{\langle \text{SNR} \rangle_{\text{MIP}}^{\text{MDCT}}} \times 100\%, \quad (10)$$

where $\langle \text{MIP} \rangle$, σ_{MIP} , and $\langle \text{SNR} \rangle_{\text{MIP}}$ are theoretical calculations directly from equations (2)–(7) with the added superscript of PCCT and MDCT to denote which simulating system was used.

4. Experimental study

To directly demonstrate the impacts of the PCCT technology to CTA MIP image quality, an experimental comparison study was performed between a benchtop PCCT system and a clinical MDCT system shown in figure 6. The MDCT system is a 64-slice commercial scanner (Discovery CT750 HD, GE Healthcare, Waukesha, WI). The PCCT system is an in-house benchtop system that consists of a cadmium telluride (CdTe) based PCD (XC-Hydra FX50, Xcounter), a rotating-anode diagnostic x-ray tube (G1952, Varian Medical Systems, Salt Lake City, UT), an 80 kW high frequency generator (Indico100, CPI, Canada), and a motorized rotary stage. The geometry of the PCCT system was kept the same as that of the MDCT system; acquisition and reconstruction parameters of the two systems were matched whenever it was possible (table 1). To match radiation dose of the two CT systems, CT dose index (CTDI) was measured using the following materials and methods: a 16 cm CTDI phantom was scanned by each CT system using the protocol listed in table 1. As shown in figure 7, a 100 mm pencil chamber (10X6–3CT, RadCal Corp., Monrovia, CA, USA) was inserted into the central bore of the phantom to measure the exposure $\bar{X}$ received during a CT scan averaged over its active length:

$$\bar{X} = \frac{1}{L} \int_{-L/2}^{+L/2} X(z) dz, \quad (11)$$

where $L = 100$ mm is the length (along z) of the active volume of the pencil chamber. Based on the instruction of AAPM Report No. 96 (McCullough *et al* 2008), the exposure reading $\bar{X}$ was converted to CTDI₁₀₀ using the following formula:

$$\begin{aligned}
 \text{CTDI}_{100} &= \frac{1}{NT} \int_{-L/2}^{+L/2} D(z) dz \\
 &= \frac{1}{NT} \int_{-L/2}^{+L/2} f \cdot C \cdot X(z) dz \\
 &= \frac{f \cdot C \cdot \bar{X} \cdot L}{NT},
 \end{aligned} \tag{12}$$

where D denotes dose to air, $f = 8.7 \text{ R mGy}^{-1}$ is the conversion factor from the measured exposure (in R) to dose to air (in mGy), $C = 1.04$ is the calibration factor for our exposure meter system, and N (number of collimated detector rows) $\times T$ (height of each detector row along z) is the collimated beam width at iso-center (20 mm for both CT systems).

After measuring CTDI_{100} at the center of the 16 cm CTDI phantom, the measurement was repeated at the edge hole in the same phantom. A weighted summation of the center and edge CTDI_{100} leads to the so-called CTDI weighted (CTDI_w):

$$\text{CTDI}_w = \frac{1}{3} \text{CTDI}_{100, \text{center}} + \frac{2}{3} \text{CTDI}_{100, \text{edge}}. \tag{13}$$

For axial scan mode used in this work, $\text{CTDI}_w = \text{CTDI}_{\text{vol}}$. Using this procedure, we first measured CTDI_{vol} for the MDCT system, and then adjusted the mAs of the PCCT system until its measured CTDI_{vol} matched that of the MDCT system.

In addition to radiation dose matching, we also matched the reconstruction kernel of the two CT systems: the PCCT reconstruction kernel was heuristically adjusted until the inplane modulation transfer function (MTF) of the PCCT system matched that of the MDCT system (figure 5(b)).

The image object used in the experimental comparison study is an anthropomorphic CT angiographic phantom (ACS Head, Kyoto Kagaku, Japan). The left hemisphere of the head phantom contains contrast-enhanced internal carotid arteries (ICA), middle cerebral arteries (MCA), and anterior cerebral arteries (ACA) with various diameters ranging from 0.5 to 4 mm (figure 6(c)). Using alignment lasers and levels, the position and orientation of the phantom was finely adjusted so that images acquired from the two CT systems were registered. After using standard filtered back projection reconstruction with a 512×512 matrix size, 22 cm field-of-view, and 0.625 mm slice thickness, CTA source images of this head phantom were generated for the two CT systems. Additional preprocessing on the PCCT system data included linear interpolation across inter-panel detector gaps and re-binning in the row direction of the sinogram data post-log to the height of each MDCT detector row (1.1 mm). Additional post-processing included a standard water and bone beam hardening correction described in Hsieh (2003) and an image domain-based ring artifact correction method described in Prell *et al* (2009).

From the CTA source images 10 mm MIPs were then generated and side-by-side comparisons of the MIP images were conducted to evaluate the performance of each CT system for visualizing cerebral vessels. We also evaluated the CTA source image quality by

measuring the signal-to-noise ratio (SNR) of a middle cerebral artery in the phantom. The measurement locations are indicated in a volume rendering image shown in figure 8.

5. Results

5.1. Validation of theory

Figure 9 provides a side-by-side comparison of MIP SNR values calculated using the theoretical model and those from repeated simulations. For all three vessel sizes and all regions (horizontal, vertical, oblique), the absolute difference between the theoretical calculation and simulation results is less than 0.19. The relative error is less than 2%. These results validated the capability of the proposed statistical model in quantitatively predicting the SNR of MIP images for an arbitrary combination of object and imaging system inputs.

5.2. Application of theory

As shown by the autocovariance (along z) results of Study 0 in figure 10, finer noise sampling offered by the PCCT system did not introduce any major change to the autocovariance matrix of the source images. However, the finer detector pixel size did improve the signal intensity by reducing the PVE. As shown in figure 11(a), the final MIP signal was effectively improved in Study 1 (on the impact of PVE), and the corresponding MIP SNR improvement increased with higher vessel attenuation level. For Study 2, the 'white' autocovariance generated from the PCCT system also improved MIP SNR by reducing MIP noise. In contrary to Study 1, the improvement is more pronounced at lower vessel attenuation level. For Study 3, the improved z spatial resolution enabled by the PCD technology also improved the MIP SNR by increasing the signal intensity; the higher the vessel attenuation was, the more improvement it achieved. Finally, when all three effects were applied to the MIP image (Study 4), the SNR improvement is at least 25% and could be as high as 38% for the 800 HU vessel. These results indicate that the MIP SNR can be effectively improved if the CT system's PVE is mitigated, noise correlation along z is reduced, and/or through-plane spatial resolution is improved. All three conditions are met when a PCD is introduced to a CT system. Therefore, PCCT can benefit CTA MIP imaging, particularly the visualization of small vessels whose SNR is often inadequate in MDCT-based images.

5.3. Experimental comparison study

Figure 12 provides side-by-side comparisons of experimental MIP images produced by the benchtop PCCT system and the commercial MDCT system. The PCCT system shows superior image quality of the orbitofrontal artery branch of the ACA (figure 12(a)) and proximal MCA branches (figure 12(b)). These branches were poorly resolved by the MDCT system. Figure 13 corresponds to another anatomical position that includes multiple MCA branches where there is an artificial stenosis of the frontopolar artery in the MDCT MIP (top ROI with arrow). The middle ROI in figure 13(a) shows a case where two small artery segments that are in close proximity of each other can be resolved more clearly with the PCCT system; the bottom ROI in figure 13(a) and the two ROIs in figure 13 show multiple small arterial segments completely missed by the MDCT system. These vessels are better depicted in the PCCT MIP images.

Figure 14 compares experimental source images from which MIP images were generated. As shown in figure 14(a), vessel segments in the anterior cerebral artery region are less conspicuous in the MDCT source image than in the PCCT source image. The top ROI of figure 14(b) demonstrates poor vessel visibility for the prefrontal artery for the MDCT system while the bottom ROI displays peripheral artery segments that are almost completely missed by the MDCT system. The improvement of individual source image eventually led to the improvement of the final MIP images in figure 12.

The improvement of source image quality is further quantified via SNR measurements. As shown in figure two-sided t-test). Note that these SNR results were generated under the condition that radiation dose and axial 15, the SNR of PCCT MIP was found to be 5.8 ± 1.3 for PCCT, compared with 4.4 ± 0.9 for MDCT ($p < 0.01$, spatial resolutions of the two CT systems were matched. The raw individual measurements of signal and noise for each CT system are reported in table 2. PCCT improved the source image signal magnitude and reduced noise magnitude; and together with reduced noise covariance along z , these improvements jointly benefited the final MIP image quality.

6. Discussion

In the past few years, multiple works have explored the advantages of PCCT over energy-integrating CT, particularly for individual CT images without the MIP operation (Shikhaliyev 2008, Schmidt 2009, Taguchi and Iwanczyk 2013, Yu *et al* 2015, 2016, Pourmorteza *et al* 2017, Symons *et al* 2017, 2018, Willemink *et al* 2018). It is straightforward to infer that the advantages introduced by PCCT to source images would transfer to MIP images. The major new contribution of this paper is the development of the theoretical model that enables statistics of the source images to be quantitatively connected to the statistics of the MIP images. By leveraging this model, the *individual* impact of PVE, autocovariance, or through-plane spatial resolution of a CT system to the MIP SNR was studied separately. This is hardly achievable by only using an experimental system, which is often jointly influenced by these physical effects. As shown by the results of the theoretical Study 1, MIP SNR can be improved if PVE is reduced. The reason is that the severity of PVE-induced nonlinear signal distortion is directly related to the intensity of the vessel in the CTA source images, namely the peak intensity of term $\langle \vec{f} \rangle$ in equation (4): when PVE is reduced, the gap between the peak element and other elements in $\langle \vec{f} \rangle$ becomes larger, which makes the span of $P_{\max}$ in equation (2) narrower and its center closer to the true peak value. Similarly, Study 3 shows that if a CT system such as PCCT has better through-plane spatial resolution, MIP SNR can also be improved because of reduced signal mixing between high contrast vessel and low contrast tissue background. Note that in reality, PVE and through-plane spatial resolution are usually correlated. However, they do not necessarily have causal relationship and need to be analyzed separately. An important message given by Studies 1 and 3 is that in order to maximize the benefits of PCCT in CTA imaging, any binning of the projection data should be performed in the post-logarithmic domain, because it is the sampling period of the pre-logarithmic domain that determines the severity of PVE.

Besides Studies 1 and 3, it was additionally shown in Study 2 that if noise covariance along z can be reduced, MIP SNR, particularly of lower contrast vessels, can also be effectively improved. This is exactly another benefit PCCT provides: the direct conversion mechanism, the low energy thresholding process, and the anti-charge sharing logic employed by PCDs can almost completely eliminate noise covariance along both the detector row and column directions. In comparison, the autocovariance of MDCT images contain certain non-negligible off-diagonal elements that broaden the multivariate PDF $P_{\vec{f}}$ in equation (4) and $P_{\max}$ in equation (2), eventually leading to larger noise variance of MIP images.

For the validation study design the smallest vessel object has a lower nominal contrast to emulate realistic physiological conditions of smaller vessels being more prone to bolus dispersion effects (resulting in lower contrast signals) because anatomically smaller vessels are more downstream from the injection site. Since the severity of PVE also depends on the vessel contrast (as shown in Study 1), a lower contrast will result in a milder PVE, therefore the SNR changes within the vertical, oblique, and horizontal regions for the small vessel object are not as significant as the larger vessel objects that have a corresponding larger nominal contrast.

To supplement the theoretical study, this work also includes an experimental phantom study so that one can directly visualize the improvement of MIP image quality by using the PCCT system. As shown by the experimental images in figures 12 and 13, PCCT provides superior vessel conspicuity when compared with a commercial MDCT system under the conditions of matched radiation exposure level and axial spatial resolution. Taking the orbitofrontal branch of the ACA shown in figure 12(a) as an example: since this artery branch runs parallel to the axial plane, it is very PVE-sensitive. The much smaller native PCD pixel size enabled PCCT to neatly mitigate PVE and therefore improved the vessel SNR. In addition, PCCT effectively reduced the artifactual stenosis of the prefrontal artery and frontopolar artery observed in the MDCT image. Better delineations of extremely distal vessel branches near the skull can also be appreciated in the PCCT image. In contrast, conventional MDCT performed poorly in imaging these distal vessels: as an example, the prefrontal artery is completely missed by the MDCT image in figure 13(b). This observation is consistent with what's reported in literature (Tomandl *et al* 2004).

In addition to MIP images, CTA source images were also examined to rule out a potential performance tradeoff. As shown by the SNR results in figure 15, no degradation in vessel SNR was observed in PCCT source images; in fact, a statistically significant improvement was demonstrated.

This work has the following limitations. Although efforts were made in matching the acquisition and reconstruction parameters of the two experimental CT systems, certain mismatch in experimental condition still exists due to hardware constraints. For example, the nominal focal spot size of the x-ray tube used in the PCCT system is 1.2 mm, compared with the 1.0 mm focal spot size of the CT tube used by the GE MDCT system. Whether further performance improvement can be achieved remains to be investigated if the focal spot size of the PCCT system can be further reduced to 1.0 mm. Similarly, the benchtop PCCT system is not equipped with anti-scatter grid and bowtie filters, which adds a confounding

factor to the attempt of a fair comparison between the two CT systems. Next, the scan speed of PCCT acquisition (50 s/rotation) is much longer than that of MDCT (0.5 s), because the maximal continuous tube current allowable (20 mA) of the laboratory tube is much lower than that of the MDCT tube (800 mA). However, it is worth noting that scan time is not a fundamental issue for the PCCT technology, as multiple studies have demonstrated the feasibility of PCCT scans at clinically acceptable speed and tube current level without severe pulse pileup effect (Yu *et al* 2015, Leng *et al* 2016, Yu *et al* 2016, Willemink *et al* 2018). Finally, only one tube potential (100 kV) was used in the experimental study. The 100 kV was chosen based on the our institution's clinical head CTA protocol that has undergone extensive optimization to achieve the desired image quality with the lowest possible radiation dose (Szczykutowicz and Myron 2016, Szczykutowicz *et al* 2016). The benefit of 100 or lower kV in cerebral CTA imaging has also been reported by other groups (Luo *et al* 2014, Tang *et al* 2015, Li *et al* 2017). However, other institutions may use 120 or higher kV for CTA scans, especially those covering not only the head but also the neck and aortic arch in a single helical pass. Since at higher kV, the signal of iodine in MDCT images may encounter more loss than in PCCT due to the difference in photon energy weighting, our experimental study operated at 100 kV may have resulted in a conservative estimation of the potential benefit of PCCT over MDCT, although this point is a hypothesis and needs to be studied in future work.

7. Conclusions

Using the statistical model of MIP images, this work demonstrated that the quality of CTA MIP images is strongly dependent on the through-plane spatial resolution, severity of partial volume effect, and through-plane noise covariance. Because of the physical characteristics of the photon counting detector, PCCT offers superior through-plane spatial resolution, almost no through-plane noise covariance, and reduced partial volume effect. Therefore, PCCT can effectively improve the image quality of CTA MIP images, benefiting the visualization of perforating or small vessels for a given radiation exposure level.

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Figure 1. Conventional MDCT-based CTA source image and MIP image of an acute ischemic stroke patient. The arrow in the MIP image points to an occluded segment of the middle cerebral artery. The dashed circle shows collateral vessels. The arrowhead points to a small vessel that is barely perceivable.

Figure 2.
The general workflow for validating the SNR model of MIP images.

Figure 3. Digital vessel phantoms used in the validation study. Each phantom consists of a vertical vessel with a connected branch containing an oblique and horizontal region.

Figure 4.

Inter-slice autocovariance matrices ($\mathbf{C}_f$) of a diagnostic MDCT system (GE Discovery CT750 HD) and a benchtop PCCT system used in this work. Each matrix contains 16×16 elements, covering a total z span of 10 mm. In-plane spatial resolutions of the two CT systems were matched when measuring $\mathbf{C}_f$.

Figure 5.

(a) Experimentally measured SSP and (b) MTF of the MDCT and PCCT systems for a high resolution reconstruction kernel.

Figure 6.

(a) Diagnostic MDCT system (GE Discovery CT750 HD) used in this work. (b) Experimental PCCT system used in this work. (c) Angiographic phantom used for the experimental comparison study.

MDCT

PCCT

Figure 7. CTDI phantom and pencil ion chamber used on each CT system for matching of CTDI_{vol} (examples of the pencil chamber in the center position are shown).

Figure 8.
Illustration of 13 SNR measurement locations in the middle cerebral artery in the physical phantom.

Figure 9.

Results of the validation study. MIP SNR results in (a) were calculated or measured using the PCCT autocovariance; results in (b) used the MDCT autocovariance. The error bars denote MIP SNR statistics performed over a set of in-plane positions within each vessel region.

Figure 10.

Comparison of autocovariance matrices generated with two different native detector sampling intervals (0.1 mm for PCCT, 1.1 mm for MDCT). The reconstruction slice thickness (0.625 mm) is matched for the two CT systems. (a) and (b) are for systems with white noise; (c) and (d) are for systems with correlated noise prior to sampling.

Figure 11.

Application of the statistical model: theoretically calculated percent (a) MIP signal enhancement factor (γ), (b) MIP noise reduction factor (β), and (c) MIP SNR improvement factor (κ) by using the PCCT system. The values were calculated using the theoretical model and plotted against reference vessel signal level. The error bars denote statistics performed over a set of in-plane positions within the vessel.

Figure 12.

Comparison of experimental MIP images generated from the two CT systems: (a) the orbitofrontal arterial branch of the anterior cerebral artery (ACA); (b) proximal MCA branches where arrow points to a distal branch that is poorly resolved by the MDCT system while the bottom ROI demonstrates a similar effect for another distal vessel. All images were displayed using the same window/level of 600/200 HU.

Figure 13.
(continued from figure 12) Comparison of experimental MIP images. All images were displayed using the same window/level of 600/200 HU.

Figure 14.
Comparison of experimental source images. All images were displayed using the same window/level of 600/200 HU.

Figure 15. Box-and-whisker plots of vessel CNR experimentally measured at 13 locations along the middle cerebral artery (MCA) in CTA source images.

Table 1.

List of CTA protocol parameters used for comparison study between MDCT and PCCT systems.

Parameter	MDCT	PCCT
Source-to-detector (cm)	94.7	94.7
Source-to-iso (cm)	53.9	53.9
System magnification	1.76	1.76
Collimation at iso (cm)	2	2
CT scan mode	Axial	Axial
Flattening filter	Medium	Not available
kV	100	100
Nominal focal spot (mm)	1.0	1.2
CTDI _{vol} (mGy)	36	36
mAs	275	250
Recon field-of-view (cm)	22	22
Recon matrix size Recon pixel size (mm ²)	512 × 512 0.43 × 0.43	512 × 512 0.43 × 0.43
Recon slice thickness (mm)	0.625	0.625
MIP range (mm)	10	10

Table 2.

Source image signal (mean pixel value), noise standard deviation, and SNR measured at 13 distinct ROIs along middle cerebral artery for both MDCT and PCCT systems. SD: standard deviation.

Location	PCCT			MDCT		
	Signal (HU)	SD (HU)	SNR	Signal (HU)	SD (HU)	SNR
1	435.1	80.1	5.4	379.2	81.8	4.6
2	376.6	50.5	7.5	383.0	138.4	2.8
3	417.5	54.2	7.7	364.3	107.8	3.4
4	396.0	64.4	6.2	358.2	75.0	4.8
5	406.4	73.6	5.5	332.8	92.8	3.6
6	434.4	96.8	4.5	341.0	84.6	4.0
7	418.2	99.8	4.2	367.1	60.4	6.1
8	392.1	55.1	7.1	323.7	66.9	4.8
9	391.8	77.8	5.0	433.1	83.1	5.2
10	340.1	64.0	5.3	383.9	98.6	3.9
11	353.6	58.6	6.0	339.3	71.7	4.7
12	356.2	97.2	3.7	375.9	75.5	5.0
13	412.1	58.4	7.1	386.2	87.2	4.4
Mean	394.6	71.6	5.8	366.7	87.2	4.4
SD	30.6	17.5	1.3	29.0	20.2	0.9