Published in final edited form as:

Proc SPIE Int Soc Opt Eng. 2018 February ; 10573: . doi:10.1117/12.2292581.

Use of a CMOS-based micro-CT system to validate a ring artifact correction algorithm on low-dose image data

Alexander R. Podgorsak^{a,b}, S.V. Setlur Nagesh^b, Daniel Bednarek^{b,c}, Stephen Rudin^{a,b,c,d}, and Ciprian N. Ionita^{a,b}

^aDepartment of Biomedical Engineering, University at Buffalo

^bToshiba (Canon) Stroke and Vascular Research Center, Buffalo NY

^cDepartment of Radiology, University at Buffalo

^dDepartment of Neurosurgery, University at Buffalo

Abstract

The imaging of objects using high-resolution detectors coupled to CT systems may be made challenging due to the presence of ring artifacts in the reconstructed data. Not only are the artifacts qualitatively distracting, they reduce the SNR of the reconstructed data and may lead to a reduction in the clinical utility of the image data. To address these challenges, we introduce a multistep algorithm that greatly reduces the impact of the ring artifacts on the reconstructed data through image processing in the sinogram space. First, for a single row of detectors corresponding to one slice, we compute the mean of every detector element in the row across all projection view angles and place the reciprocal values in a vector with length equal to the number of detector elements in a row. This vector is then multiplied with each detector element value for each projection view angle, obtaining a normalized or corrected sinogram. This sinogram is subtracted from the original uncorrected sinogram of the slice to obtain a difference map, which is then blurred with a median filter along the row direction. This blurred difference map is summed back to the corrected sinogram, to obtain the final sinogram, which can be back projected to obtain an axial slice of the scanned object, with a greatly reduced presence of ring artifacts. This process is done for each detector row corresponding to each slice. The performance of this algorithm was assessed using images of a mouse femur. These images were acquired using a micro-CT system coupled to a high-resolution CMOS detector. We found that the use of this algorithm led to an increase in SNR and a more uniform line-profile, as a result of the reduction in the presence of the ring artifacts.

Keywords

Ring artifacts; micro-CT; CMOS

1. INTRODUCTION

An important first step to image acquisition with computed tomography (CT) is the calibration of the detector panel via the flat field correction^{1,2}. This calibration step is included in the image acquisition workflow to correct for sensitivity mismatches between

pixels across the detector face. The assumed behavior across the detector face is that the sensitivity will be equal for all pixels. Due to manufacturing defects and imperfect electronics, this will not be the case. There will be regions in the detector that are more sensitive than other regions. This creates a situation where even if the same energy fluence of x-ray photons is incident on the separate regions, the output signal will not be equal. This leads to the presence of artifacts in the reconstructed volume. To prevent this from occurring, each projection image is divided by the flat field calibration image. The flat field calibration image is simply the response of the detector to a “flat” x-ray beam, meaning one of equal fluence to each detector element. The flat field image is dependent on the image acquisition parameters selected such as tube voltage and current, and is often acquired via an averaging of several flat frames of image data to improve the statistics of the acquisition.

The flat field correction process is also capable of correcting for the presence of image imperfections other than what is due to variation in exposure response of the detector elements^{3, 4}. If there is structure noise in the image data due to the presence of the phosphor, a flat field correction should properly correct for that as well. Anything which impacts the nonuniformity of detector element response, both before and after the addition of the object to the field of view should be corrected for by the flat field correction process. If the correction is perfectly carried out, the only remaining variation in the background “flat” region of the image is due to statistical fluctuations over the detector area⁵.

This flat-field correction process typically works well. However, conditions such as instabilities or non-linearities may exist which would render the flat-field correction process imperfect at normalizing the sensitivity of the pixels across the detector face. If this occurs, ring artifacts such as what can be seen in Figure 1 may be present in the image data reconstructed from projection data acquired with incomplete detector response normalization. Such ring artifacts are present in the reconstructed volume due to the presence of vertical striping in the sinogram along the detector element axis, caused by the imperfect flat field correction of the image data. An example of vertical striping present in the sinogram space that would lead to the presence of ring artifacts in the reconstructed data can be found in Figure 2. The ring artifacts greatly inhibit the qualitative utility of the image data, and quantitatively reduce the SNR of objects present in the image data and the uniformity of the background. This is a problem which is oft-reported on⁶, specifically in the context of micro-CT due to the high-resolution which is often used during imaging.

There has been much effort reported on in the literature regarding the reduction of these types of artifacts^{7, 8, 9, 10}. There are proposed algorithms that target the sinogram data prior to reconstruction, while others target the CT image data following the reconstruction. There are utilizations of wavelet transforms¹¹ for the goal of reducing the effect of the rings on the reconstructed image data, and even an implementation of machine learning¹² to achieve the same goal. A paper¹³ by Eldib and colleagues proposes a ring artifact correction algorithm that processes the uncorrected axial slices to compute a multiplicative factor to reduce the presence of ring artifacts in the sinogram space, which is then backprojected to obtain the corrected reconstructed axial slices. In this work, we propose several important modifications to this original method, and validate the results of our algorithm utilizing different reconstructed planes of a mouse femur. The image data used to reconstruct the

volume was acquired using a 49.5 μm pixel size CMOS detector (Teledyne DALSA, Waterloo, ON). This detector is coupled to a micro-CBCT unit assembled by our group.

2. MATERIALS AND METHODS

The principle steps of our proposed ring artifact correction algorithm will now be introduced. The important differences from the Eldib method will be highlighted as well. For convention, the input into this processing, the flat field corrected sinograms, will be called S , where S is a ' n_x by Θ ' matrix. n_x is the number of detector x-elements and Θ is the number of acquired projections. This processing carried out in the proposed algorithm is shown in the flowchart in Figure 3.

The first step of our algorithm is to compute what we will call the correction vector, designated c_v in this manuscript. c_v is acquired by first averaging the signal for each detector element, over all of the projection view angles. In other words, we average all of the values along the y-axis of Fig. 2, for all of the detector elements shown on the x-axis. This will be mathematically denoted as $\bar{S}$. We then take the reciprocal element-by-element of this vector, and transpose it to obtain c_v .

$$c_v(l) = 1/\bar{S}(l)$$

As an example of what is actually being acquired during this step, consider an input sinogram size 1500 elements (number of detector elements) by 360 elements (number of projection view angles). Averaging the detector elements over all of the projection view angles will obtain a 1500 element by 1 element vector, which we then compute the reciprocal of and transpose leaving a c_v sized 1 element by 1500 elements.

As detailed in Fig. 3, the next step of the ring correction algorithm is what we term the semi-correction of the projection data in the sinogram space. Consider the same sized c_v as in the previous step of the algorithm (1 element by 1500 elements). This is multiplied with each row of the sinogram (1500 elements by 1 element) to acquire what we will call the semi-corrected sinogram (SCS). Included in Figure 4 are plots of an example of a c_v , a row of uncorrected sinogram data, as well as that same row following multiplication and correction with c_v .

$$SCS = S * c_v$$

The semi-correction of the sinograms has the effect of reducing the standard deviation of the profile shown in Fig. 4b by 4.1%, when we obtain the profile in Fig. 4c. This indicates that the correction is quantitatively correcting for the vertical striping in the sinogram space, and would be the same as a flat field correction if there were no object in the field of view. However, the correction also introduces regions of enhanced contrast at the edges of the object due to an averaging between object and background. These regions are highlighted by the red circles in Fig. 4c, and their presence is why this processing step is termed the

“semicorrection” of the sinogram. This process carried out over all of the rows of the sinogram data from Fig. 2 will yield the sinogram shown in Figure 5. Included on the figure are red arrows indicating the regions of contrast enhancement due to the multiplication of the sinogram data by c_v . If the correction process were to be finished here, and the reconstructed volume were to be computed, the result would be something like what is seen in Figure 6. Note the dark region at the center of the object as referred to by the red arrow.

Similar to the image data prior to the semicorrection step, the reconstructed data resultant from a backprojection using the sinogram data does not provide adequate images. While the rings have been removed effectively, there is a dark region in the image data which would negatively impact the accuracy of quantitative analysis using the image data.

The next step of the proposed algorithm is the computation of the difference map, D , which is an element-by-element subtraction of the semicorrected sinogram normalized to the background value of the original sinogram, BG , and the original sinogram as illustrated in Figure 7. Through this step, we are extracting the differences that our processing has introduced to the original scan data. This difference map should contain both the vertical striping we remove, as well as the contrast information we lose due to the multiplication of c_v by the original sinogram. This step of the algorithm is an important first departure from the Eldib method, where the difference map was computed using reconstructed slices of the uncorrected and corrected image data, pixel by pixel. Using the sinogram data prevents the need to have to reconstruct the data at this intermediate stage, saving computation time.

$$D = (SCS * BG) - S$$

We compute this difference map for the eventual summation of the contrast information back to the semicorrected sinogram just prior to backprojection; however, it would make no sense to perform this summation without further processing of the difference map. Without any, we would just be summing the striping information directly back to the image data it was just removed from, thereby corrupting the image with the ring artifacts we are proposing the removal of. The next step in the algorithm is involved with this, and does so via the application of a blurring kernel, denoted as m , onto the difference map. We do this to reduce the presence of the striping in the difference map, while losing minimal edge information in the middle of the sinogram which is made up of the actual object. The blurring method implemented in this work for this requirement is a 1D median filter, the size of which will be dependent on how widespread the vertical striping is in the sinogram space. Typically, the size of the median filter which was used in this proposed work considers 20 neighbors across the horizontal axis. We do not blur across projections, just the detector elements (in the x-direction). The use of a median filter is a second deviation from the Eldib method, which utilized a Gaussian filter with σ equal to 10 to reduce the impact of the striping in the difference map. Figure 8 contains the difference map from Fig. 7 blurred with a median filter during this processing step. We will denote this blurred difference map as D_B . The mathematical definition of the formation of D_B can be found below, where $\otimes$ denotes the application of filter m onto the difference map D .

$$D_B = D \otimes m$$

The final processing step in this proposed method is to sum the blurred difference map onto the semicorrected sinogram element-by-element. This process results in the final the contrast corrected sinogram, *CCS*. Using this portion of the algorithm, we retain the lost contrast information in the object region of the sinogram, without summing back high intensity striping artifacts present in the original data. While it is true that we are summing back some of the striping, it is less in intensity to the contrast information that is being summed, and to the background information present in the semicorrected sinogram. The result of the summation of the blurred difference map in Fig. 8 and the semicorrected sinogram in Fig. 5 can be found in Figure 9. Note the retrieval of the object information without adding the striping back onto the sinogram.

$$CCS = SCS + D_B$$

The output from our proposed algorithm is the contrast corrected sinogram that is then backprojected to carry out the volume reconstruction. In order to assess the performance of our proposed algorithm in a specific case using real image data, this method was carried out to correct and reconstruct sinograms extracted from two planes of image acquisition of a mouse femur. One plane near the distal metaphysis, and a second extracted from the diaphysis. The type of bone will vary depending on where in the femur we consider. The first plane will be mostly trabecular bone requiring high resolution to properly visualize, and the second plane will be made up of cortical bone. Image acquisition was carried out using tube voltage of 60 kVp and wattage of 40 W with our micro-CT unit¹⁴. Exposure time was set to 1000 ms per projection, and 0.5 mm aluminum was placed in the beam. Image data was reconstructed in uncorrected form through the use of a modified¹⁵ FDK¹⁶ reconstruction algorithm, as well as in corrected form following processing with the proposed algorithm using the same reconstruction algorithm. Quantitatively, we were interested in a comparison of measured metrics such as SNR and extracted line profiles. Edge sharpness was assessed via computing the gradient from background to object image intensity as displayed on the line profiles. The expectation at the onset of this testing was that the SNR would be superior for the reconstructions computed from corrected projections as opposed to the uncorrected ones. This would indicate a successful implementation of a ring correction algorithm.

Additionally, a sinogram obtained from cropping out the majority of background out from the acquisition of the mouse femur was corrected using the proposed algorithm for the purpose of validation of the algorithm in the case of scan data which takes up most of the field of view. In this case, there will be a limited background width to compute c_v with, thus potentially impacting the quality of the correction. Additionally, it seems likely that an object wider in the sinogram space (indicating more of the field of view being filled) will have more widespread contrast enhancement, thus needing a larger median filter to properly carry out contrast correction. This may blur the edges of the object an unacceptable amount.

3. RESULTS

Figure 10a shows a reconstructed slice of the mouse femur computed using data that was not corrected using our proposed method. Figure 10b shows a slice from the same location, but computed using projection data corrected using our proposed algorithm. This specific slice shows a plane near the distal metaphysis of the mouse. Included on the figures are red regions of interest, indicating the extraction region for the SNR computation meant to serve as part of the quantitative comparison between the corrected and uncorrected data, as well as yellow linear extraction profiles used to compare the uniformity of the image data. The extracted profile from the uncorrected data (Fig. 10a) can be found in Figure 10c, while the profile for the corrected data (Fig. 10b) can be found in Figure 10d. A table containing the results of the SNR computation can be found in Table 1.

Figure 11a shows a reconstructed slice of the mouse femur computed using data that was not corrected using our proposed method. Figure 11b shows a slice from the same location, but computed using projection data corrected using our proposed algorithm. This specific slice shows a plane near the mid-shaft of the mouse femur. Included on the figures are red regions of interest, indicating the image region used for the SNR computation meant to serve as part of the quantitative comparison between the corrected and uncorrected data, as well as yellow linear profiles used to compare the uniformity of the image data. The extracted profile from the uncorrected data (Fig. 11a) can be found in Figure 11c, while the profile for the corrected data (Fig. 11b) can be found in Figure 11d. A table containing the results of the SNR computation can be found in Table 2.

A sinogram obtained from a CBCT acquisition of the cropped mouse femur data can be found in Figure 12a. In contrast to the previously shown sinograms of the mice femurs, this sinogram extends almost the entire width of the sinogram, indicating that the object filled up a large percentage of the field of view. The same sinogram following correction with our proposed algorithm can be found in Figure 12b. Included on the figures are yellow lines showing where the line profiles found in Figures 12c (uncorrected) and 12d (corrected) were obtained from, as well as red and blue extraction paths where SNR was computed. Blue is background and red is signal.

4. DISCUSSION

Using simple visual inspection, it is clear that the rings that were present in Fig. 10a are corrected for in Fig. 10b, indicating the qualitative success of our algorithm. The interior trabeculae are much better visualized in the corrected slice. While there does appear to be some residual ring artifact information present due to the contrast correction step, it tends to be spatially located away from the scanned object, and much less in intensity than the rest of the image data. On average, the ring information was 24.3 times less in grayscale intensity than the rings in the uncorrected slice. This is supported by the SNR values shown in Table 1, where the SNR computed using the red extracted region (Fig. 10a and 10b) was found to be 2.96 times higher in the corrected slice ($\text{SNR} = 12.8$) than the uncorrected slice ($\text{SNR} = 4.31$). The line profiles extracted using the yellow paths in Fig. 10a and 10b tell a similar story. Between the two profiles, there is minimal loss in edge sharpness indicating the

contrast correction step is not adding in any significant edge blurring using the median filter. The blue circles included on Fig. 10c show regions of the image data that seem to be impacted by the ring artifacts. These regions are corrected for in the profiles extracted using the corrected data, further confirming the performance of the algorithm on the specific slice shown in Fig. 10. This is a slice with plenty of high frequency information present due to the complex trabecular structure.

If we consider the slice from the mid-shaft (Fig. 11), there is a similar increase in the qualitative assessment of the result of the ring-removal algorithm. The rings degrading the interior structure of the slice are removed, allowing for a better representation of the scanned object. If the SNR computations are compared (Table 2), the SNR of the corrected slice ($\text{SNR} = 17.3$) is found to be 3.65 times higher than that of the uncorrected slice ($\text{SNR} = 4.74$). If the line profiles extracted from the two image sets are considered, the backgrounds are found to have less variation. There was a slight degradation ($\sim 3.5\%$) in the edge sharpness (as measured using the gradient from background to object using the image intensities displayed in the line profiles) following the application of the ring correction algorithm in this case due to the use of the median filter during the contrast correction step. This slice was reconstructed at the mid-shaft of the femur, meaning there would be fewer trabecular structure and more cortical bone. The edges are thicker and more pronounced in these slices, and the median filter marginally reduced how sharp the edges are reconstructed. The blue circles included on Fig. 11c indicate regions of the image data that were heavily impacted by the ring artifacts. In the corrected slices, these regions are absent. The results with this specific image data seem to indicate the potential for this method in objects with mostly lower frequency information, such as in cases where cortical bone is imaged.

An important point of discussion regarding the two previously used sets of image data is that the object in the sinogram space is very narrow; it takes up little of the field of view. There is plenty of background values to use in the computation of c_v , and a narrow object keeps the regions of contrast enhancement narrow. This will not always be the case, as the scan object can often take up a large portion of the field of view. The use of magnification is a common technique in medical imaging to better visualize the small detail in the scanned object. The use of large amounts of magnification will almost certainly make it so that the scanned object fills the sinogram width, such as what is simulated in Fig. 12a through cropping out the background. In this image, magnification is used on the femur data, and it fills up more of the field of view in the sinogram, limiting the amount of background available for the computation of the correction vector (c_v). The corrected sinogram in Fig. 12b shows similar ring reduction to the previously shown examples where the object is narrow. The vertical striping, while not eliminated from the sinogram space, is much less in frequency and amplitude. If these sinograms were to be reconstructed, there would be a noticeable reduction in the presence of the ring artifacts from the uncorrected to the corrected data.

A limitation to the method is found when we extract a line profile from the two datasets. Over the edge of the object in a selected projection angle, there was an 11% reduction in the edge sharpness from the uncorrected to the corrected sinogram. Additionally, following the semi-correction of the sinogram, there were wide regions of the image data impacted by contrast enhancement due to the width of the object in the sinogram space. This does not

seem to have been completely corrected for during the contrast correction step of the algorithm. Considering the SNR computations in Table 3, there is less of an impact than in the previous two examples with only a 1.17 times improvement in the SNR between the uncorrected (SNR = 6.86) and the corrected sinogram (SNR = 8.03). This indicates that in select cases, there is evidence of reduced effectiveness of the algorithm when there are not enough background values to average together to compute the c_v .

An additional discussion as to the impact of this algorithm on the workflow of image acquisition is important. If an image processing algorithm takes too long to perform its task, it will not be used as the amount of time it adds to the entire image acquisition process is unacceptable. The proposed algorithm adds approximately 4 seconds to the entire reconstruction process, which for our intents is an acceptable amount of overhead. Additionally, because of the easily parallelizable nature of the proposed algorithm, this process can be re-written to be computed on the GPU, thus further quickening the computational time required.

A theory regarding the cause of the striping is that they may be due to instability of the detector over the course of the acquisition. The flat field required to properly calibrate the image data will differ between the beginning and end of the acquisition, causing a condition where the data may be properly flat field corrected at the start of the acquisition, but as the detector drifts out of calibration, the calibration process fails and the vertical striping may be present due to it. If there is any form of time-variant behavior with the nonuniformity of the gain across the detector surface, it will be difficult to flat field correct with a single flat field acquired prior to the acquisition¹⁷.

5. CONCLUSION

This project was involved with the investigation and validation of an algorithm which corrects for vertical striping present in sinograms, to avoid the reconstruction of ring artifacts in the object volumes. This striping may be present in the scan data due to an improper calibration of the detector prior to image acquisition. This improper calibration may be due to an inconsistent and unstable response of pixels to equal intensity signal. The use of this algorithm in selected cases showed to be effective at reducing the presence of the vertical striping, leading to reconstructions of image data devoid of ring artifacts. For a few specific cases, the success of the algorithm was quantified in terms of SNR improvements from the uncorrected to the corrected image data, as well as comparing line profiles for background uniformity and the presence of artifacts leading to large spikes or valleys in the profile. The algorithm seemed to excel when the scanned object took up little of the field of view, as there were enough background values to obtain an accurate correction vector to carry out the correction for the ring artifacts.

An important limitation to this method appears to be the case when the object occupies more than half of the field of view, as what may occur when magnification is employed to visualize small detail in the object. In cases such as this, the correction vector is influenced too much by the object pixels, and not enough by the background flat pixels. This causes wide regions of contrast enhancement due to the multiplication of the image data by the

correction vector, reducing the SNR gains in the corrected object. Additionally, the edge information is not as well maintained when the object dominates the sinogram space. Both of these are important to consider if such an algorithm will be employed to correct for ring artifacts.

This algorithm was found to not impact our workflow of reconstruction, and has been utilized to perform ring artifact correction on many types of objects such as endovascular devices and other small animal applications. Moving forward, we will look to expand the application of this algorithm to images acquired using a clinical flat panel detector system, as well as more clinically relevant scanned objects.

Acknowledgments

This work is supported by NIH grant 2R01EB002873 and by an equipment grant from Toshiba (Canon) Medical Systems Corporation.

References

1. Seibert JA, Boone JM, Lindfors K. Flat-field correction technique for digital detectors. *Proc SPIE* 3336. 1998:348–354.
2. Kwan ALC, Seibert JA, Boone JM. An improved method for flat-field correction of flat panel x-ray detector. *Med Phys.* 2006; 33(2):391–393. [PubMed: 16532945]
3. Rowlands JA, Yorkston J. Flat panel detectors for digital radiography. *Handbook of Medical Imaging*, Vol. 1: Physics and Psychophysics. 2000:223–328.
4. Moy JP, Bosset B. How does real offset and gain correction affect the DQE in images from x-ray flat detectors. *Proc SPIE* 3659. 1999:90–97.
5. Davidson DW, Frojdh C, O'Shea V, Nillson HE, Rahman M. Limitations to flat-field correction methods when using an X-ray spectrum. *Proceedings of the 4th International Workshop on Radiation Imaging*. 2003; 509(1–3):146–150.
6. Sijners J, Postnov A. Reduction of ring artefacts in high resolution micro-CT reconstructions. *Phys Med Biol.* 2004; 49(14)
7. Kyriakou Y, Prell D, Kalender WA. Ring artifact correction for high-resolution micro CT. *Phys Med Biol.* Aug.2009 54(17)
8. Abu Anas EM, Kim JG, Lee SY, Hasan MDK. Comparison of ring artifact removal methods using flat panel detector based CT images. *BioMedical Engineering OnLine.* 2011; 10(72)
9. Sijbers J, Postnov A. Reduction of Ring Artifacts in High Resolution Micro-CT Reconstructions. *Phys Med Biol.* 2004; 49(14):247–253.
10. Titarenko S, Withers PJ, Yagola A. An analytical formula for ring artefact suppression in X-ray tomography. *Applied Mathematics Letters.* 2010; 23:1489–1495.
11. Münch B, Trtik P, Marone F, Stampanoni M. Stripe and ring artifact removal with combined wavelet — Fourier filtering. *Opt Express.* 2010; 17:8567–8591.
12. Kwon Y, Kim KI, Tompkin J, Kim JH, Theobalt C. Efficient Learning of Image Super-Resolution and compression Artifact Removal with Semi-Local Gaussian Processes. *IEEE Trans Pattern Anal Mach Intell.* 2015; 37(9)
13. Eldib ME, Hegazy M, Mun YJ, Cho MYH, Cho MIH, Lee SY. A ring artifact correction method: Validation by micro-CT imaging with flat pane ldetectors and a 2D photon-counting detector. *Sensors.* Jan.2017 17(269)
14. Ionita CN, Hoffmann KR, Bednarek DR, Chityala R, Rudin S. Cone-beam micro-CT system based on LabVIEW software. *J Digit Imaging.* 2008; 21(3):296–305. [PubMed: 17333411]
15. Patel V, Chityala RN, Hoffmann KR, Ionita CN, Bednarek DR, Rudin S. Self-calibration of a cone-beam micro-CT system. *Med Phys.* 2009; 36(1):48–58. [PubMed: 19235373]

16. Feldkamp LA, Davis LC, Kress JW. Practical cone-beam algorithm. J Opt Soc Am A. Jun.1984 1(6)
17. Lee SC, Kim HK, Chun IC, Cho MH, Lee SY, Cho MH. A flat-panel detector based micro-CT system: performance evaluation for small-animal imaging. Phys Med. 2003; 48:4173–4185.

Figure 1. Axial slice of mouse femur showing evidence of ring artifacts (red arrows) due to presence of miscalibrated pixels.

Figure 2.

Sinogram of Fig. 1. Vertical bars are the ring artifacts, caused by incomplete flat-field detector correction. The vertical axis is the projection view angle index. The horizontal axis is the detector row index.

Figure 3.

Flowchart of the algorithm proposed in this work to correct for ring artifacts present in reconstructed scan data acquired using a CMOS detector coupled to a micro-CBCT system.

Figure 4.

(a) shows example of correction vector (c_v). (b) is an example of an uncorrected row of sinogram data (one projection angle), normalized to the background intensity of the image. (c) is the same row, but multiplied by the c_v in (a) and renormalized. Note the red circles showing regions of edge enhancement due to the semi-correction process. The profile in (c) has 4.1% more uniformity than the profile in (b).

Figure 5. Sinogram from Fig. 2 corrected for the presence of vertical striping. Note the bright regions on the edge of the object (red arrows), this leads to edge enhancement in the reconstructed volume.

Figure 6. Reconstructed axial slice of a mouse femur using sinogram data from Fig. 5. Note the edge enhanced dark region at the center of the object (red arrow), this is caused by the bright regions present in the sinogram data.

Figure 7. Difference map computed by subtracting the image data in Figs. 2 and 6. This mapping contains the striping removed from the image data in the previous processing step, as well as the contrast enhancement at the edges of the sinogram.

Figure 8. Difference map from Fig. 7 blurred via application of a 1D median filter which considers 20 neighbors. Note the reduction of the presence of the striping, while still maintaining the object information in the center of the sinogram space.

Figure 9.

Result of summation of blurred difference map in Fig. 8 with semicorrected sinogram in Fig. 5. Note the retrieval of object information at the center of the sinogram, without adding the original striping back to the image data.

Figure 10.

(a) shows a flat-field corrected slice of mouse femur near distal metaphysis. (b) shows slice processed with our algorithm. Red ROI extracted for SNR computation. Yellow profile extracted for profiles shown in (c) and (d). (c) shows line profile extracted from uncorrected slice. (d) shows line profile extracted from corrected slice. Regions impacted by ring artifacts highlighted in blue circles. There is no computationally significant reduction in edge sharpness due to the use of the proposed method, as measured using the gradient from background to object.

Figure 11.

(a) shows uncorrected slice from the shaft of the mouse femur. (b) shows the slice processed with our algorithm. Red ROI extracted for SNR computation, yellow profile extracted for profiles shown in (c) and (d). (c) shows line profile extracted from uncorrected slice. (d) shows line profile extracted from corrected slice. Regions impacted by ring artifacts highlighted by blue circles. There is a 3.5% reduction in edge sharpness due to the use of the proposed method, as measured using the gradient from background to object.

Figure 12.

(a) shows uncorrected sinogram obtained from cropping acquisition of mouse femur to simulate the object taking up a majority of the field of view. (b) shows the same sinogram but following correction with the proposed algorithm. Included on (a) and (b) are extraction paths for line profiles. (c) shows line profile obtained from (a). (d) shows line profile obtained from (b). There is an 10.3% reduction in edge sharpness due to the use of the proposed method, which is higher than when the object took up less of the field of view. Red and blue profiles show regions where SNR computation was carried out using, red for the signal, blue for the background.

Table 1

Result of SNR computation using red ROI shown in Fig. 10a and 10b. The proposed correction algorithm leads to an SNR improvement by a factor of 2.96 in the extracted region, indicating the positive impact of the proposed method on acquired CBCT projection data containing high resolution structure such as trabecular bone.

SNR	
Uncorrected	4.31
Corrected	12.8

Table 2

Result of SNR computation using red ROI shown in Fig. 11a and 11b. The proposed correction algorithm leads to an SNR improvement by a factor of 3.65 in the extracted region, indicating the positive impact of the proposed method on acquired CBCT projection data containing

SNR	
Uncorrected	4.74
Corrected	17.3

Table 3

Results of SNR comparison between corrected and uncorrected sinogram data in the case of data that takes up more than half of the field of view (such as Fig. 12). Note the 1.17 times improvement in the SNR, which is less of a gain than in the previous examples.

SNR	
Uncorrected	6.86
Corrected	8.03