Published in final edited form as:

Phys Med Biol. 2009 July 21; 54(14): 4575–4593. doi:10.1088/0031-9155/54/14/013.

Radiation dose reduction in time-resolved CT angiography using highly constrained back projection reconstruction

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Abstract

Recently dynamic, time-resolved three-dimensional computed tomography angiography (CTA) has been introduced to the neurological imaging community. However, the radiation dose delivered to patients in time-resolved CTA protocol is a high and potential risk associated with the ionizing radiation dose. Thus, minimizing the radiation dose is highly desirable for time-resolved CTA. In order to reduce the radiation dose delivered during dynamic, contrast-enhanced CT applications, we introduce here the CT formulation of Highly constrained back PROjection (HYPR) imaging. We explore the radiation dose reduction approaches of both acquiring a reduced number of projections for each image and lowering the tube current used during acquisition. We then apply HYPR image reconstruction to produce image sets at a reduced patient dose and with low image noise. Numerical phantom experiments and retrospective analysis of *in vivo* canine studies are used to assess the accuracy and quality of HYPR reduced dose image sets and validate our approach. Experimental results demonstrated that a factor of 6–8 times radiation dose reduction is possible when the HYPR algorithm is applied to time-resolved CTA exams.

1. Introduction

For over 30 years, x-ray computed tomography (CT) has been one of the most important imaging modalities for medical diagnosis. CT exams are ordered for reliable, quick and easy diagnosis. It has been estimated that more than 62 million CT scans are obtained each year in the United States. Because ionizing radiation is used in CT scans, and with the increased use of CT, the very small but finite cancer risk associated with CT scans has attracted greater attention in both medical physics and clinical societies. Consensus has been reached that the ‘as low as reasonably achievable’ (ALARA) principle should be applied. This is particularly true for young patients and women.

From a medical physics standpoint, the development of methods to lower the radiation dose for CT imaging is desirable. This is particularly important for high radiation dose scanning protocols such as time-resolved CT angiography (CTA) and CT perfusion imaging. In these scanning protocols, the contrast uptake and washout process is monitored over time. Recent studies have shown that effective doses of up to 1.9 mSv (Cohnen *et al* 2006) may be delivered during a cerebral CTA. When combined with a standard multi-detector row CT (MDCT) and

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a CT perfusion protocol, total effective dose can reach up to 9.5 mSv (Cohnen *et al* 2006). Such a sequence of exams is typical for patients presenting with stroke symptoms. When one takes into account that repeated CT exams may be used to track the efficacy of treatment, the effective and local radiation doses delivered would further increase.

As research into x-ray CT advances, many different methods have been proposed to lower the radiation dose (Smith *et al* 2007). These methods include: fixed lower tube current (Murase *et al* 2005), reduced peak voltage (Wintermark *et al* 2000), automatic modulation of tube current (Kalra *et al* 2004), application of quantum de-noising filters (Sasaki *et al* 2004), less frequent or variable temporal sampling, (Wintermark *et al* 2004, Hirata *et al* 2005a) optimized scan end-time, (Hirata *et al* 2005b) and advanced reconstructions using fewer projections (Hsieh *et al* 2004). However, due to the intrinsic inverse proportionality between the noise variance and the CT dose, (Hsieh 2003, Kalender 2005) the above strategies typically suffer from deterioration of image quality due to increased image noise variance when the radiation dose is lowered.

In this paper, we present a new image reconstruction method to enable radiation dose reduction in *time-resolved* CTA (Matsumoto *et al* 2007). As we will present later, this new method fundamentally breaks the normal inverse proportional relationship between the noise variance in a CT image and the applied radiation dose used to generate the image. We refer to this method as Highly constrained back PRojection (HYPR) in this paper. The HYPR algorithm was originally developed for application to contrast-enhanced MRA as a means to shorten the data acquisition time and improve temporal resolution (Mistretta *et al* 2007). Using HYPR, it was demonstrated in MRI that the dependence of the noise variance in an individual time frame on the acquired data samples in that time frame is weakened. Instead, the noise variance is primarily determined by a synthesized composite image, which is used to constrain the reconstruction of each time frame. The *composite image* is defined as an image composed using data samples from a number of time frames that result in time-averaged spatio-temporal information, but improved image noise variance. When this new reconstruction technique is applied to x-ray CT imaging, the algorithm's noise properties provide a new way to reduce radiation dose in time-resolved x-ray CT: since the noise variance in a time frame is primarily determined by the composite image, the radiation dose in each time frame can be significantly lowered without significantly compromising image quality in each time frame. Two different approaches can be used to lower the delivered radiation dose using HYPR methods: the first method is to simply reduce the tube current, and the second method is to acquire fewer projection views (e.g., a view-angle undersampling scheme). Lowering the tube current is easy to implement without modifying the scanner hardware, but the potential drawback is that the additive detector noise level limits the radiation dose reduction factor achievable. Scanning with fewer projections does not have this limitation, but it does require modification to the current CT scanner hardware, and a means to overcome the streaking artifacts present in undersampled CT acquisitions. In this paper, the application of time-resolved CTA was used to demonstrate the potential of radiation dose reduction when the HYPR algorithm is used to reconstruct each time frame.

Both methods for radiation dose reduction were investigated using mathematical simulations and an *in vivo* animal stroke model. The undersampling scheme was implemented by retrospectively discarding portions of the fully sampled projection data. We demonstrate that a dose reduction factor of 3–4 is achievable using the lower mA approach while the radiation dose reduction factor can be as high as 6–8 when the undersampling scheme is used.

2. Materials and methods

2.1. Brief review of the HYPR local reconstruction algorithm

The basic HYPR algorithm consists of two fundamental steps used to combine spatial and temporal information in a novel way. The first step is to reconstruct a low-noise-variance composite image $C(x, y, z)$ using information from time frames surrounding the time frame of interest. In the composite image, there is no dynamic information about the image object, but the signal-to-noise level is superior to that of the individual time frame. In the second step, the composite image is used to constrain the reconstruction of a low-radiation-dose time frame denoted by $I(x, y, z; t)$. Specifically, we assume that the final image at a time frame is given by the product of the composite image and a weighting image, $w(x, y, z; t)$, as follows:

$$I(x, y, z; t) = C(x, y, z)w(x, y, z; t). \quad (1)$$

To gain an intuitive understanding of the above decomposition, consider the following extreme situation: the dynamic behavior of the image sequence is independent of image pixels. Namely, the dynamic behavior is global. In this case, one can easily decouple the spatial and temporal dependence in this hypothetical time-resolved imaging case:

$$I(x, y, z; t) = C(x, y, z)w(t). \quad (2)$$

In practice, perfect decoupling between the spatial and temporal components is not possible. Thus, in equation (1), some weak spatial dependence is locally introduced in the weighting image to make the decomposition feasible. Namely, in equation (1), the spatial dependence in the weighting image $w(x, y, z; t)$ is assumed to be weak. Because the primarily spatial-dependent component, $C(x, y, z)$, does not depend on time, its noise variance can be significantly reduced by integrating over many time frames.

We have assumed that the spatial dependence in the weighting image is weak, which implies that the accuracy of the temporal dynamics only weakly depends on the spatial resolution of the image. This argument naturally yields the following method to approximately determine the weighting image: use an available image, which has poor spatial image quality, but high temporal dynamic fidelity to estimate the weighting image. Specifically, we start with a low-quality image reconstructed either from low mA projection data or from highly undersampled projection data. The data are acquired within the temporal window of a given time frame. Thus, this low-quality image denoted as $I_L(x, y, z; t)$ contains the authentic temporal information. We decompose this low-quality image into a form of equation (1):

$$I_L(x, y, z; t) = C(x, y, z)w(x, y, z; t). \quad (3)$$

A low-pass filtering kernel, $K(x, y, z)$, is applied to both sides of equation (3) to blur the image:

$$I_L(x, y, z; t) \otimes K(x, y, z) = [C(x, y, z)w(x, y, z; t)] \otimes K(x, y, z). \quad (4)$$

Note that when a low-pass filter is applied to a low mA image, the noise is reduced, and when a low-pass filter is applied to a streaky image reconstructed from the undersampled data set, the streaking artifacts are smoothed out. Using the assumption that the weighting image, $w(x, y, z; t)$, is only weakly dependent on the spatial components, the right-hand side of equation (4) can be approximated as

$$[C(x, y, z)w(x, y, z; t)] \otimes K(x, y, z) \approx [C(x, y, z) \otimes K(x, y, z)]w(x, y, z; t). \quad (5)$$

Thus, the weighting image, $w(x, y, z; t)$, can be approximately estimated from the low-quality image as follows:

$$w(x, y, z; t) \approx \frac{I_L(x, y, z; t) \otimes K(x, y, z)}{C(x, y, z) \otimes K(x, y, z)}. \quad (6)$$

When the approximate weighting image in equation (6) is substituted into equation (1), an approximated image reconstruction algorithm for time-resolved imaging results (Liang *et al* 2003, Johnson *et al* 2008):

$$I(x, y, z; t) \cong C(x, y, z) \frac{I_L(x, y, z; t) \otimes K(x, y, z)}{C(x, y, z) \otimes K(x, y, z)}. \quad (7)$$

Using the standard error propagation property, the noise variance of the final image in equation (7) is (Johnson *et al* 2008)

$$\sigma_I^2 = \sigma_C^2 \left(1 + \frac{N_C + 2}{N_K} \right),$$

where σ_C is the noise variance in the composite image, N_C is the number of view angles used to reconstruct the composite image, and N_K is the total number of image pixels used in the blurring kernel.

Thus, when equation (7) is used to reconstruct the time-resolved CT images, the noise variance of the final image is primarily determined by the composite image. The image noise variance in the final image only weakly depends on the noise properties of the individual time frame. This property is key to implementing radiation dose reduction in time-resolved imaging.

2.2. Methods to validate the HYPR algorithm

2.2.1. Numerical phantom design and simulations—A standard MatLab Shepp–Logan phantom was modified to include a spatial resolution test pattern and regions of interest (ROI) exhibiting dynamic signal behavior; figure 1. The standard phantom was sampled on a 512×512 matrix with a pixel size of $0.43 \times 0.43 \text{ mm}^2$. Five rows of four circular ROIs were added to the Shepp–Logan phantom. The radii of the ROIs ranged from 5 to 1 pixels, and the spacing between the ROIs in each row was equal to the diameter of the ROIs. Signal versus time curves were produced for each row of ROIs to simulate typical arterial concentration curves observed during a contrast uptake. The curves were produced by combining two gamma variate functions consistent with the original uptake and recirculation of a contrast agent in vessels. Signal values were determined for 984 view angles for each simulated gantry rotation and assigned to the appropriate pixels.

Projection information for each view angle was produced using Siddon's ray-tracing approach (Siddon 1985) to produce a full time series data set of 888 detectors, 984 view angles and 50 time frames. The mask projection data set was produced by averaging each set of projections over the first five time frames.

Ground truth images for each gantry rotation were reconstructed from the fully sampled projection data and the fully sampled mask-subtracted projection data using the standard filtered back projection (FBP) algorithm. Time series were also reconstructed from the mask-subtracted projection data using a factor of 10 view-angle under-sampled FBP and HYPR algorithms. HYPR was also used to reconstruct fully sampled images with both the original and mask-subtracted projection data sets.

In order to evaluate the SNR characteristics of the HYPR algorithms, Poisson noise was added to all original projection views consistent with a range of incident photons per ray sum, i.e., line integral, to simulate changes in tube current. Reconstructions were performed for each noisy data set using standard fully sampled FBP, a factor 10 under-sampled HYPR, and fully sampled HYPR algorithms.

Metrics used to assess the accuracy of HYPR reconstructions in the numerical phantom studies include image noise variance, spatial resolution and signal fidelity. The effect of streak artifacts on noise variance measurements is a concern when evaluating undersampled images. To address this issue, image noise variance measurements were made on image matrices obtained by subtracting the corresponding undersampled image time frame with no noise added from each of the reconstructed images with noise added. This approach effectively removes the contribution of streak artifacts on the noise measurements. The spatial resolution properties of the HYPR reconstruction algorithm were tested via visual inspection of the spatial resolution test pattern in the modified Shepp–Logan phantom, and analysis of a line profile through the 4 pixel diameter ROIs.

2.2.2. In vivo animal studies—Further validation of HYPR dose reduction techniques was completed via *in vivo* animal studies. Under institutional animal research protocol approval, adult canines were imaged using standard clinical CT perfusion protocols. Acquired scans were processed and retrospectively analyzed.

A canine stroke model of middle cerebral arterial infarction was used to explore the clinical impact of dose reduction via view-angle undersampling and mA reduction. An adult beagle was anesthetized, and a unilateral middle cerebral artery occlusion was performed from an endovascular approach using autologous blood clots during an interventional procedure and confirmed by x-ray angiography. The canine was then transported to a CT suite where a standard perfusion protocol was utilized to produce data for CTA analysis. All cerebral perfusion exams were performed using 80 kVp for 50 gantry rotations of 1 s duration each. An IV bolus push of 15 cc of Iohexol 370 at 4 cc s⁻¹ provided the contrast enhancement for the study. Scans were performed at 100 and 25 mA with 10 min between each scan to allow full contrast agent washout. All protocols were completed on a GE LightSpeed VCT scanner (GE HealthCare, Waukesha, WI) with 64 detectors rows of 0.625 mm thickness each and 888 detectors per row.

2.2.3. Data acquisition and reconstruction of in vivo animal studies—Raw detector data from all animal studies were saved locally and transferred to a portable hard drive. The hard drive was transported to GE HealthCare in Waukesha, WI for pre-processing to simulate standard commercial steps. Attenuation data were produced from the raw detector data using proprietary GE software.

Reconstructions were performed retrospectively using the processed canine scan data. Static features were removed from the data using the projection-based mask-subtraction technique described in section 2.2.1. A standard FBP reconstruction was performed using the mask-subtracted projection data to serve as the ground truth for comparison with all reconstructed image sets. View-angle undersampled reconstructions at undersampling factors from 2 to 50

using both the HYPR and FBP algorithms were completed for the 100 mA scan. For all undersampled scans, fully sampled composite images were reconstructed for use in the HYPR algorithm. For each HYPR reconstruction using an undersampling factor of X , the composite image was reconstructed using the X time frames that are temporally centered about the time frame to be reconstructed. Fully sampled reconstructions were performed on the 25 mA data set using both HYPR, with a composite length of 10 time frames, and FBP algorithms. Additionally, undersampled reconstructions at view-angle reduction factors of 2 and 4 were completed using the 25 mA data set. Composite window lengths of 8 and 16 were used for the factors of 2 and 4 undersampled reconstructions, respectively.

Data sets were reconstructed at 0.625 mm slice thickness, the native axial resolution of the scanner, for the production of time-resolved CTA images. Images were reconstructed for the central 48 slices of the scanner and each slice was reconstructed on a 512×512 matrix with a field of view of 10 cm. All reconstructed time series were analyzed, and maximum intensity projections (MIPs) at a variety of time frames were produced using Matlab (Mathworks, Natick, Massachusetts). Image noise properties, root-mean-square error (RMSE) between HYPR and gold standard images, and signal fidelity of the reconstructions were also analyzed using Matlab.

3. Results and discussion

In this section, we present evaluation metrics for both phantom and *in vivo* animal experimental results. All images presented in this section were acquired, reconstructed and analyzed at the University of Wisconsin in Madison.

3.1. Numerical phantom studies

Noise variance measurements were made using a 64 pixel (8×8) ROI in the modified Shepp–Logan phantom. Image noise variance measurements are presented in table 1 for fully sampled FBP and reconstructions and a factor of 10 view-angle undersampled FBP and HYPR reconstructions at two simulated tube currents. Table 1 also includes noise variance measurements for the undersampled reconstructions with the effect of streak artifacts removed. This was achieved by subtracting a noiseless undersampled image from each noisy undersampled reconstruction.

Figures 2 and 3 present a zoom-in view of the spatial resolution test pattern in the Shepp–Logan phantom at two different simulated tube currents. Images from the fully sampled FBP and HYPR reconstructions and a factor of 10 undersampled FBP and HYPR reconstructions are presented. In figure 4, the line profile through a set of ROIs pictured in figures 2 and 3 is presented for the fully sampled FBP and factor 10 undersampled FBP and HYPR reconstruction.

The ground truth dynamic signal in an ROI in the modified Shepp–Logan phantom is plotted against time in figure 5. Also plotted in figure 5 is the signal from the same ROI reconstructed using one-tenth the number of view angles and HYPR reconstruction.

The results presented in this section demonstrate the quantitative equivalence of undersampled HYPR reconstructions to fully sampled FBP reconstructions. Table 1 illustrates the near equivalence of the noise characteristics for a factor of 10 undersampled HYPR reconstructions with those of fully sampled FBP reconstructions. Figures 2 and 3 allow for a visual appreciation of the quality and spatial resolution of the undersampled and fully sampled HYPR images compared to the FBP reconstruction. The line profiles presented in figure 4 show that spatial resolution is not sacrificed with a reduction in the number of view angles used in the reconstruction when HYPR processing is used. Furthermore, figure 5 establishes that the

temporal resolution, i.e. the values on the contrast enhancement curve, does not deteriorate with the use of HYPR. The results presented for the numerical phantom studies in this section demonstrate the equivalence of a factor of 10 undersampled HYPR reconstruction and a fully sampled FBP reconstruction for this case. The results also illustrate that a significant decrease in image noise using a fully sampled data set and HYPR processing is achievable without sacrificing spatial resolution.

3.2. In vivo studies

Noise measurements were made in a 69 pixel (approximately 8×8 pixels) ROI in an area of unenhanced tissue for each undersampled FBP and HYPR reconstructions at undersampling factors ranging from 2 to 50. A plot of the standard deviation of the signal in the ROI is plotted in figure 6 versus the undersampling factor for FBP and HYPR reconstructions. The ROIs used for noise measurements are indicated in figure 7. The results presented in figure 6 demonstrate that the HYPR process, specifically the use of a fully sampled composite image in the reconstruction, results in images with noise characteristics equivalent to those of conventional fully sampled FBP images.

Plots of the signal in a 49 pixel (8 pixel diameter circle) ROI placed in an artery in the central slice of the reconstructed volume are presented in figures 8 and 9 for FBP and HYPR reconstructions, respectively. The placement of the arterial ROI is indicated in figure 7. In both plots, the solid line is the gold standard fully sampled FBP signal, and the signal at each time frame at undersampling factors from 2 to 20 is plotted along with the ground truth signal. The contrast enhancement curves from the undersampled FBP and HYPR images presented in figures 8 and 9, and the corresponding RMSE measurements obtained from the gold standard fully sampled FBP curve demonstrate that undersampled HYPR reconstructions accurately reproduces the contrast dynamics of high contrast signals. Note that the undersampled HYPR reconstructions more closely match the fully sampled FBP than the undersampled FBP as judged by the RMSE values.

In figures 10–12, we present MIP images of the ground truth time frames (fully sampled FBP) and the undersampled FBP and HYPR reconstructions (undersampling factors of 4, 8 and 10) at representative time frames. In these figures, the overall image quality and signal fidelity of the various reconstructions may be qualitatively evaluated. Additionally, we present the RMSE values between the gold standard fully sampled FBP image and the undersampled FBP and HYPR reconstructions. The RMSE values were calculated using the pixels with values over 120 HU in the CTA images, which is the value of the noise variance measured in unenhanced tissue areas.

The equivalence of each undersampled HYPR reconstruction to the ground truth reconstruction was evaluated using the RMSE, defined as the square root of the sum of the squared difference between the HYPR and ground truth image frames over the square root of the sum of the squared ground truth image frame, between each of the HYPR reconstructed time frames and the corresponding fully sampled FBP time frames. The average RMSE between HYPR undersampled reconstructions ranging from 2 to 10 and the ground truth images are presented in table 2. As a point of reference, the RMSE between subsequent frames of the fully sampled FBP reconstructions is 11.2%. The selected subsequent FBP frames exhibited no changes in contrast dynamics and as such represent the frame-to-frame variation in the RMSE due to quantum noise. The RMSE obtained from the two adjacent FBP time frames acts as a rough figure of merit for RMSE between the HYPR and ground truth reconstructions.

Visual inspection of the CTAs presented in figures 10–12 indicate that an undersampling factor of up to 8 and HYPR image processing produces images qualitatively similar to fully sampled FBP images. Small-scale structures are distinguishable in factor 8 undersampled HYPR CTAs

but are lost at undersampling factors as low as 4 using FBP reconstruction. RMSE measurements provide a quantitative metric to evaluate the equivalence between undersampled HYPR CTAs and fully sampled FBP CTAs. The RMSE values presented in table 2 show that the average HYPR RMSE at a factor of 8 undersampling is equivalent to that of the 1.5 times the RMSE between two adjacent FBP time frames. In effect, assuming a tolerance of reconstruction error equivalent to 1.5 times the error associated with differences in image noise from adjacent time frames, an undersampling factor of 8 along with HYPR processing results in acceptable CTA exams.

For the case of HYPR reconstruction at a reduced tube current, noise measurements were made in a 106 pixel (approximately 10×10) ROI in an area of unenhanced tissue for the fully sampled FBP and HYPR reconstructions. At a tube current of 25 mA, the standard deviation of the tissue signal using a fully sampled FBP reconstruction measured was 22.3 Hounsfield units (HU). The standard deviation of the tissue signal measured for the 100 mA scan using a fully sampled FBP reconstruction was 11 HU. Image noise was also measured in the HYPR reconstructions at a tube current of 25 mA. For the fully sampled HYPR reconstruction with a composite window length of 10, we measured a standard deviation of the tissue signal of 12.9 HU. The HYPR image sets produced from the 25 mA scan data using a factor of 2 undersampling and composite window length of 8 exhibited an image with a standard deviation of 21.8 HU. The HYPR image sets produced using a factor of 4 undersampled and a composite window length 16 using the 25 mA scan data exhibited image noise with a standard deviation of 21.8 HU.

To further demonstrate the improvement in noise characteristics and image quality achieved via application of HYPR reconstruction to low mA scans, we present in figure 13 MIP images at a variety of time frames for both fully sampled FBP and fully sampled HYPR reconstructions. Furthermore, we present in figure 14 a plot of the signal in an artery for both reconstructions. Additionally, in figure 15, we show MIP images from the fully sampled FBP, fully sampled HYPR and factors 2 and 4 undersampled reconstructions of the 25 mA data set with composite window lengths of 8 and 16, respectively.

The results from the reduced tube current scans demonstrate that HYPR processing may be used to nearly replicate the noise variance seen in images acquired at a tube current a factor of 4 greater than what was used for the data acquisition. Additionally, undersampled and reduced tube current acquisitions reconstructed using HYPR produce image sets with noise characteristics nearly equivalent to those of a fully sampled reduced tube current acquisition and FBP reconstruction.

4. Discussion

In the foregoing experiments, the utility of applying the HYPR reconstruction technique to contrast-enhanced CT projection data to reduce x-ray radiation exposure or increase the signal-to-noise ratio (SNR) was demonstrated by both mathematical simulations and the use of projection data from *in vivo* canine studies. Mathematical simulations using a reduced number of view angles and simulated reduced tube current in the reconstruction of HYPR images show that the signal versus time curves, images and SNR characteristics of the undersampled, one-tenth dose HYPR reconstructions are comparable to the fully sampled, full dose FBP reconstructions. The equivalence between undersampled HYPR reconstructions and full dose FBP reconstructions was further demonstrated using projection data from an *in vivo* 100 mA clinical CT perfusion protocol. Additionally, an improvement in image noise characteristics and the maintenance of spatio-temporal characteristics for scans using a reduced tube current was established using an *in vivo* 25 mA neuro CT perfusion protocol that results in a factor of 4 reduction in radiation dose while maintaining similar noise characteristics to the 100 mA

scan. With the application of the HYPR undersampling technique to the reduced mA scan data, dose reduction factors were achieved of up to 16 from the combination of a lower tube current and a reduced number of view angles. Results from the HYPR reconstructions at these dose reduction factors show equivalent noise characteristics to those measured in reconstructions from the fully sampled low mA scan and demonstrate similar ability to depict contrast-enhanced structures.

Due to the requirement that there be a high level of spatio-temporal correlation in image space between subsequent acquisitions for HYPR to be most effective, problems do arise in cases where subject or organ motion is present and is not corrected for. In cases such as these, the HYPR method itself does not have a mechanism to account for the motion-induced blurring artifacts and streaking artifacts. This is a limitation of the present HYPR method. However, in neuro-applications, accidental motion is typically isolated to a few time frames, and an image registration step can be used to correct the mis-registration before the HYPR technique is applied. Alternatively, the new iterative reconstruction method developed by the authors' group (Chen *et al* 2008) could be used. The alternative method will potentially enable higher undersampling factors and higher radiation dose reduction factors, but it is computationally more expensive.

Another limitation of this study is the limited volume coverage due to the available z-coverage of the state-of-the-art CT scanners. We have demonstrated a reduction in the radiation dose required to produce time-resolved CTA data sets from data acquired using a standard CT perfusion protocol. With the advent of large volume CT scanners (Mori *et al* 2004) near-whole brain coverage from a standard CT perfusion protocol is possible. This increase in volume coverage will allow acquisition of data for both volumetric perfusion and angiography analysis in the same scan. With the use of the dose reduction techniques and HYPR reconstruction described above a single cine scan may be used to produce perfusion and 4D angiography results. The combination of the perfusion and angiography exams into a single acquisition will result in a further decrease in the radiation dose for each patient. The application of HYPR techniques to CT Perfusion measurements is the topic of a forthcoming report from our group.

5. Conclusions

In this paper, we have introduced the CT formulation for Highly constrained back PRojection (HYPR) and presented results from mathematical simulations and retrospective use of data from *in vivo* canine studies. HYPR is a reconstruction technique that allows for a reduction in the number of necessary view angles per gantry rotation and/or a reduction in the tube current which results in a reduction in the x-ray radiation dose delivered to each patient. This technique may be applied to axial or repeated helical, contrast-enhanced CT exams where the spatio-temporal correlation between sequential volumetric acquisitions is high. The central advantage of HYPR reconstructions is the reduction in stochastic noise via time averaging in the construction of the composite image which is propagated into the final HYPR image. With the reduction in noise in the composite image, and the use of the HYPR reconstruction step, which acts to reproduce the correct spatial and temporal information throughout the image, we produce low-noise images with the correct spatio-temporal information from what would traditionally be termed *insufficient data*.

To implement the HYPR technique on clinical CT scanners some hardware and software modifications are necessary. For view-angle undersampled HYPR reconstructions, the x-ray tube must be modified to allow pulsing of the current at interleaved angles in the rotation. However, when the low mA scheme is implemented, there is no need to change the hardware of a clinical CT scanner. The proposed HYPR technique is essentially post-processing software, and is all that is needed to implement the proposed low mA dose reduction method.

Our experiments provide a strong foundation for continued exploration of achievable undersampling factors and feasible mA reduction factors for contrast-enhanced axial CT protocols. The potential benefit of reducing the delivered x-ray radiation exposure to patients, particularly those needing to undergo repeated or sequential CT exams, motivates our pursuit of optimal reconstruction parameters and clinical applications of dose reduction techniques followed by HYPR reconstruction.

Acknowledgments

The work presented in this paper is partially supported by an NIH grant: R01EB7021 and by a research grant from GE Healthcare.

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Figure 1.

An FBP reconstruction of the modified Shepp–Logan phantom with a dynamic spatial resolution test pattern in the lower right portion of the phantom used in our mathematical simulations to analyze the HYPR algorithm is shown above. Poisson noise consistent with a fluence of 1×10^4 photons per detector element was added to the projection data prior to reconstruction.

Figure 2.

Reconstructions of the spatial resolution test pattern (10 000 photons per view) from the modified Shepp–Logan phantom in figure 1. Clockwise, from top left are FBP, factor 10 undersampled FBP, factor 10 undersampled HYPR and fully sampled HYPR reconstructions with root-mean-square error (RMSE) values between the FBP and other reconstructions of 4%, 2% and 1.6%, respectively.

Figure 3. Reconstructions of the spatial resolution test pattern (1000 photons/view) from the modified Shepp–Logan phantom in figure 1. Clockwise, from top left are FBP, factor 10 undersampled FBP, factor 10 undersampled HYPR and fully sampled HYPR reconstructions with RMSE values between the FBP and other reconstructions of 9.7%, 5.7% and 3.7%, respectively.

Figure 4.

A line profile through the center of one set of the ROIs in the spatial resolution test pattern in the modified Shepp–Logan phantom in figure 1 is plotted above. The diameter of each ROI is 6 pixels. Results for the line profile through the fully sampled FBP gold standard, factor of 10 undersampled FBP, and factor of 10 undersampled HYPR reconstructions are plotted.

Figure 5.

The signal from an ROI in a simulated artery in the modified Sheep–Logan phantom (figure 1) is plotted above. The gold standard signal from a fully sampled FBP reconstruction is plotted as well as the signal from a factor of 10 undersampled HYPR reconstruction and a fully sampled HYPR reconstruction. The RMSE between the FBP contrast enhancement curve and the undersampled FBP, undersampled HYPR and fully sampled HYPR curves are 8%, 5.9% and 1.8%, respectively.

Figure 6.

The standard deviation of the signal in an unenhanced region of canine brain is plotted above versus an undersampling factor. Measurements were made using reconstructions from the 100 mA scan and undersampled FBP and HYPR reconstructions are plotted. Also plotted for comparison is the quantum limit noise behavior associated with view-angle undersampling.

Figure 7.
ROIs used for contrast enhancement curve measurements and noise measurements in the canine scans are shown in the image above.

Figure 8.

The signal in a canine artery from the central reconstructed slice from the 100 mA scan is plotted above. The solid line is the signal in the gold standard fully sampled FBP reconstruction, and plotted on top of the ground truth signal are the signals from a variety of undersampled FBP reconstructions. The RMSE between the fully sampled FBP curve and each undersampled curve are 1.9%, 3.7%, 4.8%, 5.3%, 7.5% and 10.1%.

Figure 9.

The signal in a canine artery from the central reconstructed slice from the 100 mA scan is plotted above. The solid line is the signal in the gold standard fully sampled FBP reconstruction, and plotted on top of the ground truth signal are the signals from a variety of undersampled HYPR reconstructions. The RMSE between the fully sampled FBP curve and each undersampled curve are 1.8%, 2.3%, 3.3%, 3.4%, 5.1% and 6.5%.

Figure 10.

Presented at the far left (both top and bottom rows) is the gold standard maximum intensity projection (MIP) image from a coronal orientation of the 100 mA scan canine brain vasculature at time frame 8 is presented. The top images to the right of the gold standard image from left to right are MIPs of the same time frame constructed using factors 4, 8 and 10 undersampled FBP reconstructions. Pictured below the undersampled FBP MIPs are MIPs constructed using HYPR at the same undersampling factors. RMSE between the gold standard image and the undersampled FBP images are 27.1%, 50.6% and 56.0% and 9.0%, 12.44% and 13.6% for the HYPR images (from left to right).

Figure 11.

Presented at the far left (both top and bottom rows) is the gold standard MIP image from a coronal orientation of the 100 mA scan of canine brain vasculature at time frame 12. The top images to the right of the gold standard image from left to right are MIPs of the same time frame constructed using factors 4, 8 and 10 undersampled FBP reconstructions. Pictured below the undersampled FBP MIPs are MIPs constructed using HYPR at the same undersampling factors. RMSE between the gold standard image and the undersampled FBP images are 22.4%, 44.3% and 49.9% and 9.3%, 12.7% and 13.6% for the HYPR images (from left to right).

Figure 12.

Presented at the far left (both top and bottom rows) is the gold standard MIP image from a coronal orientation of the 100 mA scan canine brain vasculature at time frame 16 is presented. The top images to the right of the gold standard image from left to right are MIPs of the same time frame constructed using factors 4, 8 and 10 undersampled FBP reconstructions. Pictured below the undersampled FBP MIPs are MIPs constructed using HYPR at the same undersampling factors. RMSE between the gold standard image and the undersampled FBP images are 23.3%, 44.3% and 49.9% and 10.8%, 14.5% and 15.7% for the HYPR images (from left to right).

Figure 13.

At top, from left to right we present MIP images from a coronal orientation constructed using fully sampled FBP reconstructed 25 mA scan data of the canine brain at time frames 8, 12 and 16. Directly below each FBP time frame, we present a MIP of the same time frame and scan constructed using HYPR reconstruction (composite window length = 10 s).

Figure 14.

The signal in a canine artery from the central reconstructed slice from the 25 mA scan is plotted above. The solid line is the signal in the gold standard fully sampled FBP reconstruction, and plotted on top is the signal measured in the ROI from HYPR reconstruction (composite window length = 10 s) of the same data.

Figure 15.

MIP images from the coronal orientation produced from reconstructions of the 25 mA canine data set. At top left, the fully sampled conventional FBP reconstruction is presented, and at top right, the fully sampled HYPR reconstruction is shown. At bottom left and right are factors of 2 and 4 undersampled HYPR reconstructions of the 25 mA data set.

Normalized noise variance for FBP and HYPR reconstructions for both full sampling and a factor of 10 view-angle undersampling in the modified Shepp-Logan phantom shown in figure 1. Results are presented for the initial photon fluence and a factor of 10 reduced photon fluence to simulate tube current reduction. Streakless noise measurements were performed by subtracting a noiseless undersampled image from each of the noisy undersampled reconstructions.

Table 1

	Normalized full dose FBP noise variance	Normalized one-tenth dose FBP noise variance	Normalized one-tenth FBP noise variance (streakless)	Normalized 1/10 th dose HYPR noise variance	Normalized 1/10 th dose HYPR noise variance (streakless)
10 000 photons per ray	1	9.3	7.3	1.2	1.3
1000 photons per ray	9.0	45.1	43.1	3.1	2.8

Table 2

Average RMSE measurements for undersampled FBP and HYPR images over the time frames with contrast present were calculated. RMSE was measured for pixels with values greater than that of the noise variance in the fully sampled FBP image (120 HU). The fully sampled FBP image at each time frame was used as the gold standard from which RMSE was determined.

	Factor 2	Factor 4	Factor 6	Factor 8	Factor 10
Undersampled FBP RMSE	9.1%	26.2%	38.9%	46.6%	51.8%
Undersampled HYPR RMSE	8.2%	12.7%	15.2%	16.8%	18.2%