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Time-Resolved C-arm Cone Beam CT Angiography (TR-CBCTA) imaging from a single short-scan C-arm cone beam CT acquisition with intra-arterial contrast injection

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Abstract

Time-resolved C-arm cone-beam CT (CBCT) angiography (TR-CBCTA) images can be generated from a series of CBCT acquisitions that satisfy data sufficiency condition in analytical image reconstruction theory. In this work, a new technique was developed to generate TR-CBCTA images from a single short-scan CBCT data acquisition with contrast media injection. The reconstruction technique enabling this application is a previously developed image reconstruction technique, Synchronized Multi-Artifact Reduction with Tomographic Reconstruction (SMART-RECON). In this new application, the acquired short-scan CBCT projection data were sorted into a union of several sub-sectors of view angles and each sub-sector of view angles corresponds to an individual image volume to be reconstructed. The SMART-RECON method was then used to jointly reconstruct all of these individual image volumes under two constraints: (1) each individual image volume is maximally consistent with the measured cone-beam projection data within the corresponding view angle sector and (2) the nuclear norm of the image matrix is minimized. The difference between these reconstructed individual image volumes is used to generate the desired subtracted angiograms. To validate the technique, numerical simulation data generated from a fractal tree angiogram phantom were used to quantitatively study the accuracy of the proposed method and retrospective *in vivo* human subject studies were used to demonstrate the feasibility of generating TR-CBCTA in clinical practice.

1. Introduction

X-ray projection images encode the variations of the x-ray attenuation properties of an image object into the transmitted x-ray photons to produce the shadow image of the object. However, tissues are superimposed in projection images, degrading diagnostic performance. When the specific anatomy such as vascular structures become the focus of the clinical

imaging task, a variety of subtraction techniques (Mistretta 1974) can be introduced to remove the overlapping structures that are not relevant to the clinical imaging task from the projection image. In the applications of contrast-enhanced angiography, two images, one with contrast enhancement (referred to as a filled acquisition) and one without (referred to as a mask acquisition), can be subtracted to enable visualization of vascular structures without obscuring background signal. Although the idea of the temporal subtraction of two images is not new (des Plantes 1934, des Plantes 1961) in modern digital imaging, it was Digital Subtraction Angiography (DSA) (Mistretta 1980, Strother et al. 1980, Crummy et al. 1980, Mistretta et al. 1982, Kruger & Riederer 1984) that first provided the clinically needed image quality to revolutionize the modern image-guided interventional procedures. Currently, DSA is an indispensable imaging tool in angiographic suites and remains the clinical gold standard for diagnosis and performing image-guided interventions for vascular abnormalities such as occlusions, stenoses, aneurysms, and so forth.

Although anatomical superposition is greatly alleviated in two-dimensional DSA (2D-DSA) compared with unsubtracted images, 2D-DSA images remain a two dimensional projection of intrinsically three-dimensional (3D) vascular structures. Thus the acquisition of multiple DSA images from several different gantry angles is often needed to provide physicians adequate 3D visualization and understanding of complex vasculature. The desire to alleviate overlapping vasculature in 2D-DSA motivated the concept (Cornelis et al. 1972) and experimental implementation of 3D-DSA via tomographic reconstruction (Voigt et al. 1975, Saint-Felix et al. 1994, Ning & Kruger 1996, Fahrig et al. 1997). 3D-DSA was initially achieved using image intensifiers and are currently acquired using digital flat-panel detectors (Klucznik 2002) (Note that 3D-DSA has also been referred to as 3D rotational digital subtraction angiography in literature). In clinical practice, the introduction of 3D-DSA in interventional suite has been found to have great value in diagnosis and in providing image-guidance to the treatment of vascular diseases with improved sensitivity and specificity (van Rooij et al. 2008, Racadio et al. 2006, Kumar et al. 2014, Abe et al. 2002, Anxionnat et al. 2001, Hochmuth et al. 2002, Beck et al. 2006, Missler et al. 2000, Sugahara et al. 2002, Cebal et al. 2005, Söderman et al. 2005, Klucznik 2002, Brinjikji et al. 2009, Toyota et al. 2008, Okahara et al. 2002).

Technically speaking, most current 3D-DSA implementations require two separate cone beam CT (CBCT) data acquisitions, one mask and one filled scan (see. Fig. 1). Following data acquisition, one can either perform subtraction to generate 2D-DSA projection images at each gantry angle followed by a tomographic reconstruction to generate 3D-DSA image volume, or alternatively, one can reconstruct two CBCT image volumes (one from the mask and one from the filled scan), then perform a subtraction of the two CBCT image volumes to generate 3D-DSA image volume. In each case, the potential challenges that are intrinsic to 3D-DSA imaging include misregistration artifacts due to patient motion and a potential doubling of the radiation dose to patients due to the use of two separate CBCT data acquisitions. Additionally, due to the injection of an exogenous contrast medium during the CBCT data acquisition in the filled scan, the contrast of the image object changes from one view angle to another. As a result, the acquired CBCT projection data are not consistent with the fundamental assumption in tomographic reconstruction: the image object remains static during the tomographic data acquisition. These inconsistent CBCT projection data will lead

to artifacts in the reconstructed CBCT images such as vessel distortion, blooming, and shading artifacts around vessels. These artifacts may compromise the accuracy of the quantitative measurements such as the size of aneurysms and dome-to-neck ratio measurements in clinical practice (Brinjikji et al. 2009).

In clinical applications, particularly for surgical planning purposes, clinicians may need to identify antegrade or retrograde filling of feeding arteries, to assess collateral circulation, or to differentiate feeding arteries from draining veins in arteriovenous malformation (AVM) patients. In these clinical scenarios, high temporal resolution time-resolved CBCT angiographic (TR-CBCTA) is highly desirable. Technically, one may think that this can be achieved using an acquisition protocol of multiple sequential 3D-DSA acquisitions. However, without new techniques to improve temporal resolution, the TR-CBCTA generated in this manner would not be clinically useful. Additionally, the need to perform multiple 3D-DSA acquisitions may contribute to increased accumulated radiation doses to patients. Furthermore, repeated scans are prone to inadvertent patient motion during and between subsequent data acquisitions. The desire to overcome these challenges motivates the work presented in this manuscript: to generate time-resolved CBCTA (TR-CBCTA) images from a single, contrast-enhanced CBCT short-scan data acquisition.

To achieve this goal, an immediate technical challenge which needs to be addressed is how to reconstruct more than two CBCT image volumes of *the entire Field-of-View (FOV)* from a single short-scan CBCT projection data. In addition, these reconstructed image volumes must have significantly different contrast enhancement to generate TR-CBCTA images which provide the clinically needed image quality. Unfortunately, the acquired C-arm CBCT projection data from a short-scan angular range of 200° and a cone angle of 20° are *only sufficient* (Tuy 1983) to reconstruct a temporally averaged image volume with the entire FOV, provided that the conventional filtered backprojection (FBP) reconstruction method is used. Attempts to reconstruct more than two different images with FBP will inevitably lead to devastating limited-view artifacts. With some recent advances in iterative reconstruction, for example, using the Prior Image Constrained Compressed Sensing (PICCS) algorithm (Chen et al. 2008, Chen et al. 2009, Tang et al. 2010), one can indeed reconstruct two image volumes of the entire FOV from a short-scan data set (Chen et al. 2009, Tang et al. 2010). However, the subtraction of the two reconstructed image volumes can only generate one subtracted image volume at the best, which is insufficient to achieve TR-CBCTA.

A recently published image reconstruction technique, Synchronized Multi-Artifact Reduction with Tomographic Reconstruction (SMART-RECON) (Chen & Li 2015), was shown to be able to reconstruct more than two sub-image volumes without significant limited view artifacts from a single short-scan scan CBCT acquisition with an intra-venous (IV) injection protocol. This new reconstruction technique offers a new opportunity to generate TR-CBCTA from a single cone-beam CT short-scan acquisition. However, it is not known yet whether this technique can truly achieve TR-CBCTA with sufficient accuracy or whether the concept of TR-CBCTA is feasible in clinical experimental systems. This is especially challenging, given the selective intra-arterial (IA) contrast injection protocol used in most current clinical applications.

This work explores the technical feasibility and optimization of the data sorting scheme and reconstruction parameters for SMART-RECON to generate TR-CBCTA from a single short-scan CBCT acquisition. At the same time, the following central scientific questions will also be addressed:

- i. How many images with high temporal fidelity and negligible limited-view artifacts can be generated from a single short-scan CBCT acquisition using SMART-RECON?
- ii. What are the optimal reconstruction parameters for SMART-RECON to achieve TR-CBCTA from a single short-scan CBCT acquisition and in what sense are they optimal?
- iii. Does this novel technique enable the generation of TR-CBCT from a single CBCT short-scan acquisition with rapid contrast changes in clinical intra-arterial (IA) injection protocols?

To optimize the number of angular sub-sectors that the SMART-RECON method can support, a high temporal resolution anthropomorphic phantom combined with a fractal tree based vascular structure was used to generate synthetic CBCT projection datasets with known ground truth contrast dynamics of the vasculature. Several new quantitative metrics were introduced to characterize the trade-off between limited-view artifacts and temporal-average artifacts, and these metrics were used to seek for the optimal number of angular sub-sectors and optimal regularization parameter in SMART-RECON. The numerical simulations were followed by retrospective human subject studies to demonstrate the feasibility of generating high-quality TR-CBCTA images from a single CBCT short-scan acquisition. Specifically, to validate the proposed technique in a clinical setting, CBCT projection data from a clinical 3D-DSA protocol (Fig. 1) (Sandoval-Garcia et al. 2017) were retrospectively analyzed. As in most clinical 3D-DSA acquisitions, each of these clinical 3D-DSA datasets included two acquisitions: one with and one without contrast present. Using only the data from the contrast enhanced scan, multiple CBCT image volumes with contrast variations were then reconstructed using the SMART-RECON method. An image-domain subtraction was used to generate TR-CBCTA to demonstrate the clinical feasibility of the proposed techniques.

2. Methods and Materials

2.1. Brief review of the SMART-RECON method

In contrast enhanced CBCT data acquisitions, temporal variations of the tissue attenuation are encoded into the acquired CBCT projection data at each view angle. Under the assumption that contrast enhancement changes smoothly with the progress of CBCT data acquisition, the temporal information encoded in CBCT projection data also change smoothly from one view angle to another. As a result, the relative change of the image object caused by contrast enhancement decreases for a smaller view angle range (given a fixed rotation speed), and thus the CBCT projection data acquired from these view angles can be said to be relatively consistent. When view angle range increases, the level of data inconsistency among the acquired CBCT projection data also increases due to the relatively

larger difference of the image contrast during the data acquisition. This observation motivated us to divide the acquired CBCT projection data from a short-scan acquisition into N contiguous angular sub-sectors in SMART-RECON (Chen & Li 2015) with each angular sub-sector corresponding to an image vector, so that the total of N image vectors can be arranged into a spatial-temporal image matrix $\mathbf{X}$.

The SMART-RECON algorithm was then formulated to solve the following convex optimization problem (Chen & Li 2015):

$$\tilde{\mathbf{X}} = \arg \min_{\mathbf{X}} \left[\frac{1}{2} (\vec{\mathcal{Y}} - \mathcal{A} \vec{\mathbf{X}})^T \mathbf{D} (\vec{\mathcal{Y}} - \mathcal{A} \vec{\mathbf{X}}) + \lambda \|\mathbf{X}_A\|_* \right], \quad (1)$$

where $\vec{\mathcal{Y}}$ is the vectorized projection data, $\mathcal{A}$ is a modified system matrix, and $\vec{\mathbf{X}}$ is the vectorized spatial-temporal image matrix $\mathbf{X}$. The diagonal matrix $\mathbf{D}$ has the raw counts of each measured datum before the log-transform as its diagonal elements. $(\cdot)^T$ denotes the matrix transpose operation. The parameter λ is introduced to control the balance between the data fidelity term and the regularizer strength. To suppress the potential limited-view artifacts that are associated with the each image column in spatial-temporal image matrix $\mathbf{X}$, a prior image vector that does not contain limited-view artifacts was introduced in SMART-RECON method to augment the spatial-temporal matrix $\mathbf{X}$ to generate an augmented spatial-temporal matrix $\mathbf{X}_A$ as follows:

$$\mathbf{X}_A = (\vec{X}^p | \mathbf{X}): = \begin{pmatrix} X_1^p & X_1^1 & X_1^2 & \cdots & X_1^N \\ X_2^p & X_2^1 & X_2^2 & \cdots & X_2^N \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_M^p & X_M^1 & X_M^2 & \cdots & X_M^N \end{pmatrix}, \quad (2)$$

where $\vec{X}^p$ denotes the prior image vector, M denotes the total number of voxels in a single image frame and N is the total number of time frames to be reconstructed.

The nuclear norm of this augmented image matrix was used as the regularizer in the SMART-RECON algorithm as shown in Eq. (1). Namely, the regularizer is given as below:

$$\|\mathbf{X}_A\|_* = \|\mathbf{U} \mathbf{\Sigma} \mathbf{V}^T\|_* = \sum_r \sigma_r, \quad (3)$$

where $\mathbf{U} \mathbf{\Sigma} \mathbf{V}^T$ is the singular value decomposition (SVD) of the matrix $\mathbf{X}_A$. In this decomposition $\mathbf{U}$ and $\mathbf{V}$ are two orthogonal matrices, and $\mathbf{\Sigma} = \text{diag}\{\sigma_r\}$ is a diagonal matrix with the singular values of $\mathbf{X}_A$, σ_r ($r = 1, 2, \dots$), as the entries. Details of the numerical implementation of SMART-RECON can be found in previously published papers (Chen & Li 2015, Li, Niu & Chen 2015, Li, Niu, Tang & Chen 2014).

2.2. Generation of the prior image

As mentioned in previous section, one of the main motivations to introduce the prior image in the augmented spatial-temporal matrix $\mathbf{X}_A$ was to suppress the potential limited-view angle artifacts. Therefore, it is natural to use the short-scan FBP reconstructed image as the prior image column. The caveat by doing so is that the FBP reconstructed image is a temporally averaged image. Therefore this temporal average property of the prior image may be propagated into all other image columns in the image matrix $\mathbf{X}$ in the iterative reconstruction procedure. To take advantage of limited-view artifacts free nature of the short-scan FBP reconstruction while to reduce the potential temporal confounding effects introduced by the short-scan FBP reconstructed image, the prior image in this paper was generated from the FBP reconstruction of the short-scan data followed by an intensity-based vessel segmentation procedure as shown in Figure 2. Namely, using the acquired short-scan CBCT projection data set, one can use the conventional FBP method to reconstruct a single CBCT image volume which is a temporally averaged image volume, but it does not contain limited-view artifacts. The FBP image volume was then classified into four different tissue types, air, soft tissue, contrast-enhanced vessel and bone, with adaptively determined intensity thresholding values (Otsu 1975). A non-vessel mask (Figure 2(b)) which is the complement of the vessel mask was used to generate the image without vasculature as shown in Figure 2(c)). The prior image (Figure 2(d)) was then generated by replacing the values of the vascular space in the non-vessel image (Figure 2(c)) with the mean values of the surrounding soft-tissue.

2.3. Numerical Simulation Experiments

To enable TR-CBCTA proposed in this paper from a single short-scan CBCT acquisition with an IA contrast injection protocol, the following two scientific questions must be addressed:

- i. How many images with high temporal fidelity and negligible limited-view artifacts can be generated from a single short-scan CBCT acquisition using SMART-RECON?
- ii. Which reconstruction parameters are appropriate for SMART-RECON to achieve TR-CBCTA from a single short-scan CBCT acquisition?

To answer these questions, it is important to quantify any inaccuracy caused by the temporal averaging effect, the level of limited-view artifacts, and the overall reconstruction accuracy for vasculature. A realistic numerical simulation phantom with known ground truth plays a critically important role to achieve these objectives. In this section, a novel anthropomorphic phantom has been designed to have human-like anatomy for bony structures, soft tissues, and vasculature with ground truth contrast dynamics. The phantom construction and the corresponding quantitative evaluation metrics are presented in the following sub-sections.

2.3.1. Construction of Numerical Phantom with Ground Truth Contrast Enhancement Dynamics

—In numerical simulations, both the data acquisition protocol and contrast injection protocol were specifically designed to simulate a clinical 3D-DSA (Sandoval- Garcia et al. 2017) with intra-arterial injection protocol.

The anthropomorphic phantom consists of two components: a static head phantom generated from clinical human head image volume and a dynamic vasculature generated using a fractal tree. The static head phantom with brain tissue and skull was generated using the the first frame of a high spatial and temporal resolution anthropomorphic phantom (Aichert et al. 2013, Manhart et al. 2013) [‡]. This phantom has realistic skull and brain tissue CT numbers. The dynamic vasculature phantom was generated using a fractal tree model (Johnson et al. 2013) [§]. In this model, a branching vascular network was created starting with a set of feeding arteries. Subsequently, terminal vessel endpoints were iteratively added and connected to the tree such that connecting pattern minimizes viscous drag (Kamiya & Togawa 1972). Vessel diameters are scaled to equalize wall shear stress and each vessel was prescribed with an average arrival time based on flow within the tree.

After the generation of the image volume of the static structure and the time-resolved vasculature at each time frame, the two image volumes were combined to generate final time-resolved image volumes. These time-resolved image volumes were then forward projected to generate simulated CBCT projection data for TR-CBCTA using the Siddon method (Siddon 1985) to forward project a unique volume corresponding to the time point for that specific view. The system geometry used was a C-arm CBCT acquisition platform (Artis Zee bi-plane system, Siemens Healthineers, Forchheim, Germany). The simulated total data acquisition time was 10 seconds which is similar to the data acquisition protocol used in one of the clinical 3D-DSA acquisition protocols, and a total of 248 cone beam projections were generated. Each cone beam projection view includes 1240×960 line integrals. The angular span of the data acquisition was a short-scan angular span with a 20° cone angle (total scan range is 200°). The ground truth of the phantom and contrast enhancement curve are shown in Fig. 3.

Poisson noise was added to the projection data to simulate the quantum noise in x-ray data acquisitions. The initial photon fluence at each ray was 1×10^5 photons per ray to achieve an equivalent noise level as that in current clinical 3D-DSA protocols with intra-arterial injection.

2.3.2. Quantification of image artifacts—Two key aspects of quantitative image quality assessment must be performed to understand the performance of the proposed TR-CBCTA technique. The first aspect is the temporal averaging effect which is a main measure of temporal fidelity of the reconstructed images in TR-CBCTA. Successful generation of TR-CBCTA requires that the temporal averaging effect should be minimized, otherwise the subtraction of the reconstructed image volumes will not yield the desired time-resolved 3D angiograms. In general, the temporal averaging effect can be mitigated by reducing the angular span of the data used to reconstruct the individual image time frame. However, reducing the angular span inevitably exacerbates the associated limited view angle artifacts in SMART-RECON. Therefore, to choose the appropriate image reconstruction parameters that achieve a balance between the temporal averaging and limited view artifacts, it is

[‡]source code available: <https://www5.cs.fau.de/research/data/>

[§]source code available: <https://bitbucket.org/kmjohnson3/mri-fractal-phantom>

important to isolate and quantify these two types of image artifacts in the reconstructed images.

To isolate and quantify these two types of reconstruction accuracy, let's suppose $\mathbf{X}_{\text{truth}}$ is the ground truth of the spatial-temporal image matrix. From the spatial-temporal image matrix, one can generate a temporal Maximal Intensity Projection (tMIP) image X_{tMIP} . Using the ground truth tMIP image, one can isolate the primary vascular content from background using the following work flow as shown in Figure 4: an intensity based thresholding segmentation was performed over the tMIP image X_{tMIP} to generate an angiography mask M_{angio} and a background mask $M_{\text{bkg}} = \mathbb{I} - M_{\text{angio}}$ where $\mathbb{I}$ is a matrix where every element is equal to one.

When SMART-RECON was applied to the simulated CBCT projection dataset from the aforementioned time-resolved anthropomorphic digital phantom, a series of images, X^t , was reconstructed with a matrix size of $512 \times 512 \times 400$ with $0.5 \text{ mm} \times 0.5 \text{ mm} \times 0.5 \text{ mm}$ voxels. The difference image between these SMART-RECON reconstructed images and the corresponding ground truth image series, X_{truth}^t , was then generated. These error images at each time frame may contain both temporal-average and limited-view artifacts.

Inaccuracy caused by temporal averaging is most dominant in the high-contrast and rapidly changing vessel voxels. Thus, in order to assess the temporal averaging artifacts, the contrast dynamics in the vascular tree alone should be considered. To achieve this, an entry-wise (Hadamard) product of a vessel mask (M_{angio}) and the difference image was taken, and the temporal averaging artifacts were assessed in the resulted vasculature (see Eq. 4). Similarly, since the limited-view artifacts primarily contaminate the nonvascular structures and thus they can be quantified in non-vascular structures. These structures were isolated by the Hadamard product of the mask M_{bkg} and the difference image.

Using the isolated vascular contribution and limited-view artifacts contributions in the difference image, the following normalized mean square errors for temporal averaging artifacts (TAA) and limited view artifacts (LVA) were defined to quantify the severity of the corresponding artifacts:

$$\text{TAA} = \frac{\sum_t \|M_{\text{angio}} \circ (X^t - X_{\text{truth}}^t)\|_2}{\sum_t \|M_{\text{angio}} \circ X_{\text{truth}}^t\|_2}, \quad (4)$$

$$\text{LVA} = \frac{\sum_t \|M_{\text{bkg}} \circ (X^t - X_{\text{truth}}^t)\|_2}{\sum_t \|M_{\text{bkg}} \circ X_{\text{truth}}^t\|_2}, \quad (5)$$

where $\circ$ is the Hadamard product. To generate a combined total artifacts level (TAL), these two metrics were combined as follows:

$$TAL = \sqrt{TAA^2 + LVA^2}. \quad (6)$$

This combined metric was used to optimize the reconstruction parameters as described in next section.

Since the projection data were sorted into several sub-sectors, the central view angle of each sub-sector is known. Since a ground truth volume was generated for each individual view angle, the ground truth image volume corresponding to the central view angle of each sub-sector is also known. All of the quantitative metrics used in this work, the TAA, LVA, TAL, and overall reconstruction accuracy (quantified as the relative root mean square error (rRMSE) in Eq. (7), are based on the comparison between the reconstructed image volume using data corresponding to each sub-sector and the ground truth image volume at the central view angle of the corresponding sub-sector.

2.3.3. Optimization of Reconstruction Parameters

- i. Relative measure of the regularization parameter λ : Without an appropriate reference value, it is hard to say whether a parameter is large or small. In this paper, to quantify the regularization strength, the largest singular values of the spatial-temporal matrix $\mathbf{X}$ in *the first iteration* was used as the reference value for the regularization parameter. In other words, the regularization parameters were represented as $\lambda = x\%$ of σ_1 where σ_1 is the largest singular value from the spatial-temporal matrix $\mathbf{X}$ in *the first iteration*. A direct benefit of this normalization method of regularization is to mitigate the potential dependence of parameter on details of data acquisitions.
- ii. Optimization of regularization parameter λ and number of angular sub-sectors N : To investigate the dependence of SMART-RECON on the numbers of angular sub-sectors and regularization parameter λ , the generated short-scan synthetic data set was retrospectively sorted into $N = \{1, 2, \dots, 8\}$ angular sub-sectors and the regularization parameters were changed from $\lambda = 30\%, 3\%, 0.3\%, 0.1\%, 0.03\%, 0.01\%, 0.003\%, 0.001\%$ of σ_1 . Among these pairs of parameters, the pair of parameters (λ, N) giving the lowest TAL was selected to be the optimal reconstruction parameters.

2.3.4. Overall reconstruction accuracy

- i. Accuracy of reconstructed CT numbers: To quantify the accuracy of the reconstructed CT number of the vascular tree, CT number of the region of interest (ROI) shown in Figure 3 (d). To obtain its mean and standard deviation, reconstructions were first performed for 50 noise realizations of CBCT projection data using the optimized reconstruction parameters. The mean and standard deviation values were calculated from these 50 independent reconstructions.

- ii. Overall relative Root Mean Square Error (rRMSE): The overall reconstruction accuracy of the SMART-RECON generated image series can be further quantified by the relative Root Mean Square Error (rRMSE) metric with the noiseless angiograms as ground truth. The rRMSE is defined as follows:

$$\text{rRMSE}(t) = \frac{\|X^t - X_{\text{truth}}^t\|_2}{\|X_{\text{truth}}^t\|_2} \times 100\%. \quad (7)$$

This error was calculated for each time frame at time stamp t .

- iii. After reconstruction parameters were optimized, the optimal reconstruction parameters were used to reconstruct the dataset to assess the overall image quality regarding temporal fidelity and rRMSE.

2.4. Comparison with other state-of-the-art reconstruction methods over limited view angle range

In this paper, a prior image $\vec{X}_p$ vector was introduced to generate the augmented spatial-temporal image matrix $\mathbf{X}_a$ and the nuclear norm of the matrix $\mathbf{X}_a$ was used to regularize the reconstruction. Therefore, it is interesting to study the impact of this prior image in the performance of the SMART-RECON algorithm. In this paper, images were reconstructed using SMART-RECON with and without the introduction of the first prior image column to study the impact of the prior image column in TR- CBCTA applications. Additionally, it is also interesting to compare the performance of the SMART-RECON method with the prior image constrained compressed sensing (PICCS)(Chen et al. 2008) method, another state-of-the-art reconstruction method which leverages the use of a prior image in image reconstruction.

2.4.1. SMART-RECON without the prior image column—To demonstrate the impact of the prior image column in SMART-RECON algorithm, the qualitative and quantitative image quality assessment was performed over the image reconstructed using SMART-RECON without the incorporation of prior image in spatial-temporal image matrix. In this case, the augmented image matrix in Eq. (2) is reduced to the following form:

$$\mathbf{X} = \begin{pmatrix} X_1^1 & X_1^2 & \cdots & X_1^N \\ X_2^1 & X_2^2 & \cdots & X_2^N \\ \vdots & \vdots & \ddots & \vdots \\ X_M^1 & X_M^2 & \cdots & X_M^N \end{pmatrix}. \quad (8)$$

The reconstruction parameters in this case were optimized using the same method as that used in SMART-RECON with prior image. In other words, the regularization parameter λ

was optimized using the previously defined metrics (LVA, TAA, and TAL) when the same optimized number of angular sectors (N) was obtained.

2.4.2. Prior Image Constrained Compressed Sensing (PICCS) Algorithm—The performance of the proposed SMART-RECON based TR-CBCTA was also compared with the state-of-the-art PICCS algorithm (Chen et al. 2008, Chen et al. 2009, Tang et al. 2010). As shown in previous publications, PICCS enables one to reconstruct two image volumes of the entire FOV from a short-scan data set (Chen et al. 2009, Tang et al. 2010). Therefore, it is interesting to benchmark the overall performance of the proposed SMART-RECON technique when the PICCS algorithm was applied to the same data set with the same prior image.

2.5. Validation studies using human subject data sets

To demonstrate the feasibility of TR-CBCTA from a single short-scan CBCT acquisition with an IA contrast injection protocol, anonymized human subject data acquired using a clinical 3D-DSA acquisition protocol with intra-arterial injection were retrospectively analyzed with institutional review board (IRB) approval. In this acquisition protocol, two 3D acquisitions were performed for each subject: one 12 second acquisition without contrast injection and the other one with 12 second acquisition with IA contrast injection. The contrast medium was injected with a power injector. For intra-arterial contrast injection, 21 ml of iodinated contrast agent were injected at a rate of 3 ml/s with no x-ray delay in data acquisition.

In this 12-second acquisition protocol, a total of 304 CBCT projections were acquired over a 260° angular range which is more than that of a short-scan angular range of 200° . To validate the TR-CBCT technique in this paper, the acquired data were manually trimmed down to 234 CBCT projections for a short-scan angular range. Each cone beam projection includes 1240×960 measured line integrals. The data were acquired using a C-arm CBCT data acquisition platform (Artis Zee bi-plane system, Siemens Healthineers, Forchheim, Germany).

In this study, only the short-scan CBCT projection data from the second acquisition with contrast injection was used to demonstrate the feasibility to generate TR-CBCTA images from a single CBCT short-scan acquisition using the SMART-RECON algorithm. An image matrix size of $512 \times 512 \times 400$ with $0.5 \text{ mm} \times 0.5 \text{ mm} \times 0.5 \text{ mm}$ voxel size, was used to reconstruct the entire image volume for each time frame.

3. Results

3.1. Results from Numerical Simulation Studies

3.1.1. Reconstruction Parameter Optimization—In this study, the level of limited-view artifacts was quantified using the LVA metric, the temporal averaging inaccuracy was quantified using the TAA metric, and the total artifacts level was quantified using the TAL metric as that defined in previous section. The changes in LVA, TAA, and TAL with respect to the reconstruction parameters (λ , N) were presented in Figure 5. As shown in this figure,

$N=5$, $\lambda = 0.3\%$ of σ_1 yields the lowest TAL and thus were selected to be the optimal reconstruction parameters.

3.1.2. Overall Image Quality: Qualitative Assessment of un-subtracted images

For each selected number of angular sub-sectors, images were reconstructed using PICCS and SMART-RECON with and without the incorporation of a prior image. As an example, the results for $N=5$ and $\lambda = 0.3\%$ of σ_1 are presented in Fig. 6. When these reconstructed images were compared with the corresponding ground truth images (first row in Fig. 6), one can clearly observe that without the inclusion of the prior image, SMART-RECON generate images with some significant residual temporal averaging artifacts in the first two sub-sectors while small vessels in sub-sectors 4 and 5 are not well reconstructed. As a comparison, these residual temporal averaging artifacts are greatly mitigated in SMART-RECON with prior image. As another comparison, although the same prior image was incorporated in PICCS, PICCS methods cannot generate TR-CBCTA with the desired temporal fidelity as shown in second row in Fig. 6.

3.1.3. Overall Image Quality: Qualitative Assessment of Angiograms

Since the focus of this paper is angiography, it is important to evaluate the image quality of the angiograms. To do so, reconstructed image volumes of sub-sector 2–5 were subtracted from the first sub-sector image to generate the subtracted image volume. A whole brain MIP was used to generate the corresponding MIP images of the angiograms as presented in Fig. 7 and Fig. 8. The corresponding ground truth MIP image was presented in the first row for a comparison. As shown in Fig. 7 and Fig. 8, residual limited-view artifacts in PICCS reconstructed image volumes can be observed in MIP images. Specifically, the vessel tree in the PICCS reconstruction is blurry and distorted, deviating from the ground truth. In comparison, the vessel tree in the SMART-RECON images is qualitatively similar to the ground truth.

To highlight the impact of prior image to the imaging performance, in Fig. 6 – Fig. 8, SMART-RECON without and with prior image as the first column in image matrix were also compared. Temporal variation encoded in each sub-sector can be recovered by SMART-RECON without prior image to some extent, as one can observe in Fig. 7 and Fig. 8. However, SMART-RECON without prior image underestimates the vessel intensity for all sub-sectors. Due to residual limited-view artifacts, the vessel tree generated using SMART-RECON without the prior image is also blurry and deviates from the ground truth. Overall, one can also observe that small vessel branches may not be accurately recovered by either PICCS or SMART-RECON without prior image. It is also interesting to observe that, as a result of the balanced limited view artifacts and temporal averaging artifacts via optimization of reconstruction parameters to generate images with the lowest overall artifacts level, one can observe some residual artifacts around the skull in both PICCS and SMART-RECON with prior image.

3.1.4. Overall image quality assessment: Quantitative Assessment

The overall reconstruction accuracy was investigated using the temporal fidelity and the rRMSE. In Fig. 9, the temporal fidelity comparison among short-scan FBP, limited-view PICCS, and limited-view SMART-RECON without and with prior image were performed on an ROI

placed on artery as shown in Fig. 3. As shown in Fig. 9, reconstruction accuracy of SMART-RECON with prior image is superior to that of the FBP, PICCS or SMART-RECON without prior image.

Comparisons of rRMSE among short-scan FBP over the entire short-scan angular range, limited-view PICCS, and limited-view SMART-RECON without and with prior image are summarized in Fig. 10. Overall, the rRMSE value achieved by SMART-RECON with prior image is about one-third of that achieved by short-scan FBP and one-half of that achieved by PICCS or SMART-RECON without prior image. Note that the rRMSE is measured for the entire image volume rather than a specific ROI. In Fig. 10, the rRMSE between the short-scan FBP image reconstructed from all of the acquired data within the same view angle range and the corresponding ground truth image in each sub-sector were calculated as a comparison.

3.2. Results from retrospective human subject studies

Based upon the optimized reconstruction parameters, the entire projection dataset for each human subject was sorted into five contiguous angular sub-sectors, each sub-sector corresponds to a temporal window of 2.4 seconds and an angular span of 40°. As a reference, the FBP reconstruction of the contrast enhanced CBCT scan over the short-scan angular range was performed to generate a single temporal-average image. This reference image was used to benchmark the performance of SMART-RECON.

3.2.1. Overall qualitative image quality assessment: without subtraction—To show the overall reconstruction quality of the SMART-RECON over five sub-angular sectors, the reconstructed image volumes were reformatted into thin slab MIP with 10 mm thickness (20×0.5 mm) in three different perspective view angles: axial, coronal, and sagittal. Results were presented in Fig. 11. As one can observe in the presented images, there are no perceptible limited-view artifacts present in SMART-RECON, and one can also appreciate the contrast change in vasculature from one angular subsector to another in sequential order. The contrast changes in these images indicate the contrast dynamics encoded into CBCT projection data has been recovered in SMART-RECON. In comparison, clinical FBP reconstruction can only provide a single limited-view artifact-free image volume with averaged contrast dynamics.

3.2.2. TR-CBCTA from single short-scan CBCT acquisition—The contrast change in vasculature presented in Fig. 11 indicates the potential opportunity to generate TR-CBCTA by a subtraction operation between the images from sub-sectors 2–4 and the image from the first sub-sector which has very little contrast enhancement. Results from three human subjects were presented in Fig. 12 to demonstrate the feasibility of the proposed techniques. These images demonstrate the time-resolved information of the cerebrovascular contrast dynamics. As one can observe from these images, conspicuity of the neurovascular abnormalities such as aneurysms and stenoses was improved in the SMART-RECON enabled single-sweep TR-CBCTA images.

Specifically, in the first of these three human subjects, one can clearly observe the contrast change from the early arterial phase to peak enhancement in arterial phase and then

transitioned into venous phase when both arteries and veins are enhanced. In the second subject who suffered from arterial-venous malformation (AVM), the TR-CBCTA provides a potential to distinguish the feeding arteries from draining veins which the static 3D-DSA cannot provide this piece of clinically important information. In the third human subject who suffered from aneurysms, the presented TR-CBCTA provides the potential to delineate the filling of the aneurysm.

3.2.3. 3D-DSA derived from TR-CBCTA images—Given the feasibility of TR-CBCTA from a single short-scan acquisition with IA contrast injection, one may also generate a static 3D-DSA from TR-CBCTA by a temporal MIP. Given the significant contrast variation in SMART-RECON images, the temporal MIP of the TR-CBCTA may generate a static 3D-DSA with better contrast enhancement in vasculature than that of the clinical 3D-DSA from the FBP reconstruction using short-scan data sets: one with and one without contrast enhancement. The result from the human subject #2 was presented in Fig. 13 to show this possibility. As a comparison, the clinical 3D-DSA image was presented to show the difference. As one can observe in the presented images, SMART-RECON can achieve better delineation of contrast enhanced vasculature than that of the “state-of-the-art” clinical 3D-DSA image quality. Additionally, there are pronounced mis-registration artifacts presented in the clinical 3D-DSA image since the clinical 3D-DSA image was generated from two separate CBCT acquisitions.

4. Discussion and Conclusion

In this work, a method to achieve TR-CBCTA from a single short-scan CBCT acquisition with IA contrast injection using SMART-RECON was proposed and validated. To validate the technique, extensive numerical simulation studies have been performed to optimize the reconstruction parameters which include the number of SMART-RECON supported angular sub-sectors and the corresponding regularization strength λ . The parameters were optimized to minimize both the limited-view angle reconstruction artifact (LVA) and temporal averaging artifacts (TAA) when combined into a total artifacts level (TAL) metric. A new fractal tree vascular phantom was fused with the realistic static phantom of a human head to make the anthropomorphic phantom simulates the human anatomy. The ground truth built into the phantom enabled the quantitative assessment of the reconstruction accuracy and parameter optimization. The optimal threshold value for the regularization was found to be 0.3% of the largest singular value of the augmented spatial-temporal matrix and the optimal number of the angular sub-sectors in SMART-RECON was determined to be 5. That means a short-scan angular range can be divided into 5 non-overlapping contiguous angular sub-sectors.

Using the optimized reconstruction parameters, human subject data acquired in clinical practice were retrospectively used to demonstrate the clinical feasibility of the TR-CBCTA technique. The results demonstrated that it is feasible to generate TR-CBCTA images from a single short-scan CBCT acquisition with IA injection. From the TR-CBCTA images, one can also generate static 3D-DSA image by a temporal MIP operation.

As demonstrated in Figures 6 – 10, the prior image presenting contrast non-enhanced status and anatomical morphology of the image object to be reconstructed mitigates limited-view artifacts in the limited view reconstruction. As a result, temporal fidelity can be improved in SMART-RECON with the introduction of an appropriate prior image. In this case, a less aggressive regularization strength can be used to enforce image at each sub-sector consistent to data corresponding to that sub-sector.

The major contributions in this work fall into two categories: Basic science research and clinical practice. Regarding the basic science contribution, to the best of the authors' knowledge, this is the first time it has been demonstrated that more than two CBCT image volumes can be reconstructed from a single short-scan acquisition without the devastating limited-view angle artifacts in a contrast enhanced CBCT acquisition. Second, SMART-RECON enabled the generation of multiple images from a single short-scan CBCT acquisition with sufficient contrast variation to indicate the temporal averaging effect is substantially mitigated. On the clinical side, the feasibility to generate TR-CBCTA images was demonstrated in clinical setting. Given that there is no need to perform two separate CBCT acquisitions to generate both TR-CBCTA and static 3D-DSA, an immediate benefit of the proposed technique was to reduce mis-registration artifacts in 3D-DSA as that can be observed in Fig. 13. A second benefit is to reduce radiation dose since there is only one CBCT acquisition is needed. A third potential clinical benefit of this novel approach is the capability to obtain both 3D spatial information and temporal information and the spatial-temporal information is critically important in assessing cerebrovascular obstructions, visualizing collateral circulation, and determining the flow direction in vessels for surgical planning from a single IA contrast enhanced CBCT acquisition. A fourth clinical benefit may also be derived from the feasibility to generate time-resolved CBCTA from a short-scan CBCT acquisition. Note that the success to generate five time-resolved CBCT image volumes from a short-scan CBCT acquisition indicates that the effective temporal resolution of C-arm CBCT is improved from the native 4–5 seconds down to about 1.0 second. This improvement in temporal resolution may become an enabling technical factor for performing CBCT perfusion imaging, provided that a back-and-forth CBCT acquisition mode is equipped with the current C-arm CBCT acquisition platform and an intravenous (IV) contrast injection protocol is properly developed (Giordano et al. 2012, Manhart et al. 2013, Fieselmann et al. 2012, Yang et al. 2015, Niu et al. 2016). In CBCT perfusion acquisition scenarios, the application of SMART-RECON to the multi-sweep CBCT data set has the potential to generate both time-resolved CBCTA to cover the entire contrast time course for better delineation of the contrast dynamics and CBCT perfusion maps for functional analysis of cerebral haemodynamics. However, a detailed study is needed to demonstrate the feasibility of this clinical application and is beyond the scope of the current paper.

4.1. Potential limitations and future work

There are still several limitations in the current work which warrant further investigations in the future studies. First, although the feasibility of TR-CBCTA techniques was demonstrated in this paper using clinical data, the potential clinical utility of the TR-CBCTA images has not been performed. Only can a rigorous reader study of TR-CBCTA image quality

determine whether the generated TR-CBCTA has the needed image quality for clinicians to perform clinical diagnosis and how the generated TR-CBCTA benefit clinical diagnosis. Second, it remains unknown how the reconstruction performance depends on the details of contrast injection protocol. Therefore, it would be interesting to investigate how much contrast medium is needed and what is the optimal injection rate for the proposed SMART-RECON enabled TR-CBCTA. This kind of studies would help answer the questions such as whether the technique can help reduce the contrast dose in clinical practice etc. Additionally, the experimental data used in the feasibility studies presented in this paper were not acquired for the purpose of the proposed SMART-RECON based TR-CBCTA. It would be interesting to investigate what would be the needed contrast injection protocol and x-ray delay in acquisition to maximally benefit from the proposed SMART-RECON based TR-CBCTA. Third, although SMART-RECON can eliminate inter-sweep artifacts completely and to reduce intra-sweep motion artifacts by reducing the temporal averaging artifact in each angular sub-sector, the inadvertent patient motion may still occur and thus residual motion artifacts may still appear in the final TR-CBCTA image. Therefore, some image registration between SMART-RECON images and other image post-processing techniques may still be needed to further improve image quality. Finally, given the potential that the SMART-RECON images may also greatly reduce image noise, it is thus possible to further reduce radiation dose for the C-arm CBCT acquisition, but further careful studies are needed to quantify the potential benefit of radiation dose reduction. Note that the noise reduction factor alone is inadequate to predict radiation dose reduction factors for nonlinear reconstruction methods. (Li, Tang & Chen 2014, Li, Garrett, Ge & Chen 2014, Li, Gomez-Cardona, Hsieh, Lubner, Pickhardt & Chen 2015)

4.2. Conclusion

It is feasible to generate TR-CBCTA images from a single C-arm CBCT short-scan data acquisition using the SMART-RECON algorithm. The SMART-RECON based TR-CBCTA images may be used to reduce the overall image acquisition time, to mitigate artifacts associated with inadvertent patient motion within one sweep, to eliminate artifacts induced by patient motion between mask scan and filled scan, and to reduce radiation dose by a factor of two via elimination of the mask CBCT acquisition.

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Figure 1. Illustration of most of the current 3D-DSA data acquisition protocol. The protocol requires two scans, one without and one with the contrast medium injection.

Figure 2.

Illustration of the prior image generation. An FBP reconstructed image was segmented into different tissue classes to generate the corresponding mask images. The non-vessel mask was defined as the complement of the vessel-mask, i.e., $\text{Mask}_{\text{non_vessel}} = 1 - \text{Mask}_{\text{vessel}}$. A Hadamard product between the non-vessel mask and the original FBP image was used to generate the image (c) without vasculature. Finally, the mean tissue image values was used to replace the zero values in the vascular space shown in (c) to generate the final prior image shown in (d).

Figure 3.

Illustration of the hybrid phantom used in the numerical simulation studies. (a)-(c): representative slices of the phantom; spatial coronal (d) and sagittal (e) MIP images of the vasculature along coronal direction and sagittal direction; (f): contrast enhancement curve of arteries. The data were acquired during the time frame indicated by the grey region. In quantification of CT numbers and relative root mean square error (rRMSE), the measurements were taken at the region of interest (ROI) labeled in blue dot at shown in (d).

Figure 4. Generation of the angiogram and background mask used to calculate TAA in Eq. (4) and LVA in Eq. (5).

Figure 5.

The dependence of the TAA (a), the LVA (b), and the TAL (c) with respect to the number of angular sub-sectors and relative regularization strength. For display purposes, the log transforms of the three metrics are shown in (a)-(c). The parameters that minimizes the TAL ($N=5, \lambda = 0.3\%$ of σ_1) are indicated with the white dot in (c). Note that a linear interpolation scheme was used to generate the continuous contour maps shown in this figure from a discrete grid of data points (N, λ).

Figure 6.

Results of anthropomorphic phantom using optimal parameters of five angular sub-sectors ($N=5$). For SMART, the regularization strength of 0.3% of the maximum singular value was used. For PICCS, the soft thresholding parameter $\mu=5$ and prior image parameter $\alpha=0.5$ were used. The prior image used in PICCS is same as that used in SMART-RECON. Images were displayed in W/L: 300/50 HU and with a 10 mm slice thickness.

Figure 7.

Coronal MIP images generated from ground truth, PICCS and SMART-RECON without and with prior image. Parameter selections of both PICCS and SMART-RECON are same as those used in Fig. 6.

Figure 8. Sagittal MIP images generated from ground truth, PICCS and SMART-RECON without and with prior image. Parameter selections of both PICCS and SMART-RECON are same as those used in Fig. 6.

Figure 9.

The quantification of temporal fidelity of the images reconstructed by short-scan FBP, limited-view PICCS and limited-view SMART-RECON without and with prior image. Both PICCS and SMART-RECON images were generated using corresponding optimal reconstructed parameters. The selected ROI for artery is indicated by the blue dot in Fig. 3 (d).

Figure 10.

The quantification of rRMSE of the images reconstructed by short-scan FBP, limited-view PICCS and limited-view SMART-RECON without and with prior image. Both PICCS and SMART-RECON images were generated using corresponding optimal reconstructed parameters. Image generated by limited-view reconstructions (PICCS, SMART-RECON w/o and w/ prior image) at each sub-sector was compared with the corresponding ground truth at each sub-sector. For the static FBP image, only a single reconstruction was available which was compared against the ground truth image at each sub-sector to calculate the rRMSE for each sub-sector.

Figure 11. Reconstruction results of human subject #1 with IA injection. Images were displayed in W/L: 3300/1150 HU and with a 10 mm slice thickness.

Figure 12.

Volume rendering images of three human subjects at different time frame. Contrast dynamics can be well resolved from a single-sweep CBCT data acquisition for all human subjects.

Clinical reconstruction

SMART-RECON (temporal MIP)

Figure 13.

Spatial MIP images of human subject #2. SMART-RECON achieves better image quality than that of the “state-of-the-art” clinical method. Images were displayed in W/L: 5000/2000 HU and with a 238 mm slice thickness.