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Quantification of Temporal Resolution Improvement Factor in SMART-RECON Based Time-Resolved C-arm Cone Beam CT Angiography (TR-CBCTA)

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Abstract

In a recently published paper by Li *et al* (Li et al. 2018), reconstruction parameters were optimized for the so-called Synchronized MultiArtifact Reduction with Tomographic reconstruction (SMART-RECON) method to enable time-resolved cone beam CT angiography (TR-CBCTA) from a single short-scan CBCT data set. However, the paper did not quantitatively address how much temporal resolution can be improved by using the SMART-RECON algorithm in TR-CBCTA. The purpose of this note was to present a method to quantify this temporal resolution improvement factor and to use that method to quantify the improvement in temporal resolution using SMART-RECON and optimized reconstruction parameters. In the method proposed in this note, the potential temporal blurring caused by SMART-RECON was modeled as a convolution between a temporal Gaussian blurring kernel and the ground truth temporal enhancement curve. The width parameter of the resulting Gaussian blurring kernel was used as a surrogate metric for temporal resolution to quantify the achievable temporal resolution for the conventional filtered backprojection (FBP) and SMART-RECON methods. The ratio of the surrogate temporal resolutions for the two reconstruction methods was calculated to quantify the factor of temporal resolution improvement. The quantitative results show that the temporal resolution is improved by a factor of 4.5 using SMART-RECON compared with FBP.

1. Introduction

For tomographic imaging systems such as x-ray computed tomography (CT), it is not easy to quantify the achievable temporal resolution. However, the achievable temporal resolution is an important characteristic metric to assess the performance of dynamic imaging tasks such as time-resolved contrast enhanced CT angiography and cardiac CT imaging. For cardiac

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CT imaging, quite a few surrogate temporal resolution metrics have been introduced to define surrogate temporal resolution metrics. These methods include the effective temporal window for data usage in cardiac reconstruction (Taguchi & Anno 2000, Taguchi 2003), the temporal sensitivity profile (TSP) (Hu et al. 2000), the temporal modulation transfer function (MTF) (Ertel et al. 2008), and the quantification of severity of motion artifacts (McCollough et al. 2008, Tang et al. 2010, Schöndube et al. 2011, Maaß & Kachelrieß 2011, Chen et al. 2012, Schöndube et al. 2013). Similarly, for time-resolved CT angiography, the method of using the effective temporal window defined by the weighting function in a short-scan acquisition and reconstruction (Taguchi 2003) can be directly used to estimate temporal resolution provided that the conventional filtered backprojection (FBP) reconstruction method was used.

However, it is not clear whether the aforementioned temporal window of data usage method can be directly generalized to the recently proposed iterative image reconstruction methods that incorporate a low temporal resolution prior image (Chen et al. 2008, Chen & Li 2015) as a constraint in the reconstruction process. For example, in a recently published paper by Li et al (Li et al. 2018), the reconstruction parameters were optimized for a model based image reconstruction algorithm, viz., Synchronized MultiArtifact Reduction with Tomographic reconstruction (SMART-RECON) (Chen & Li 2015), to enable time-resolved cone-beam CT angiography (TR-CBCTA) from a short-scan cone beam CT data set acquired from a C-arm CBCT acquisition platform with intra-arterial contrast injection protocol. Specifically, it was demonstrated that, with optimized reconstruction parameters, five individual CBCT image volumes can be generated from SMART-RECON with clear contrast dynamics for TR-CBCTA. However, as shown by Li et al (Li et al. 2018), the success of SMART-RECON in TR-CBCTA is partially due to the use of a prior image and partially due to the fact that all five image volumes are jointly reconstructed. As a result, it is possible that the temporal information in each reconstructed image volume is contaminated by the use of the prior image and information sharing among all target image volumes during the reconstruction process. Therefore, one may wonder whether the temporal window of the data used for imposing data consistency in each image volume can still be used as a surrogate temporal resolution metric. To begin to answer this question, an alternative way to define temporal resolution without invoking the use of the temporal window of data used in reconstruction is needed. The purpose of this note was to present such a method to quantify the achievable temporal resolution with SMART-RECON in TR-CBCTA directly from the temporal fidelity of the final reconstructed vasculature, rather than the naive use of the temporal window. The results from the independent metric can be used to check whether the simple temporal window of the data usage can still be used as the rule-of-thumb estimation of temporal resolution for TR-CBCTA with SMART-RECON.

2. Methods and Materials

In SMART-RECON based TR-CBCTA (Li et al. 2018), there is only one short-scan CBCT projection data set used in image reconstruction. As a result, the time-resolved CBCTA only covers a short period of contrast enhancement. In this note, to quantify temporal resolution, the same short-scan CBCT acquisition and corresponding optimized SMART-RECON reconstruction parameters obtained in Li et al (Li et al. 2018) were extended over multiple

short-scan acquisitions such that a much longer temporal window of the contrast uptake curve can be sampled using short-scan acquisition protocols and SMART-RECON method. The resulting contrast enhancement of the vasculature is then extracted and the contrast enhancement curve is compared to the ground truth contrast enhancement curve to determine how much the ground truth contrast enhancement curve is blurred due to SMART-RECON. From the extracted temporal blurring kernel function, one can define metrics to quantify temporal resolution for SMART-RECON based TR-CBCTA. In this strategy, a good numerical phantom with ground truth contrast enhancement plays a pivotal role, and the phantom design should incorporate sufficiently complex anatomical structures to challenge the reconstruction algorithm. Such a phantom will be described in next subsection.

2.1. Numerical phantom

To quantitatively assess the temporal resolution and reconstruction accuracy of the SMART-RECON enabled TR-CBCTA method (Li et al. 2018), a phantom with ground truth temporal dynamics is important. In this note, a numerical time-resolved CBCTA phantom was constructed using a fractal tree model (Johnson et al. 2013) for the generation of vasculature. The phantom is generated by combining three compartments, i.e., arterial, venous, and brain tissue (see figure 1), into one volume. Each compartment includes a time of arrival (TOA) map and a map of linear attenuation coefficients. For each voxel, the peak value of the contrast uptake curve was determined using the attenuation map, and the time of enhancement (when contrast first appears in a given voxel) was determined using the values in the generated TOA map.

The time course for a given voxel was then defined using a gamma variate function with two parameters, α and β , which has been shown to be a reasonable approximation of real contrast indicator transit times (Thompson et al. 1964). The gamma variate function is defined as follows:

$$f(t; \alpha, \beta) = \frac{\beta^\alpha t^{\alpha-1} e^{-\beta t}}{\Gamma(\alpha)}, \quad (1)$$

where $\Gamma(\alpha)$ is the Gamma function. Using this function, a unique volume could be generated for each discrete time point corresponding to a single, simulated projection view. Thus, this phantom provides the needed ground truth temporal information as to how the simulated vasculature is enhanced.

2.2. Simulated acquisition system

The simulated data acquisition geometry was a Siemens Artis Zee system (Siemens Medical Solutions, Forchheim, Germany), and a standard multi-sweep perfusion acquisition protocol was simulated. In this protocol, the gantry rotates back and forth, acquiring repeated short scan CBCT datasets. As previously stated, the motivation in using this particular acquisition scheme rather than a single acquisition was to acquire data over a sufficiently long period of time that the majority of an intravenous contrast uptake curve can be imaged. For each sweep, 248 projection views over a 200° angular span were acquired ($180^\circ + 20^\circ$ for a short-

scan acquisition). The detector was simulated using 4×4 binning (resulting in a $0.616 \times 0.616 \text{ mm}^2$ detector element size), since that is currently the fastest detector read-out mode for the clinical system used as the basis for this work. Using this mode, the total rotation time for a short-scan acquisition was 4.2 s with a 1.0 s pause required between the forward and reverse sweeps. A total of 10 acquisitions (5 forward/reverse sweeps) were simulated, with the first 2 acquisitions used as masks to remove bone and unenhancing structures from the remaining datasets. After subtraction, eight total contrast enhanced short-scan datasets over approximately 42 s are available for reconstruction.

The simulated projection data for the phantom were generated assuming a monochromatic (60 keV) x-ray point-source. Forward projection was performed using Siddon's method (Siddon 1985). A unique volume was generated corresponding to the specific time point for each view. We note the voxel size of the volumes used for forward projection was a factor of two times smaller ($0.2 \times 0.2 \times 0.2 \text{ mm}^3$) than the eventual desired reconstruction volume to avoid aliasing artifacts (Goertzen et al. 2002).

2.3. Reconstruction methods

Each short-scan acquisition dataset was reconstructed using two techniques: (1) the standard cone beam FBP reconstruction method, viz., the FDK method (Feldkamp et al. 1984) with a Parker weighting scheme (Parker 1984) and (2) SMART-RECON method (Chen & Li 2015) with the following optimized reconstruction parameters (Li et al. 2018) for each short-scan data set: 5 sub-sectors per sweep with no angular overlap between sub-sectors and $\lambda = 0.3\%$ of σ_1 , where σ_1 is the largest singular value of the SVD. Both FDK and SMART-RECON used a reconstruction matrix size of $512 \times 512 \times 512$, with an isotropic voxel size of $0.4 \times 0.4 \times 0.4 \text{ mm}^3$. Since only a single reconstructed volume is achievable with FDK for each short-scan acquisition, 8 total volumes were reconstructed, whereas for SMART-RECON 40 total volumes were reconstructed.

2.4. Temporal resolution improvement factor from the direct generalization of temporal window in data usage

Using the aforementioned optimized reconstruction parameters, each angular segment covers a 40° angular range which corresponds to a $4.2 \text{ s}/5 = 0.84 \text{ s}$ data acquisition window. Thus, a 0.84 s temporal resolution provided that the naive generalization of the temporal window of the data usage can be applied to SMART-RECON method. In contrast, when the short-scan FDK reconstruction with the Parker weighting scheme is used, the achievable temporal resolution can be estimated to be about $180/200 * (4.2 \text{ s}) = 3.8 \text{ s}$. Therefore, one may conclude that the application of SMART-RECON may improve that temporal resolution by a factor of about $4.5 = 3.8 \text{ s}/0.84 \text{ s}$. This estimation of temporal resolution improvement factor will have to be validated using a new temporal resolution assessment method presented in next section.

2.5. Quantification of temporal resolution from reconstructed images

2.5.1. Modeling of temporal blurring of obtained contrast uptake curves—If the ground truth time curve is available and a reconstructed time curve is generated, we can consider the following question to assess the temporal resolution: How much does the

ground truth curve need to be blurred to match the temporally blurred contrast enhancement curve generated from the SMART-RECON method? For simplicity, in this note, it is assumed that the temporal blurring of the reconstructed time-density curve of each voxel can be modeled as the convolution of the corresponding ground truth curve with a Gaussian temporal blurring kernel defined as follows:

$$k(t, c, t_0, \sigma) = \frac{c}{\sigma_w \sqrt{2\pi}} e^{-\left(\frac{t-t_0}{\sigma_w}\right)^2} \quad (2)$$

where c is a scalar, t_0 is the center of the Gaussian kernel, t indicates the temporal index, and σ_w is the Gaussian width parameter. An example of this problem is shown with a ground truth curve, blurred ground truth curves with different blurring widths, and the distorted reconstructed curves is shown in figure 2.

To assess temporal resolution, one will need to determine the Gaussian width parameter by solving the following non-linear least squared error minimization problem:

$$\tilde{\sigma}_w = \arg \min_{\sigma_w} \left\| \sum_j [I_j(t) - k(t, c, t_0, \sigma_w) * I_{j,GT}(t)] \right\|_2^2, \quad (3)$$

where j indicates the index of the sweep. The solution, $\tilde{\sigma}_w$, describes the amount of temporal blurring compared with the ground truth for a given method. The optimization problem in equation (3) was solved numerically using a constrained interior-point method (Nocedal & Wright 1999); the optimization was terminated when the cost function value reached fell below 1×10^{-8} .

We note, it is possible to consider other blurring kernels for this problem as well. A rectangular (boxcar) function might be an intuitive choice, however for digital data a rectangular function has two issues: 1. The function is defined for discrete widths and doesn't smoothly change widths; 2. The discontinuities in the rectangular function make the optimization problem in equation 3 numerically unstable. Thus, a Gaussian is a natural choice as a smooth relaxation of the rectangular function that alleviates both of these issues.

2.5.2. Surrogate Temporal Resolution Metrics from Gaussian blurring kernel

—In the limit of $\tilde{\sigma}_w \rightarrow 0$, the Gaussian blurring kernel approaches a Dirac delta function; in this case, the temporal resolution is perfect. However there is always some finite temporal blurring in reality. The Gaussian width parameter has units of seconds and can be used to define the surrogate temporal resolution metrics. However, it is not clear what scaling factor, s , of the Gaussian width parameter is appropriate to define temporal resolution. For example, the achievable temporal resolution could be defined as $\tilde{\sigma}_w$, $2\tilde{\sigma}_w$, $3\tilde{\sigma}_w$, or the Gaussian full width half maximum (FWHM) defined as $\text{FWHM} = 2\sqrt{2\log 2}\tilde{\sigma}_w$, but one would not know a priori which is the best choice to use as a definition for temporal resolution. In this note, we

report all four different choices, but we note that since $\tilde{\sigma}_w$ is the measured quantity in the optimization, the other presented values are simply that measured value scaled accordingly. To determine which of these choices of scaling yields the most useful surrogate metric, each scaled measurement ($s\tilde{\sigma}_w$) was compared to the predicted values using a relative error. For a given expected temporal window (denoted Δt and previously described in section 2.4), the relative error is defined as:

$$\text{Relative Error} = 100\% \times \frac{s\tilde{\sigma}_w - \Delta t}{\Delta t}. \quad (4)$$

The relative error describes the deviation from the expected value. Under- and overestimation of the measured value is indicated with negative and positive values, respectively.

The temporal resolution improvement factor relative to the standard FDK reconstruction with a Parker weight, i.e., the ratio of the measurement for FDK/SMART-RECON was also calculated. This ratio is independent of the scaling factor, s , used for $\tilde{\sigma}_w$, and instead directly compares the relative temporal resolution of the two methods.

To determine if any differences in the measured average values of $\tilde{\sigma}_w$ was significant, a two-sample t-test (significance threshold: $\alpha = 0.01$) was performed in MATLAB (R2017a, The MathWorks, Natick, MA). The null hypothesis was that the means were equal, $H_0 : \mu_1 = \mu_2$, and thus the alternative hypothesis is a difference in the mean measured value, $H_1 : \mu_1 > \mu_2$.

2.6. Quantification of reconstruction accuracy

In temporal resolution quantification, it is also important to assess the reconstruction accuracy relative to ground truth. In this note, two different metrics were used to quantify the reconstruction accuracy. The first metric for reconstruction accuracy was the commonly used relative root mean square error (rRMSE). The rRMSE was defined using the ground truth curve $I_{GT}(t)$ for the time curve at each voxel, $I(t)$, as follows:

$$\text{rRMSE}(I(t)) = 100\% \times \frac{\sqrt{\sum_t [I(t) - I_{GT}(t)]^2}}{\sum_t |I_{GT}(t)|}. \quad (5)$$

The second metric for reconstruction accuracy was the Kullback-Leibler Divergence (KL-Divergence or D_{KL}). The KL divergence is closely related to the relative entropy, and is a non-symmetric measure of the difference between two probability distributions. In this study, the KL-Divergence was used to quantify how close the reconstructed time-density curve is relative to the corresponding ground truth. When the reconstruction is perfect, then the reconstructed time-density curve would perfectly overlap with the ground truth, thus yielding a zero KL-divergence. Namely, inferior reconstruction fidelity corresponds to a larger value of KL-Divergence. Mathematically, the KL divergence was defined as

$$D_{\text{KL}}(I'_{\text{GT}}(t) || I'(t)) = \sum_t I'_{\text{GT}}(t) \log \frac{I'_{\text{GT}}(t)}{I'(t)} \quad (6)$$

where $I'_{\text{GT}}(t)$ and $I'(t)$ are the normalized time curves (where $I'(t) = I(t) / (\sum_t I(t))$) for the ground truth and comparison curves, respectively.

Since rapidly enhancing vessels may be more difficult to reconstruct accurately, the rRMSE and D_{KL} were both measured in both arteries and veins independently as well as in all vessel voxels together. Once again, to determine if any difference in measured average values was significant, a two-sample t-test (significance threshold: $\alpha = 0.01$) was performed in MATLAB (R2017a, The MathWorks, Natick, MA). The null hypothesis was that the means were equal, $H_0 : \mu_1 = \mu_2$, and thus the alternative hypothesis is a difference in the mean measured value, $H_1 : \mu_1 > \mu_2$.

2.7. Computational facilities

Both the SMART-RECON and FDK algorithms were implemented in Visual C (Microsoft, Inc., Redmond, WA) and CUDA (NVIDIA Corporation, Santa Clara, CA) and executed on a local workstation with dual Xeon E5-2620 CPUs (Intel Corporation, Santa Clara, CA) and 72 GB of RAM and GTX Titan Xp and GTX Titan X (NVIDIA, Santa Clara, CA) GPUs, each with 12 GB of RAM.

3. Results

3.1. Temporal resolution measurement

The temporal resolution measurements are shown in table 1. SMART-RECON outperformed FDK and the ratio of the $\tilde{\sigma}_w$ (FDK/SMART-RECON) was 4.5. The improvement was statistically significant ($p < 0.001$). The FWHM of the Gaussian ($2\sqrt{2\log 2}\tilde{\sigma}_w \approx 2.4\tilde{\sigma}_w$) matched the predicted temporal windows better than the other scaled values of the Gaussian width with a relative error for both FDK and SMART-RECON less than 5 %.

3.2. Reconstruction accuracy quantification

Example contrast curves for several tissue types are shown in figure 3 to demonstrate the improvement with SMART-RECON. In this figure, it is clear that the FDK reconstructions may over or underestimate the underlying curve, and that for lower contrast levels the uncertainty can be quite high. These errors are reflected in the curve quantification for the two reconstruction techniques, shown in tables 2 and 3. For the rRMSE and D_{KL} measurements, the improvement using SMART-RECON was 75% and 40% for rRMSE and D_{KL} , respectively. In each case, the difference was statistically significant ($p < 0.001$).

4. Discussion

In the results presented in table 1, it is clear that the choice of scalar used to define a surrogate for temporal resolution has a dramatic impact on the absolute number of the

reported temporal resolution. In fact, if $\tilde{\sigma}_w$ or $4\tilde{\sigma}_w$ are used, the measured values under or overshoot the theoretical prediction using the temporal window significantly. Of the different scaling factors used in this work, the FWHM of the Gaussian ($s \approx 2.4$) yielded the values that most closely matched the theoretical prediction ($< 5\%$ for each reconstruction method). Integration under the Gaussian curve to the FWHM includes $\approx 76\%$ of the area under the Gaussian curve. Thus, one could argue the FWHM is the best surrogate metric for temporal resolution of the values used in this work, although whether this choice of scaling factor is generalizable is not clear from these results. However, regardless of the chosen scaling factor (s), the relative improvement (the ratio of the measured $\tilde{\sigma}_w$ values) will be constant and in this work the measured ratio value of 4.5 match the theoretical prediction calculated from the naive temporal window for each angular sector very well. Since this ratio has no dependence on the choice of scaling, it is likely the most useful and generalization metric for comparing temporal resolution between two reconstruction methods.

This study has several limitations in scope. The first limitation of this study is that for now only a single numerical phantom with a single acquisition system is presented to demonstrate the utility of the method. The second limitation is that the reconstruction method used for validation is performed using a single set of previously optimized parameters. In practice, these parameters will need to be changed and optimized for different acquisition protocols. Thus, the temporal resolution improvement factor of 4.5 found in this note does not necessarily apply to other reconstruction parameter sets or acquisition protocols. However, we emphasize that the methodology presented in this note is applicable to other cases. Third, the method in this work is only tested using a single prior-model based iterative reconstruction technique. Despite these limitations, the proposed method should be viable for any dataset or reconstruction method where a known ground truth is available. Although it is beyond the scope of this note, it would be very interesting to apply the proposed method to additional phantom datasets, imaging systems, acquisition protocols, and iterative reconstruction techniques.

5. Conclusions

The temporal resolution improvement factor for SMART-RECON in TR-CBCTA is quantified to be 4.5 using a metric directly deduced from the temporal fidelity of SMART-RECON generated vasculature. This improvement factor is the same as that calculated from the nominal temporal window of data usage for each image volume and thus the temporal window of the data acquisition may be useful as a rule-of-thumb estimation of temporal resolution for SMART-RECON based TR-CBCTA and possibly other prior-model based reconstruction methods. This agreement also indicates that the effect of temporal contamination among different image volumes is minimal regardless the use of prior image and potential data sharing in SMART-RECON.

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Figure 1.

The compartments of the numerical phantom viewed as sagittal maximal intensity projections (MIPs). Each compartment has a corresponding linear attenuation map and time of arrival map. The linear attenuation map is displayed as CT Numbers (Hounsfield Units or HUs) at 60 keV.

Figure 2.

An example of ground truth contrast uptake curves and their blurred counterparts generated using different values for σ_w . In this case, blurring with a kernel with a width parameter $\sigma_w = 2.5$ provides the best fit between the blurred ground truth image and the reconstructed curve and $\sigma_w = 0$ simply yields the ground truth curve.

Figure 3.

An example contrast uptake curve from an artery voxel (a), a vein voxel (b), and a brain tissue voxel (c).

Table 1.

The measured temporal resolution values shown as $\tilde{\sigma}_w$, $2\tilde{\sigma}_w$, $4\tilde{\sigma}_w$, and the FWHM ($2\sqrt{2\log 2}\tilde{\sigma}_w$).

	$\tilde{\sigma}_w \pm \text{Std.Dev. (s)}$	$2\tilde{\sigma}_w \pm \text{Std.Dev. (s)}$	$4\tilde{\sigma}_w \pm \text{Std.Dev. (s)}$	FWHM $\pm \text{Std.Dev. (s)}$
FDK	1.55 ± 2.72	3.09 ± 5.45	6.19 ± 10.89	3.64 ± 6.41
Relative error	−59%	−18%	63%	−4%
SMART-RECON	0.34 ± 0.17	0.69 ± 0.34	1.38 ± 0.67	0.81 ± 0.40
Relative error	−59%	−18%	64%	−4%

Table 2.

The measured rRMSE values

	rRMSE $\pm$ Std.Dev. (%)		
	Arteries	Veins	All vessels
FDK	15.0 $\pm$ 7.9	14.9 $\pm$ 6.7	15.2 $\pm$ 7.9
SMART-RECON	4.4 $\pm$ 2.4	2.9 $\pm$ 1.9	3.6 $\pm$ 2.2

Table 3.

The measured D_{KL} values.

	$D_{KL} \pm \text{Std.Dev.}$		
	Arteries	Veins	All vessels
FDK	0.035 ± 0.159	0.064 ± 0.197	0.057 ± 0.209
SMART-RECON	0.027 ± 0.028	0.020 ± 0.039	0.024 ± 0.036