A Compressed-Sensing Based Blind Deconvolution Method for Image Deblurring in Dental Cone-Beam Computed Tomography

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Abstract

In cone-beam computed tomography (CBCT), reconstructed images are inherently degraded, restricting its image performance, due mainly to imperfections in the imaging process resulting from detector resolution, noise, X-ray tube's focal spot, and reconstruction procedure as well. Thus, the recovery of CBCT images from their degraded version is essential for improving image quality. In this study, we investigated a compressed-sensing (CS)-based blind deconvolution method to solve the blurring problem in CBCT where both the image to be recovered and the blur kernel (or point-spread function) of the imaging system are simultaneously recursively identified. We implemented the proposed algorithm and performed a systematic simulation and experiment to demonstrate the feasibility of using the algorithm for image deblurring in dental CBCT. In the experiment, we used a commercially available dental CBCT system that consisted of an X-ray tube, which was operated at 90 kV_p and 5 mA, and a CMOS flat-panel detector with a 200-μm pixel size. The image characteristics were quantitatively investigated in terms of the image intensity, the root-mean-square error, the contrast-to-noise ratio, and the noise power spectrum. The results indicate that our proposed method effectively reduced the image blur in dental CBCT, excluding repetitious measurement of the system's blur kernel.

Keywords Image deblurring · Compressed-sensing · Blind deconvolution · Cone-beam computed tomography

Introduction

Panoramic radiography [1], which was introduced in the 1960s, is the standard clinical examination in dentistry that provides clinicians with a single comprehensive planar image of the patient's jaw and maxillofacial structure. Nevertheless, there has always been a need for three-dimensional (3D) imaging to overcome the inherent limitations of two-dimensional (2D) images (including magnification, distortion, and superimposition), but the technology has only recently become readily available. Although traditional computed tomography (CT) [2, 3], which uses a fan-shaped X-ray beam in a spiral progression to obtain a 3D representation, has been clinically

available in the early 1990s, its use in dentistry has become limited due mainly to cost, access, and radiation dose considerations. With the recent development of large-area flat-panel detectors, the advent of cone-beam CT (CBCT) [4, 5] in the mid-1990s has been extensive advancement in dental imaging, shifting dental imaging from a 2D to a 3D approach to data acquisition, and image reconstruction with faster scan time and lower radiation dose than in conventional CT. Present state-of-the-art CBCT scanners produce 3D images with excellent high resolution, making dental implant planning and surgical placement simple and reliable. CBCT is now becoming another standard examination of dental care, and its roles in maxillofacial surgery, temporomandibular joint disorders, orthodontics, and endodontics are widely described lately [6, 7]. More recent medical applications of the CBCT have included radiotherapy guidance [8] and mammography [9] as well as dental imaging.

However, CBCT images are inherently degraded, restricting its image performance, due mainly to imperfections in the imaging process resulting from detector resolution, noise, X-ray tube's focal spot, and reconstruction procedure. Thus, the recovery of CBCT images from their degraded

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Fig. 1 Simplified diagram of the proposed blind deconvolution method where both the image to be restored, f , and the blur kernel, psf , are simultaneously recursively optimized. The method consisted of two

successive iterative loops based on the CS framework and the CG solver for seeking optimal solutions of the f and the psf , respectively

version, collectively referred to as *image deblurring*, is essential for improving image quality. Various image deblurring methods have already been established in the literature, including Wiener filtering, least squares filtering, and wavelet-based algorithms [10, 11]. Nevertheless, regarding the aforementioned deblurring problem, a difficulty exists concerning the presence of noise in the input blurred image, which results in imperfect image deblurring.

In this study, we investigated a compressed-sensing (CS)-based blind deconvolution method to solve the blurring problem in CBCT where both the image to be recovered and the blur kernel (or point-spread function (PSF)) of the imaging system are simultaneously recursively identified. The CS is a relatively new mathematical theory for solving the inverse problems, which exploits the sparsity of the image with substantially high accuracy [12, 13]. We implemented the

proposed algorithm and performed a systematic simulation and experiment to demonstrate the viability of the algorithm for image deblurring in dental CBCT. In the following sections, we briefly describe the proposed image deblurring method and present our simulation and experimental results.

Materials and Methods

Proposed Image Deblurring Method

In most image deblurring methods, it is necessary to model the original (or exact) image, $f(x,y)$; the observed (i.e., blurred noisy) image, $g(x,y)$; and the imaging process in which blur occurs. Imaging systems are typically assumed to be linear

Fig. 2 3D numerical Shepp-Logan phantom ($400 \times 400 \times 400$) (top left) used in the simulation and the physical phantoms of skull (model 603A, CIRS Ltd.) (top right), anchovy (bottom left), and animal bone (bottom right) used in the experiment

and shift-invariant, and thus, the image formation can be described as follows:

$$g(x, y) = f(x, y) \otimes \text{psf}(x, y) + n(x, y), \quad (1)$$

where $\text{psf}(x, y)$ is the 2D PSF of the imaging system, $n(x, y)$ is the accompanying noise, and the operator $\otimes$ represents 2D convolution. The mathematical interpretation of the convolution modeling leads to a deconvolution operation to remove the blur in the presence of PSF. To date, most methods

employed in image deblurring may be classified as *non-blind* and *blind* deconvolution. The difference between the two lies in that whether the PSF is known. In non-blind deconvolution, the main difficulty has to do with the presence of noise in the observed image, and the noise, even if very weak, can strongly contaminate the deblurred image. To overcome this difficulty, several non-blind deconvolution methods make use of prior information on the image to be recovered, such as Bayesian or maximum posteriori methods [14]. Blind deconvolution involves separating two convolved signals, $f(x, y)$ and $\text{psf}(x, y)$,

Fig. 3 The commercially available dental CBCT system (Expert7™, Vatech Co.) used in the experiment. The system consisted of an X-ray tube, which was operated at 90 kV_p and 5 mA, and a CMOS flat-panel detector with a 200-μm pixel size and an active area of 234 × 288 mm

Table 1 Parameters used in the simulation and experiment

Parameter	Dimension
Source-to-object distance	450 mm
Object-to-detector distance	200 mm
Angle step ($\Delta\theta$)	1°
Number of projections	360
Voxel size	0.15 mm
Voxel dimension	400 × 400 × 400
Pixel size	0.20 mm
Test phantom	Shepp-Logan, Skull, anchovy, animal bone
Reconstruction algorithm	FBP-based
Deblurring algorithm	CS/CG-based
Balancing parameter (α) in CS	0.01
Tolerance (ε) in CS	10 ⁻⁵
Number of iterations	20 for CS, 10 for CG

when both the signals are either unknown or partially known. This is challenging because it is an ill-conditioned problem;

the number of unknowns exceeds the number of known image data. There are two main approaches to the blind deconvolution. First, one estimates the PSF first from all information that the observed image provides, and in the later step, it uses the estimated PSF to recover the original image using one of several non-blind deconvolution algorithms because the blur kernel is already known. Second one is to combine the estimate of the PSF and the original image together as a merging task. This approach can simultaneously recursively identify both the PSF and the image itself. This usually leads to more complex algorithms. The comprehensive reviews of both deconvolution methods can be found in [15, 16].

The PSF is the impulse response of an imaging system that describes the degree of blur by the system. It is typically measured using a slit camera with a width of approximately 10 μm . In CBCT, however, it is sometimes difficult to measure PSF accurately because the reconstruction procedure also affects the image degradation, which will result in imperfect deconvolution results. In addition, in most practical situations, it is repetitious to measure the PSF depending on individual tasks and X-ray imaging conditions. In this study, we

Fig. 4 Simulation procedure that we used to verify the accuracy of the overall blur kernel estimated by the proposed method (i.e., PSF_{Est}). Here, the image matrix of a PSF_{Des} (standard deviation 1.5 in pixel units, kernel

size 15 × 15) was backprojected at each projection angle after the FBP filtering, and the PSF_{Rec} was then deduced from the central slice image of the reconstructed image

Fig. 5 Example gradient images of the reconstructed CBCT images (blurred) and their final recovered images (deblurred) of the Shepp-Logan phantom (top) and the skull phantom (bottom) used for estimating PSF_{Est}

investigated a blind deconvolution method based on the CS framework incorporated with a total-variation (TV) regularization penalty. The TV is the ℓ^2 norm of the gradient image and is often used as an effective penalty in many image recovery problems such as denoising, deblurring, and inpainting owing to its ability to preserve image edges [17].

Fig. 6 Comparison of the 1D intensity profiles of the designed PSF (PSF_{Des}), the reconstructed PSF (PSF_{Rec}), and the estimated PSF (PSF_{Est}). The PSF_{Est} well agreed with the PSF_{Rec} within approximately 0.1% difference in full width at half maximum

Figure 1 shows the simplified diagram of the proposed blind deconvolution method. The method consisted of two successive iterative loops based on the CS framework and the CG solver for seeking optimal solutions of the image to be recovered, f , and the blur kernel, psf , respectively. In brief, the reconstructed CBCT image of the examined object (g) (①) and the initial guess of the PSF ($\text{psf}^{(0)}$) (②) enter the CS framework as the current image ($f^{(k)}$) and the current PSF ($\text{psf}^{(k)}$), respectively. The next updated image ($f^{(k+1)}$) is then computed by minimizing the following objective function, $\phi(f)$, as the solution (f^*) to a convex optimization problem (③), given by

$$\begin{aligned} \phi(f) &= \frac{1}{2} \|f \otimes \text{psf} - g\|_2^2 + \alpha \|f\|_{TV}, \\ \|f\|_{TV} &= \sum_{i=1}^M \sum_{j=1}^N |\nabla f_{i,j}| = \sum_{i=1}^M \sum_{j=1}^N \sqrt{(f_{i,j} - f_{i-1,j})^2 + (f_{i,j} - f_{i,j-1})^2}, \\ f^* &= \arg \min_{f \in Q} \phi(f), \end{aligned} \quad (2)$$

where $1/2 \|f \otimes \text{psf} - g\|_2^2$ is the fidelity term, $\|f\|_{TV}$ is the TV penalty term, and α is the parameter that balances the two terms and is chosen so that signal-to-noise ratio is maximized ($\alpha = 0.01$ was used in this study); M and N are the numbers of rows and columns of the image f , respectively, and Q is the set of feasible f . The next step is to estimate the latent PSF. By

Fig. 7 Reconstructed CBCT images of the Shepp-Logan phantom in axial (*top*), coronal (*middle*), and sagittal (*bottom*) views for the cases of blurring and deblurring. The corresponding phantom slices are also shown on the *left* as the reference

using the gradient images of g and $f^{(k+1)}$, the next updated PSF ($psf^{(k+1)}$) is computed efficiently by solving the equation below using the CG solver (4):

$$\begin{aligned} \nabla g &= \nabla f^{(k+1)} \otimes psf^*, \\ psf^{(k+1)} &= psf^*, \end{aligned} \quad (3)$$

where ∇ is the gradient operator and psf^* is the optimal solution for Eq. (3). The role of the gradient image within the

Fig. 8 Comparison of the intensity profiles as measured along $\overline{AB}$ in Fig. 7. The intensity profile of the corresponding phantom slice is also shown as the baseline

algorithm is to enhance fine details of the image from which the latent PSF may be more efficiently estimated than using other image quantities. The CG solver is an algorithm for the numerical solution of particular systems of linear equations; namely, those whose matrix is symmetric and positive-definite [18]. It is very efficient, rapidly converging, and less time-consuming in solving Eq. (3). The deblurred image $f^{(k+1)}$ is successively updated through the iteration loops to obtain the final deblurred image until the mismatch between the current and the next updated images converges to a specified tolerance ε ($\varepsilon = 10^{-5}$ was used in this study) (5).

Simulation and Experimental Setup

We implemented the proposed algorithm using MATLAB (version 8.3) and performed a systematic simulation and experiment to investigate the image characteristics. Figure 2 shows the 3D numerical Shepp-Logan phantom ($400 \times 400 \times 400$) (top left) used in the simulation and the physical phantoms of skull (model 603A; CIRS Ltd.) (top right), anchovy (bottom left), and animal bone (bottom right) used in the experiment. Figure 3 shows the commercially available dental CBCT system (Expert7™, Vatech Co.) used in the experiment. The system consisted of an X-ray tube, which was operated at 90 kV_p and 5 mA, and a CMOS flat-panel detector with a 200- μ m pixel size and an active area of 234×288 mm. The source-to-object distance and the object-to-

Fig. 9 Reconstructed CBCT images of the skull phantom in **a** axial, **b** coronal, and **c** sagittal views for the cases of blurring and deblurring. Only three slice images for each view are indicated for simplicity

detector distance were 450 and 200 mm, respectively. In the simulation, the Shepp-Logan phantom was forward-projected first using the distance-driven method [19] to produce original projections, and the projections were then convolved by a 2D PSF designed to obtain their degraded version. All projections

used in the simulation and experiment were taken with an angle step $\Delta\theta = 1^\circ$, and the CBCT image was reconstructed using the standard filtered-backprojection (FBP) algorithm with a 150- μm voxel size. The number of iterations in the proposed algorithm was set to 20 for saving the processing time. The parameters used

Fig. 10 Enlarged images of the areas indicated by boxes A, B, and C in Fig. 9 for the cases of blurring and deblurring

in the simulation and experiment are listed in Table 1. Although the implemented algorithm has not yet been accelerated by the graphics processing unit, the total processing time for image deblurring in CBCT was less than 10 min on a normal workstation (OS Windows 10, CPU 2.13 GHz, RAM 32 GB).

The image characteristics were quantitatively investigated in terms of the image intensity, the root-mean-square error (RMSE), the contrast-to-noise ratio (CNR), and the noise power spectrum (NPS). The RMSE measures the error of the restoration ($\hat{f}$) from the exact image (f), which is defined as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^N \left(f_i(x, y) - \hat{f}_i(x, y) \right)^2}{N}}, \quad (4)$$

Fig. 11 1D normalized NPS curves measured from the background area indicated by the box D in Fig. 9a for the cases of blurring and deblurring

where N is the number of the image pixels. The smaller the RMSE is, the closer to the exact image values. The CNR is a commonly used indicator of image quality and is expressed as

$$\text{CNR} = \frac{|\bar{x}_{ROI_1} - \bar{x}_{ROI_2}|}{\sqrt{\frac{\bar{\sigma}_{ROI_1}^2}{2} + \frac{\bar{\sigma}_{ROI_2}^2}{2}}}, \quad (5)$$

where $\bar{x}_{ROI_1}$ and $\bar{x}_{ROI_2}$ are the mean pixel values of the predefined regions of interests (ROIs), ROI_1 and ROI_2 , respectively, and $\bar{\sigma}_{ROI_1}$ and $\bar{\sigma}_{ROI_2}$ are the standard deviations from the corresponding mean values. The larger the CNR is, the better the image quality achieved. The noise characteristics of an image are quantified as the NPS, which expresses the average area occupied by individual photons per unit area (mm^2):

$$\text{NPS}(u, v) = \frac{\langle |\mathcal{F}\{\text{flat area}(x, y)\}|^2 \rangle}{N} d^2, \quad (6)$$

where $\langle |\mathcal{F}\{\text{flat area}(x, y)\}|^2 \rangle$ represents the ensemble average of the squares of the Fourier amplitudes of a selected flat-intensity area, the operator $\mathcal{F}$ represents Fourier transform, N is the number of the image pixels used in the calculation, and d is the detector pixel size. Detailed description on the NPS measurement can be found in [20].

Results

Figure 4 shows the simulation procedure that we used to verify the accuracy of the overall blur kernel estimated by the proposed method (i.e., PSF_{Est}).

Fig. 12 The original (blurred noisy) X-ray image of the anchovy (*top*) and its deblurred images by the proposed method (*middle*) and the Wiener filtering (*bottom*). Enlarged images of the area indicated by the box *A* are also shown on the *right*

Fig. 13 The reconstructed CBCT images of the animal bone for the cases of blurring (*middle*) and deblurring (*bottom*). The original projection images are also shown on the *top*

Table 2 Results of the RMSE measurement with the Shepp-Logan phantom

View	Blurred image	Deblurred image
Axial	5.15	1.01
Coronal	6.10	1.13
Sagittal	5.74	1.07

Figure 5 shows example gradient images of the reconstructed CBCT images (blurred) and their final recovered images (deblurred) of the Shepp-Logan phantom (top) and the skull phantom (bottom) used for estimating PSF_{Est} . Figure 6 shows the comparison of the one-dimensional (1D) intensity profiles of the designed PSF (PSF_{Des}), the reconstructed PSF (PSF_{Rec}), and the estimated PSF (PSF_{Est}).

Figure 7 shows the reconstructed CBCT images of the Shepp-Logan phantom in axial (top), coronal (middle), and sagittal (bottom) views for the cases of blurring and deblurring. The corresponding phantom slices are also shown on the left as the reference. Figure 8 shows the comparison of the intensity profiles as measured along $\overline{AB}$ in Fig. 7. The intensity profile of the corresponding phantom slice is also shown as the baseline.

Figure 9 shows the reconstructed CBCT images of the skull phantom in (a) axial, (b) coronal, and (c) sagittal views for the cases of blurring and deblurring. Only three slice images for each view are indicated for simplicity. Figure 10 shows enlarged images of the areas indicated by boxes A, B, and C in Fig. 9 for the cases of blurring and deblurring. Figure 11 shows the 1D normalized NPS curves measured from the background area indicated by the box D in Fig. 9a for the cases of blurring and deblurring.

Figure 12 shows the original (blurred noisy) X-ray image of the anchovy (top) and its deblurred images by the proposed method (middle) and the Wiener filtering (bottom). Figure 13 shows the reconstructed CBCT images of the animal bone for the cases of blurring (middle) and deblurring (bottom). The original projection images are also shown on the top.

Discussion

The key for the success of the proposed algorithm in CBCT is to estimate the overall blur kernel accurately, which ultimately

Table 3 Results of the CNR measurement with the skull phantom

View	Blurred image	Deblurred image
Axial (at $z = +100$)	1.75	3.24
Coronal (at $y = 0$)	0.96	2.77
Sagittal (at $x = 0$)	1.58	3.19

determines the deblurring quality of the resultant image. We performed the simulation procedure indicated in Fig. 4 to verify the accuracy of the PSF_{Est} . Here, the image matrix of a PSF_{Des} (standard deviation 1.5 in pixel units, kernel size 15×15) was backprojected at each projection angle after the FBP filtering, and the PSF_{Rec} was then deduced from the central slice image of the reconstructed image. As shown in Fig. 6, the PSF_{Est} well agreed with the PSF_{Rec} within approximately 0.1% difference in full width at half maximum, which verifies the accuracy of the blur kernel estimated by the proposed method. In addition, the standard deviation of the PSF_{Est} was approximately 1.95 in pixel units, which is larger by a factor of approximately 1.3 than that of the PSF_{Des} due to the effect of the reconstruction procedure on the image degradation.

As shown in Figs. 7 and 8, the deblurred CBCT images of the Shepp-Logan phantom were more clearly visible than the blurred images, and the difference in intensity between the deblurred images and the corresponding phantom slices were very small. The overall RMSE value for the deblurred images was approximately 1.61, approximately 3.5 times smaller than that for the blurred images (Table 2).

The experimental image results with the skull phantom were similar to the simulation results. As shown in Figs. 9 and 10, the deblurred images were more clearly visible than the blurred images. The overall CNR value for the deblurred images was approximately 3.07, approximately 2.1 times larger than that for the blurred images (Table 3). The noise characteristic for the deblurred images was improved, compared to that for the blurred images (Fig. 11), possibly due to the use of TV regularization penalty in the CS framework in which the negligible components of the gradient images are assumed to be nearly zeros. The NPS value evaluated at a spatial frequency of 1.5 line pairs/mm for the deblurred image was approximately $1.7 \times 10^{-6} \text{ mm}^2$, approximately 17.4 times smaller than that for the blurred image.

We conducted two additional real-life case analyses in order to support the effectiveness of the proposed algorithm for image deblurring in radiography and CBCT (Figs. 12 and 13). The deblurred X-ray image of the anchovy by the Wiener filtering [21] was also obtained to compare that by the proposed method. As shown in Fig. 12, the deblurred X-ray images by both the proposed method and the Wiener filtering were improved in image visibility than that of the blurred image. Note, however, that the deblurred image by the Wiener filtering was somewhat noisier than that by the proposed method due to the high-pass filtering in the deconvolution process. The image result with the animal bone was nearly similar to that with the skull phantom (Fig. 13); the overall CNR value for the deblurred images was approximately 4.07, approximately 2.4 times larger than that for the blurred images. We therefore conclude that the proposed blind deconvolution method effectively reduced the image blur in both radiography and CBCT, improving image visibility as a result.

One thing that should be addressed is that the CBCT image results above were based on 2D deconvolution (Eq. (1)), not 3D, and thus, the images were processed slice by slice because it was simple and easy to be implemented. Note, however, that the intensity variation among image views that could be caused by the slice-by-slice processing was not discernably observed in the resultant deblurred images (see Figs. 9 and 10). It is necessary to perform image deblurring based on 3D deconvolution in CBCT for further study.

Conclusion

We investigated a CS-based blind deconvolution method to solve the blurring problem in CBCT where both the image to be recovered and the blur kernel of the imaging system are simultaneously recursively identified. We implemented the proposed algorithm and performed a systematic simulation and experiment to demonstrate the feasibility of using the algorithm for image deblurring in dental CBCT. Our simulation and experimental results indicate that the phantom's structure in the deblurred image was more clearly visible than in the original blurred noisy image, which demonstrates the viability of the proposed method for image deblurring in dental CBCT. The overall RMSE value for the deblurred images was approximately 1.61, approximately 3.5 times smaller than that for the blurred images (Table 2). The CNR value for the deblurred images was approximately 3.07, approximately 2.1 times larger than that for the blurred images (Table 3). The NPS value evaluated at a spatial frequency of 1.5 line pairs/mm for the deblurred image was roughly $1.7 \times 10^{-6} \text{ mm}^2$, approximately 17.4 times smaller than that for the blurred image. Consequently, the proposed blind deconvolution method effectively reduced the image blur in dental CBCT, excluding repetitious measurement of the system's blur kernel.

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