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Simulation and experimental studies of three-dimensional (3D) image reconstruction from insufficient sampling data based on compressed-sensing theory for potential applications to dental cone-beam CT

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ABSTRACT

In practical applications of three-dimensional (3D) tomographic imaging, there are often challenges for image reconstruction from insufficient sampling data. In computed tomography (CT), for example, image reconstruction from sparse views and/or limited-angle ($<360^\circ$) views would enable fast scanning with reduced imaging doses to the patient. In this study, we investigated and implemented a reconstruction algorithm based on the compressed-sensing (CS) theory, which exploits the sparseness of the gradient image with substantially high accuracy, for potential applications to low-dose, high-accurate dental cone-beam CT (CBCT). We performed systematic simulation works to investigate the image characteristics and also performed experimental works by applying the algorithm to a commercially-available dental CBCT system to demonstrate its effectiveness for image reconstruction in insufficient sampling problems. We successfully reconstructed CBCT images of superior accuracy from insufficient sampling data and evaluated the reconstruction quality quantitatively. Both simulation and experimental demonstrations of the CS-based reconstruction from insufficient data indicate that the CS-based algorithm can be applied directly to current dental CBCT systems for reducing the imaging doses and further improving the image quality.

1. Introduction

In practical applications of three-dimensional (3D) tomographic imaging, such as computed tomography (CT), digital tomosynthesis (DTS), *etc.*, there are often challenges for accurate image reconstruction from insufficient sampling data. In CT, for example, image reconstruction from sparse views and/or limited-angle ($<360^\circ$) views would enable fast scanning with reduced imaging doses to the patient. In particular, limited-angle scanning allows the geometry of the system to be open and, thus, the X-ray beam path is more favorable than in conventional CT; this allows the system to be designed more compact. Insufficient data problems may occur in several cases due to the scan geometry, radiation exposure, or imaging hardware, but the cases that we considered in this paper are related to sparse-view (≤ 150 projections) and limited-angle ($\leq 180^\circ$) samplings in dental cone-beam CT (CBCT). In those cases, the projection data are theoretically insufficient for exact reconstruction and the use of analytic reconstruction algorithms, such as filtered-backprojection (FBP), will lead to under-sampling and short-scan related artifacts in the reconstructed images [1]. Fig. 1 shows schematic illustration of the data acquisition geometries in (a) an ordinary CT, (b) a sparse-view CT, and (c) a limited-angle CT. In the ordinary CT, over 1000 projections acquired with a single gantry rotation are typically used for image reconstruction.

One approach to overcome these difficulties may employ one of iterative statistical algorithms. They successively update the reconstructed image to minimize the mismatch between the measured projection data and the computed projection data from the current updated image, which leads to 3D image reconstruction with higher resolution at lower doses. In addition, with recent advances in the compressed-sensing (CS) theory, the development of 3D reconstruction algorithms for incomplete data has received growing attention during the last decade and, thus, has the potential for reductions in imaging doses and times [2–4].

In this study, we investigated and implemented a CS-based algorithm for image reconstruction from incomplete data and performed both systematic simulation and experimental works

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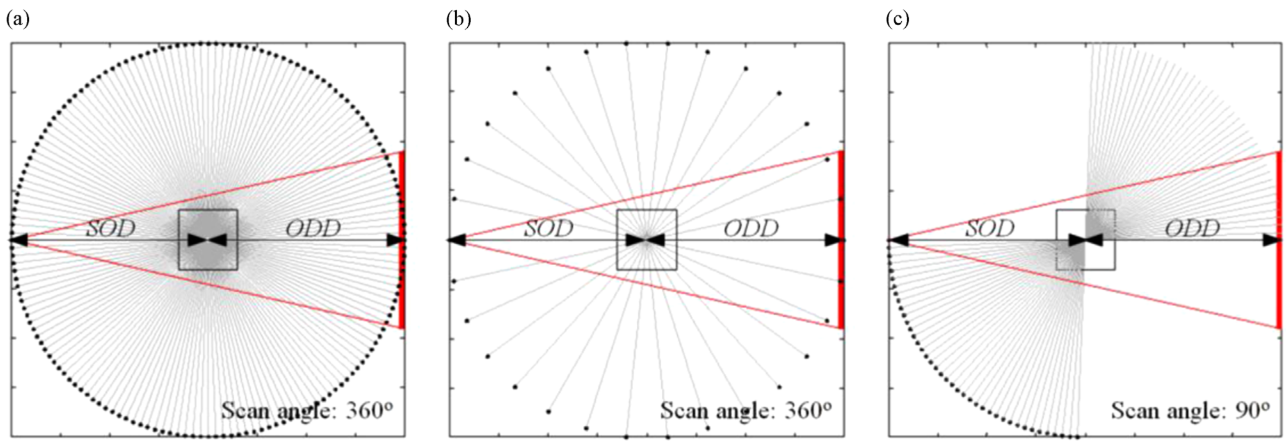

Fig. 1. Schematic illustration of the data acquisition geometries in (a) an ordinary CT, (b) a sparse-view CT, and (c) a limited-angle CT. Here, triangular regions and center boxes represent the cone beam of X-rays and the imaging volume to be reconstructed, respectively.

to investigate the image characteristics. In the following sections, we briefly describe the implementation of the CS-based reconstruction algorithm and the imaging conditions used in the studies, and we present the simulation and the experimental results.

2. Material and methods

The formation of X-ray images can be modeled approximately by a discrete linear system as follows:

$$\mathbf{A}x = b, \tag{1}$$

$$x = (x_1, x_2, ..., x_N)^T,$$
$$b = (b_1, b_2, ..., b_M)^T,$$
$$\mathbf{A} = \{a_{ij}\}, i = 1, 2, ..., M \text{ and } j = 1, 2, ..., N, \tag{2}$$

where x is the original image vector to be reconstructed, N is the number of voxels, the superscript T is the transpose operator, b is the measured projection vector, M is the total number of sampling points in the projection data, and $\mathbf{A}$ is the system matrix, relating x and b. In the CS framework, x is normally recovered as the optimal solution, x^*, for the convex optimization problem described in Eq. (3) by minimizing the following objective function, $f(x)$:

$$x^* = \underset{x \in Q}{\arg\min} f(x),$$
$$f(x) = \frac{1}{2}\|\mathbf{A}x - b\|_2^2 + \alpha \sum_{i=1}^{N} \|D_i x\|_2, \tag{3}$$

where Q is the set of feasible x, α is a parameter specifying the relative weighting between the fidelity term and the sparsity term, and D_i is the forward difference approximation to the gradient at voxel i. The convex optimization problem in Eq. (3) can be solved approximately, but efficiently, by using the accelerated gradient-projection-Barzilai–Borwein (GPBB) method [5]. Fig. 2 shows a simplified flowchart of the CS-based image reconstruction procedure. Firstly, the measured projections (b^m) are acquired from the imaging system. Then, the initial image ($x^{(0)}$) is assumed as the reconstructed image by simple backprojection (BP), followed by forward projection to obtain the computed projections (b^c). By using the measured and the computed projections, and the derivative image ($\mathbf{D}x$), the objective function $f(x)$ is computed to determine the step size (Δs) for the next updated image. The image x is successively updated until the mismatch between the current and the updated images converges to a specified tolerance (ε). During the iterative procedure, as shown in Fig. 2, each iteration loop requires one forward projection and one backward projection which are performed with the system matrix $\mathbf{A}$. For precise construction of the system matrix, we used a modified version of the distance-driven method [6].

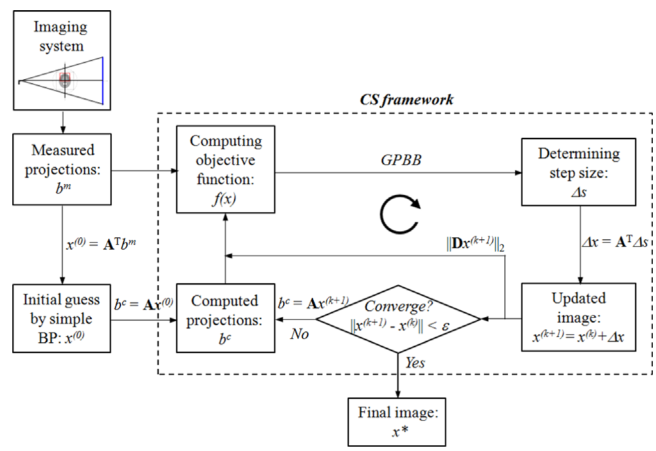

Fig. 2. A simplified flowchart of the CS-based image reconstruction procedure.

Based upon the above descriptions, we developed a CS-based reconstruction algorithm in our previous works and performed systematic simulations to evaluate the imaging characteristics [7,8]. In this work, we demonstrated the advantage of using CS-based algorithm experimentally, compared to conventional FBP. Fig. 3 shows two phantoms used in the studies: (a) 3D Shepp–Logan phantom for simulation and (b) a mouth phantom (a lower mouth part of Kelvin™ phantom, CIRS Ltd., USA) for experiment. Fig. 4 shows a photograph of a commercially-available dental CBCT system (Expert7™, Vatech Co., South Korea) used in the experiment. It consists of an X-ray tube (90 kV_p, 5 mA), a CMOS-type flat-panel detector having a pixel size of 200 μm, and a mechanical support for object installation. A voxel size of 400 μm and a voxel dimension of $206 \times 206 \times 32$ were used in the experimental reconstruction for reducing reconstruction time. Detailed test conditions used in the simulation and the experimental studies are listed in Table 1.

3. Results and discussion

For all reconstruction results, the number of iterations used was 300 and the weight assigned to the sparsity term in the objective function (*i.e.*, α) was 0.1. For the simulation results, no statistical noise in the data was considered.