Computerized Medical Imaging and Graphics 34 (2010) 149–159

Contents lists available at ScienceDirect

Computerized Medical Imaging and Graphics

journal homepage: www.elsevier.com/locate/compmedimag

Motion compensated iterative reconstruction of a region of interest in cardiac cone-beam CT

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ARTICLE INFO

Article history:
Received 28 November 2008
Received in revised form 27 May 2009
Accepted 17 August 2009

Keywords:
Motion compensation
Computed tomography (CT)
Iterative reconstruction
Region of interest
Cardiac motion estimation

PACS:
87.57. –s
87.57.nf
87.57.Q –

ABSTRACT

A method for motion compensated iterative CT reconstruction of a cardiac region-of-interest is presented. The algorithm is an ordered subset maximum likelihood approach with spherically symmetric basis functions, and it uses an ECG for gating. Since the straightforward application of iterative methods to CT data has the drawback that a field-of-view has to be reconstructed, which covers the complete volume contributing to the absorption, region-of-interest reconstruction is applied here. Despite gating, residual object motion within the reconstructed gating window leads to motion blurring in the reconstructed image. To limit this effect, motion compensation is applied. Hereto, a gated 4D reconstruction at multiple phases is generated for the region-of-interest, and a limited set of vascular landmarks are manually annotated throughout the cardiac phases. A dense motion vector field is obtained from these landmarks by scattered data interpolation. The method is applied to two clinical data sets at strongest motion phases. Comparing the method to standard gated iterative reconstruction results shows that motion compensation strongly improved reconstruction quality.

1. Introduction

Cardiovascular diseases are the major cause of mortality and morbidity in most of the developed countries. Coronary artery disease is one of the main cardiovascular diseases.

Owing to recent advances in imaging hardware, diagnostic quality of coronary computed tomography (CT) has improved [1], and the role of CT in the (non-invasive) diagnosis of coronary arteries is expanding. Cone-beam computed tomography (CBCT) has proven to be useful in providing detailed morphological images of the coronary arteries. Still, the heart pulsation continues to be a limiting factor in cardiac CT. Electro-cardiogram (ECG) gated [2–7] or triggered [8,9] reconstruction methods can mitigate this problem, but never remove it completely. The standard gated CT reconstruction method assumes that the heart is stationary within the cardiac time window, which is an approximation.

If the motion of the object during acquisition can be recovered, motion compensation can be applied during image reconstruction to remove blurring due to cardiac motion [10–14]. In addition, such an approach can potentially limit the radiation dose, as information from all of the acquired phases can be used for the reconstruction. For cardiac CT, estimating the heart motion vector field (MVF) is non-trivial issue and several methods have been proposed in literature. A first common step in many MVF estimation methods is to reconstruct a gated 4D dataset, i.e. a time sequence of 3D images.

Automatic MVF estimation methods have been proposed by Blondel et al. [10] and Jandt et al. [15]. Both presented a motion compensated (MC) reconstruction method that employed a 3D coronary centerline model to estimate the MVF of the coronary vessel tree from rotational X-ray projections. Stevendaal et al. [13] proposed a whole heart MVF estimation by applying model-based segmentation and shape tracking. Prümmer et al. [16] proposed a 4D FDK-like algorithm that used image registration techniques for heart motion estimation. Taguchi et al. [17,18] proposed an iterative projection-based method that exploits a block-matching algorithm [19] to estimate the heart MVF from a 4D cardiac image data set. Schirra et al. [20] presented a MC analytical reconstruction method, where a rigid image registration was applied during quiescent cardiac phases to determine the MVF of calcified lesions of the coronary arteries. Here, temporal interpolation in parameter space was used in order to estimate motion during strong motion phases.

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doi:10.1016/j.compmedimag.2009.08.004

For coronary stent reconstruction, a manual MVF estimation method based on detecting 2D markerball centers of the stent in projection image data has been proposed by Perrenot et al. [21]. Stevendaal et al. proposed [13] a MC ROI analytical reconstruction by using a MVF obtained by manually identifying a limited number of right coronary artery (RCA) landmarks.

Generally, MVF estimation methods yield an irregular distribution of measurements. To obtain a dense MVF, the measurements need to be resampled. The nearest-neighbor by inverse distance weighting (NNIDW) [22] and the thin-plate-spline (TPS) [23] interpolation methods can be used to interpolate or extrapolate a dense MVF to the entire image domain [24].

This paper presents a method for MC gated iterative CT reconstruction of a cardiac region-of-interest (ROI). The cardiac MVF is derived from a limited set of manually indicated landmarks. A method's landmarks indication error-sensitivity study is carried out. The maximum landmark position indication-error is determined which can be tolerated without degrading the MC reconstructed images by motion blurring. In order to obtain a dense MVF at the resolution of the regular reconstruction grid, the NNIDW and the TPS interpolation are applied, and results are compared. Reconstruction results for two clinical cases are shown and compared to standard gated iterative reconstruction results. Moreover, a motion-compensated filtered back-projection reconstruction method [13] is used, and the analytical and iterative reconstructed images are compared.

The article is organized as follows: Section 2 describes the MC iterative reconstruction algorithm, the MVF estimation and the scattered data interpolation methods. The experiments and results on the clinical data sets are presented in Section 3 and discussed in Section 4. Finally, conclusions are drawn in Section 5.

2. Methods and materials

2.1. Introduction

In the following subsections MC iterative reconstruction is presented. First, the basic iterative algorithm is introduced (Section 2.2). Subsequently, in Section 2.3, it is described how a motion vector field can be incorporated in the iterative ROI reconstruction framework, and an efficient forward- and back-projection model for MC iterative reconstruction is presented. Finally, a manual method for MVF estimation of cardiac landmarks is described. In this subsetcion, a brief overview on the TPS and the NNIDW methods is given.

2.2. Basis functions and the iterative statistical reconstruction method

Transmission tomography aims at the reconstruction of a density distribution f of the object scanned. The continuous function f can be represented as a linear combination $\tilde{f}$ of a limited set of basis functions b, placed on a 3D grid with N equidistant grid points, $\boldsymbol{x_j}$:

$$\tilde{f}(\boldsymbol{x}) = \sum_{j=1}^{N} \mu_j b(\boldsymbol{x} - \boldsymbol{x_j}), \tag{1}$$

where $N = N_x N_y N_z$ and N_x, N_y, and N_z are the number of grid points in x, y, and z directions, respectively. The set of numbers μ_j are the coefficients of expansion which describe the function f relative to the chosen set of basis functions $b(\boldsymbol{x} - \boldsymbol{x_j})$. Lewitt [25] investigated how different sets of basis functions can influence the quality of the images. Spherically symmetric volume elements are alternatives to the more conventional voxels for the reconstruction of volume images. In the reconstructions presented in this paper, the Kaiser–Bessel basis functions [26] are used. These spherically symmetric basis functions (also called blobs) are spatially limited and effectively frequency limited. The standard parameters are used for the Kaiser–Bessel basis functions, which satisfy the frequency criteria described in [27]. Blobs as basis functions have many advantages compared with simple cubic voxels, e.g. their appearance is independent of the source position [26].

For the iterative ROI reconstruction presented in this paper, an aperture weighted cardiac modified version of the iterative ordered subsets convex maximum likelihood (OSML) algorithm [28] is used. The OSML method is an ordered subset modification of the convex ML method [29], in which one update of the OSML method requires the sum over only a subset S_m of all projections simultaneously. The OSML reconstruction method takes the Poisson statistics of the measured photons into account. In a general CT acquisition, the various projections, i, measuring photon counts, Y_i, are independent. The log-likelihood function $L(\boldsymbol{u})$, with the absorption coefficient, μ_j, at position j can be written as

$$L(\boldsymbol{u}) = \sum_i \left(-d_i e^{\sum_j A_{ij}\mu_j} - Y_i \sum_j A_{ij}\mu_j \right) + c_1, \tag{2}$$

where $\boldsymbol{u}$ is the image vector $\boldsymbol{u} = (\mu_1, \mu_2, \ldots, \mu_j)$, d_i is the expected number of photons leaving the source towards the i-th projection. A_{ij} are the elements of the system matrix, and c_1 is an irrelevant constant that does not depend on $\boldsymbol{u}$. The function $L(\boldsymbol{u})$ has to be maximized to find the optimally reconstructed image. As described in Kamphuis et al. [28], an approximate solution of maximizing Eq. (2) leads to the following iterative step ($n \mapsto n+1$) in the OSML method:

$$\mu_j^{n+1} = \mu_j^n + \lambda \mu_j^n \frac{\sum_{i \in S_m} A_{ij}[d_i e^{-\langle A_i \mu^n \rangle} - Y_i]}{\sum_{i \in S_m} A_{ij} \langle A_i \mu^n \rangle d_i e^{-\langle A_i \mu^n \rangle}}, \tag{3}$$

with $\mu_j^n > 0$, and forward projections $\langle A_i \mu^n \rangle = \sum_j A_{ij}\mu_j$. The relaxation parameter, λ, is included to control convergence speed.

An aperture weighted cardiac modified version (AWCOSML) of the iterative algorithm based on Eq. (3) can be written as

$$\mu_j^{n+1} = \mu_j^n + \lambda \mu_j^n \frac{\sum_{i \in S_m} w_i^c w_i^a A_{ij}[d_i e^{-\langle A_i \mu^n \rangle} - Y_i]}{\sum_{i \in S_m} w_i^c w_i^a A_{ij} \langle A_i \mu^n \rangle d_i e^{-\langle A_i \mu^n \rangle}}, \tag{4}$$

where $w_i^c (w_i^a)$ is the cardiac (aperture) weight for the measurement i [30]. Nielsen et al. [5] investigated the effect of various cardiac gating function shapes on image quality; following their results a rectangle with smooth edges is used in this evaluation. The reference phase time point ϕ_k^P which define the k th center of the gating windows with $1 \leq k \leq K$, is determined from the patient's ECGs, which are recorded in parallel with the CT acquisition.

In helical CT object points enter and leave the cone. Empirically, it was found that this leads to artifacts which can be reduced by means of introducing an aperture weighting function w_i^a in the iterative reconstruction update formula [6,30]. The aperture weighting function is the same for all projections and only depends on the distance of a detector pixel, i, from the XY-plane defined by the source position. For the reconstructions presented in this article, a $\cos^2$ aperture weighting function is used. Once all subsets are processed, one iteration is completed. Each subset S_m contains projections that have a constant angular increment inside each gating window, and the sequence of the subset is determined randomly.