Chapter Five

Fully automatic non-rigid registration-based local motion estimation for motion-corrected iterative cardiac CT reconstruction

All truths are easy to understand once they are discovered; the point is to discover them.

— Galileo Galilei (1564 – 1642)

Abstract — A method for motion-corrected iterative CT reconstruction of a cardiac region of interest is proposed. Given a precomputed (non-motion compensated) gated 4D ROI image data set, a fully automatic elastic image registration is applied to recover a dense cardiac displacement field of the ROI from a chosen cardiac reference phase to a number of phases within the RR interval. Here, a stochastic optimizer and multi-resolution approach are adopted to speed up the registration process. Subsequently, motion-compensated iterative reconstruction using the determined motion field is carried out. For the image representation volume-adapted spherical basis functions (blobs) are used in order to take the volume change caused by a divergent motion vector field into account. The method is evaluated on phantom data and in four clinical data sets at a strong cardiac motion phase. Comparing the method to standard gated iterative reconstruction results shows that motion compensation strongly improves the image quality in these phases. A qualitative and quantitative accuracy study is presented for the estimated cardiac motion field. For the first time a blob-volume adaptation is applied on clinical data, and in the case of divergent motion it yields improved image quality.

5.1 Introduction

Cardiovascular computed tomography (cardiovascular CT) is increasingly used for diagnosis and therapy planning of cardiovascular disease. In cardiovascular CT, the reconstructed images are analysed to detect possible abnormalities in cardiac anatomy or function. Early detection and evaluation of stenotic segments in the coronary arteries is an important clinical application of cardiac CT imaging, as it can be used for diagnosing coronary artery disease and guiding therapy options to prevent acute myocardial infarctions.

Up to now, ECG-gated CT reconstruction methods [26, 45, 47, 57, 86, 122] are the gold standard for the diagnosis of cardiovascular diseases. These techniques lead to images with reduced motion artifacts at the expense of an increased radiation dose to the patient and a limited temporal resolution. The ECG is used to select only the projections acquired during a time window centered in a chosen quiescent cardiac phase. For cardiac cone-beam CT, Manzke et al. [74] proposed an adaptive method to determine the optimal ECG-gating window width without user interaction. This method guarantees that all voxels receive data over an interval of at least $\pi$ during the backprojection. In this way, the temporal resolution is optimized since only data from the smallest possible time window width is selected. Furthermore, this algorithm leads to a trade-off between temporal resolution and improved image signal-to-noise ratio (SNR), obtained using over scan data. For cardiac C-arm CT, an ECG-gated image reconstruction method is also feasible [62], but the slower rotation speed of the C-arm scanner leads to a temporal spread of the ECG-gated projections that is much higher compared to that produced by a clinical CT scanner. Within the automatically (or manually) determined time window the heart is assumed stationary. The frequent appearance of motion blurring artifacts in the reconstructed images proves this assumption to be violated.

A potential solution to reduce motion artifacts due to the heart pulsation is motion-compensated (MC) CT reconstruction [5, 39, 40, 71, 92, 98, 112, 136]. A fundamental pre-requisite for MC reconstruction is the knowledge of the three-dimensional (3D) object motion vector fields (MVF) from a reference phase of the heart pulsation to all other phases within the RR interval.

Several cardiac motion estimation methodologies have been proposed in literature [5, 40, 43, 95, 124, 136]. Usually, these methods attempt to find a correspondence between a limited number of automatically tracked or manually indicated anatomical landmarks from a given four-dimensional (4D) cardiac image data set. This procedure provides a sparse and irregular distribution of displacement vectors. To determine a dense MVF for the whole regular reconstruction grid, resampling is necessary. Generally, a spatial resampling interpolation method (e.g. Thin-plate-spline [6] or Nearest Neighbor by inverse distance weighting [116]) is used for this purpose. In order to improve accuracy, the estimation of a dense MVF directly from the image data would be of interest. This can for example be achieved using image registration techniques [14, 33, 55, 59, 70, 71, 98, 113], which have been frequently applied in the domain of motion analysis.

Elastic (or non-rigid) image registration techniques (EIR) based on B-spline basis functions [129] have been used extensively in biomedical imaging applications for the
monomodal or multimodal registration of pairs of clinical images [55,59,109], or for recovering directly a dense MVF of a chosen cardiac region of interest (ROI) [65]. In recent work, Prümmer et al. [98] proposed a 4D FDK-like algorithm that used a non-rigid 3D-3D image registration method for heart motion estimation.

The main drawback of EIR techniques is their long computation time, mainly caused by the calculation of the derivative of the similarity criterion for all degrees of freedom during each iteration of the optimization step. To solve the EIR problem, two classes of optimizers can be considered: deterministic methods [41, 97] that assume an exact knowledge of the criterion and its derivatives; and stochastic methods [52, 102, 118] which assume that only an approximation of the cost function is known. A popular search technique is the stochastic gradient descent method by Robbins-Monro [102]. Recently, with this approach, Klein et al. [55] have shown that the EIR computation time can be strongly decreased, without affecting the rate of convergence, accuracy, or robustness.

Iterative reconstruction algorithms are able to reconstruct images of transmission CT scans even in situations where the data elements are noisy and where only a sparse number of projections is available. Generally, iterative reconstruction methods may be divided into two groups. The first group including the algebraic reconstruction technique (ART) [25], solves a system of linear equations and does not take in account the statistics of the measurements. To the second group belong all the statistical iterative reconstruction methods, such as the convex Maximum Likelihood method (ML) [60], which take care of the photon statistics in the measurement, resulting in a higher SNR of the reconstructed images compared to the analytical reconstruction methods [85,93,126].

A well known drawback of conventional iterative reconstruction methods is the necessity that a field-of-view (FOV) has to be reconstructed that covers the whole volume, which contributed to the absorption. In the case of a high resolution reconstruction, this imposes very large memory and computation requirements during reconstruction. ROI reconstructions [149] can mitigate this problem.

In this chapter a method for MC iterative CT reconstruction of a cardiac ROI is proposed. Given a precomputed (non-motion compensated) gated 4D ROI image data set, a fully automatic elastic image registration is applied to recover a dense MVF of the ROI from a chosen cardiac reference phase to a number of phases within the RR interval. To speed-up the whole registration algorithm a stochastic Robbins-Monro optimization method and a multiresolution approach [82,132] are adopted.

The method is evaluated on a dynamic cardiac phantom and on four clinical data sets performing reconstructions at a strong cardiac motion phase, and images of the right (RCA) and left (LCA) coronary arteries, of the left ventricle (LV), and of the aortic and mitral valves are presented.

This chapter is organized as follows: Section 5.2 describes in detail the implementation of the proposed motion compensation framework. Section 5.3 presents the results of the experimental validation of the method. Section 5.4 and 5.5 contain the discussion and conclusion, respectively.
5.2 Methodology

5.2.1 Introduction

The method for correcting the motion in cardiac CT is based on three subsequent steps: As a first step, the projection data are acquired in low-pitch helical acquisition mode together with the ECG and are reconstructed at different phase points. As a second step, the motion-vector field is calculated from the reconstructed images with the help of fully automatic elastic image registration. Finally, a motion-corrected iterative reconstruction is carried out for a reference phase using those projections, which cover the part of the cardiac cycle for which the motion-vector field has been determined. These steps are described in the following sections 5.2.2–5.2.5.

5.2.2 Generation of 4D image data sets

As an input for the determination of the motion-vector field, a 4D image data set is required. The images can be obtained by a low-pitch helical acquisition mode together with the ECG and a reconstruction at different cardiac phase points. This can be achieved, e.g., by an aperture weighted cardiac reconstruction (AWCR) [57].

In order to perform a 4D image reconstruction, the projection data have to be reconstructed at different phase points within the cardiac cycle. A list of \( N_r \) R-peaks at angular CT system positions \( \phi^R_k \) is determined from the patient’s electrocardiogram (ECG) recorded synchronously with the acquisition of the projection data. From the list of R-peaks, the phase points at angular positions \( \phi^P_k \) can be determined using, for example, a fixed percentage \( P \in [0, 1) \) of the RR interval. The same percentage is used for all heart cycles.

\[
\phi^P_k = \phi^R_k + P \left( \phi^R_{k+1} - \phi^R_k \right) \forall k = 1, \ldots, N_p. \tag{5.1}
\]

\( N_p = N_r - 1 \) phase points are obtained. A cardiac gating function with a width \( w_k \) is centered in each phase point \( P \) at angular position \( \phi^P_k \). The width \( w_k \) of the gating function determines which projection data from each cycle are used for the reconstruction and primarily determines the temporal resolution. In general, reconstructions of 3D images are performed at equidistant phase points \( P \) throughout the entire cardiac cycle with the smallest possible gating window width [74].

Due to the non-linearity of the cardiac motion during one single heart beat, and its rate variation between each beat, it can be expected that different motion blurring is observed in the gated reconstruction phases. A non-equidistant phases selection according to a typical heart motion model could lead to more homogeneous cardiac motion states. Nevertheless, to find a heart motion model which fit well to the cardiac motion of each patient is a non-trivial issue that goes beyond the scope of this work.

5.2.3 The elastic image registration (EIR) framework

The pre-requisite for performing a motion-corrected cardiac iterative reconstruction [39] of the acquired projection data is the existence of an MVF. For a volumetric cardiac reconstruction the MVF is represented by a \( \mathbb{R}^3 \to \mathbb{R}^3 \) mapping \( \mathbf{m}(\mathbf{x}, (\hat{R}), R, P) \),
which displaces each grid point $x_i(R)$ at a reference heart phase $R$ to a new position $x_i^*(P)$ in an arbitrary heart phase $P$ by

$$x_i^* = x_i^*(P) = x_i(R) + m(x_i(R), R, P), \quad (5.2)$$

where $R \in [0, 1)$ is the selected reference percentage of the RR interval, and $i = 1, 2, \ldots, N$ with $N = N_x N_y N_z$ and $N_x, N_y$, and $N_z$ are the number of grid points in $x$, $y$, and $z$ directions, respectively.

Given a reference image $f_r$ and a test image $f_t$, the EIR finds a correspondence function $T : \mathbb{R}^3 \to \mathbb{R}^3$, which relates points in the test image $f_t$ to the reference image $f_r$ (Fig. 5.1). A minimization problem is solved to determine the deformation field $T$ which minimizes an image similarity measure that is computed for each grid position in the reference $f_r$ and warped test $f_w(x) = f_t(T(x))$ images. In our implementation $T$ is modeled using cubic B-splines [109,129–131].
5.2.3.1 B-spline interpolation

The 3D deformation function $T$ is described by uniformly spaced cubic B-spline:

$$ T(x) = x + \sum_{j \in J_c} c_j \beta_3(x/h - j), \quad (5.3) $$

where $\beta_3$ is a 3D tensor product of 1D centered cubic B-spline, $J_c$ is a set of parameter indices, and $h = (h_x, h_y, h_z)$ is the knot spacing. The scale parameter $h$ can be used to set the desired node spacing, which determines the level of smoothness of the deformation field $T$. The second term in Eq.5.3 corresponds to the MVF from the reference to the test image.

5.2.3.2 Similarity measure and invertibility

Since here a mono-modal image registration is required, the sum of squared differences (SSD) is used as similarity measure. The SSD metric relies on the assumption that intensity representing homologous point must be the same in both images. The SSD measure is defined by

$$ E^S_c = \sum_{i=1}^{N} (f_r(x_i) - f_w(x_i))^2, \quad (5.4) $$

Due to the high degrees of freedom, EIR is inherently an ill-posed problem and could lead to unrealistic folding of the deformation fields in the absence of suitable constraints [14]. Since the human organ and tissue motion is invertible, one important physical constraint for the estimated deformation $T$ is that it should be invertible as well. By the inverse function theorem [108], the invertibility is guaranteed if the Jacobian $\det J_T(x) \neq 0 \forall x$. Moreover, since the determinant is continuous in the spatial domain, $\det J_T$ must be positive since it is assumed that there are regions with identity transformations (i.e. $\det J_T(x) = 1 \forall x$). Penalty functions have been often used to prevent Jacobian determinant from being negative [53, 104, 109]. For unconstrained optimization it is useful to add a penalty function $M(c)$ to the similarity measure $E^S_c$, and look for a minimum of the combined criterion

$$ E^M_c(c) = E^S_c(c) + \gamma M(c), \quad (5.5) $$

where $E^M_c$ is the criterion to be optimized, $\gamma$ is the regularization parameter, and $c$ is the vector of the parameters $c_j$ describing the deformation function $T$ (Eq. 5.3).

For the 3D registrations presented in this chapter a topology-preserving smooth penalty function $M(c)$ proposed by Chun et al. in [12] is used, and reads

$$ M(c) = \sum_{l \in \{x,y,z\}} \sum_{i,j,k} \left[ p \left( c_{l,i+1,j,k} - c_{l,i,j,k}; \varsigma_{l,x}^{1}, \varsigma_{l,x}^{2} \right) 
+ p \left( c_{l,i,j+1,k} - c_{l,i,j,k}; \varsigma_{l,y}^{1}, \varsigma_{l,y}^{2} \right) 
+ p \left( c_{l,i,j,k+1} - c_{l,i,j,k}; \varsigma_{l,z}^{1}, \varsigma_{l,z}^{2} \right) \right]. \quad (5.6) $$
5.2 Methodology

where \( \varsigma_{1}^{l,r} = h_k l \) for \( \forall r \in \{x, y, z\} \), \( \varsigma_{1}^{l,r} = h_k l \) for \( \forall r \neq l \) and \( \varsigma_{2}^{l,r} = h_k K_l \) for \( \forall r = l \), \( k_l \) and \( K_l \) are positive constants, and \( p \) represents the following piecewise quadratic function:

\[
p(t; \varsigma_1, \varsigma_2) = \begin{cases} 
\frac{1}{2} (t + \varsigma_1)^2, & t < -\varsigma_1 \\
0, & -\varsigma_1 \leq t \leq \varsigma_2 \\
\frac{1}{2} (t - \varsigma_2)^2, & \varsigma_2 < t 
\end{cases}
\]  

(5.7)

where the argument \( t \) denotes a difference between two adjacent deformation coefficients.

This penalty function encourages positive Jacobian determinants by bounding the differences of two adjacent deformation coefficients in the \( x, y, z \) direction. By constraining the differences only instead of the coefficients, even large deformations \( T(x) \) with gradients within the bounds are included in the search solution space. Compared to the direct Jacobian penalty methods, this approach has the advantages to enforce the invertibility on the continuous domain, it is memory-efficient, and finally it has faster computation because no interpolation for Jacobian values is needed [12].

5.2.3.3 Fast stochastic optimization methods

As shown in Eq. 5.3, the deformation function \( T \) is represented by a summation of B-spline basis functions, where \( c_j \) denote the expansion coefficients. Given our parametric deformation model in Eq. 5.3, and the combined criterion in Eq. 5.5, the solution of the registration problem can be defined as the result of the following minimization:

\[
c = \arg\min_{c} E_{c}^{M}.
\]  

(5.8)

To find the optimal deformation \( T \) that minimizes the cost function in Eq. 5.5, a suitable optimization method should be applied.

In this work the stochastic gradient descent of Robbins-Monro [102] (RM) is used, since it has the advantage to decrease the computation time per iteration, without affecting the rate of convergence, final precision, or robustness [55].

The RM follows the same scheme as the deterministic gradient descent [97] with the distinction that the gradient of the cost function, \( \nabla_{c} E_{c}^{M}(c^{(n)}) \), is replaced by an approximation \( \nabla_{c} \tilde{E}_{c}^{M}(c^{(n)}) \), resulting in the following update rule:

\[
\Delta c^{(n)} = -\rho_n \nabla_{c} \tilde{E}_{c}^{M}(c^{(n)}).
\]  

(5.9)

The gain factor \( \rho_n \) can be defined as a decaying function of the iteration number \( n \) and in practice the following expression is often used [55,119]:

\[
\rho_n = \frac{a}{(n + A)^{\alpha}},
\]  

(5.10)

with \( A \geq 1 \) and the user-defined constants \( a > 0 \) and \( 0 \leq \alpha \leq 1 \).

A stochastic approximation of the derivative of the similarity criterion \( \nabla_{c} \tilde{E}_{c}^{M} \) can be determined by using a new, randomly selected subset of voxels in every iteration of the optimization process. In this way, a bias in the approximation error is avoided. This technique, commonly called stochastic subsampling, has been evaluated on non-rigid registration in Klein et al. [55].
For the EIRs presented in this chapter, the selection of uniformly distributed samples follows a quasi-Monte Carlo Halton sequence [27] (Fig. 5.1).

5.2.3.4 Multiresolution elastic image registration

A multiresolution approach [82, 132] can improve the robustness and the efficiency of the EIR algorithm. First, the problem is solved at a coarse level, with subsampled images and a deformation field with reduced number of degrees of freedom. Subsequently, the results are propagated to the next finer level. This iterative procedure will expand alternately the grids of the B-spline control points of the images and of the deformation field until the finest level is reached. In this work, the multiresolution approach uses 3D B-spline reduce/expand operators [132] of factor of two to build the pyramid (i.e. a set of gradually reduced versions of the original images and the deformation field), which is optimal in the L2-sense. As an example, in Fig. 5.2 a 2D-2D registration of the Lena image is shown.

5.2.4 Extraction of the cardiac motion vector fields

Since the second term in Eq. 5.3 represents the MVF from the reference to the test image, the EIR can be used to estimate the MVF between a pair of volumes for each grid position \( x_i \). Due to the severe motion artifacts in the images reconstructed at phases of fast cardiac motion, it is advantageous to apply the EIR only between images related to phases of relatively weak motion. In this way, it is possible to avoid the accuracy degradation of the motion estimation produced by the matching errors.

To determine appropriate motion phases within the RR interval, a motion map (MM) technique is used [74, 113]. Hence, from the determined motion map the desired strong motion reference phase \( R \) and a limited set of quiescent motion phases \( Q \), with \( Q \in [0, 1) \), are selected.

A temporary reference phase \( R_T \), with \( R_T \in [0, 1) \), is chosen from the set of quiescent phases. Therefore, in order to recover the relative MVFs, a number of 3D-3D EIRs are performed between the volumes reconstructed at the phase \( R_T \) and the other quiescent phases \( Q \) selected. A continuous 4D displacement vector \( m(x_i(R_T), R_T, P) \) from the temporary reference phase \( R_T \) to all the arbitrary phases \( P \) within the RR interval is obtained by applying a cubic-spline interpolation using as knots all the EIR’s MVFs computed previously.

After the last interpolation step, the MVF \( m(x_i(R_T), R_T, R) \) from the temporary \( R_T \) to the actual reference phase \( R \) is available. Given the determined \( m(x_i(R_T), R_T, R) \), it is possible to recover the inverse MVF \( \text{im}(x_i(R), R, R_T) \) in the opposite direction from the actual \( R \) to the temporary \( R_T \) reference phase, by using a fixed-point-based iterative approach [11].

The displacement vector \( m(x_i(R), R, P) \) from the reference phase \( R \) to all the arbitrary phases \( P \) in the RR interval is determined by:

\[
m(x_i(R), R, P) = \text{im}(x_i(R), R, R_T) + m \left( \text{im}(x_i(R), R, R_T), R_T, P \right).
\]  

(5.11)

Once the vector \( \text{im}(x_i(R), R, R_T) \) is obtained for each grid position \( x_i \) at the actual reference phase \( R \), the corresponding codomain points \( s_i \) can be determined.
5.2 Methodology

Figure 5.2. The Lena 2D-2D registration. In order, in the top row the reference (a), the test (b) and the warped test (c) images are shown. In the middle row the absolute difference images before (d) and after (e) the registration, and the estimated transformation \( T \) (f) are given. While, in the bottom row the \( x \) (g) and the \( y \) (h) components and the determinant of the jacobian matrix of \( T \) (\( \text{det} J_T \) ) (i) are presented. Here g.u.=grayscale unit. (Image size: 256 × 256, deformation size: \( 8 \times 8 \), 3 resolution levels, RM optimizer, \( a = 3500 \), \( A = 51 \), \( \alpha = 0.602 \), 2000 iterations per resolution level, 2000 randomly selected voxels per iteration, topology-preserving regularizer, \( \gamma = 0.001 \)).
on the grid at the quiescent temporary reference phase point \( R^T \) (see Fig. 5.3, middle grid). Since the vectors \( m(x_i(R), R^T, P) \) are available for the only grid positions \( x_i \), in a second step a B-spline interpolation is applied to recover the \( m(s_i(R^T), R^T, P) \) values at off-grid positions \( s_i \). Finally, the \( m(x_i(R), R, P) = t_{P,i} \) can be easily determined by summing the \( m(x_i(R), R, R^T) \) and the \( m(s_i(R^T), R^T, P) \) (Fig. 5.3).

\[
m(x_i(R), R, P) = \text{im}(x_i(R), R, R^T) + m(\text{im}(x_i(R), R, R^T), R, R^T, P),
\]

\( \text{im}(x_i(R), R, R^T) = s_i \)

\( m(s_i(R^T), R^T, P) = t_{P,i} \)

**Figure 5.3.** Extraction of the MVF \( m(x_i(R), R, P) \) from the actual strong moving reference phase \( R \) to all the arbitrary phase points \( P \) within the RR interval in two steps.

### 5.2.5 Motion-corrected image reconstruction with SART

Once an MVF is determined, an MC cardiac iterative reconstruction can be performed for the cone-beam projection data, which are acquired with a CT scanner equipped with a rigidly coupled focus-centered 2D detector and a X-ray source moving on a helical path around the object.

Volumetric CT reconstruction algorithms determine the density absorption function \( f \) of the object irradiated using a set of 2D projections measured at different angles. A linear combination \( \tilde{f} \) of a limited set of basis functions \( b \) can be used to represent the continuous function \( f \):

\[
\tilde{f}(x) = \sum_{i=1}^{N} \mu_i b(x - x_i),
\]

where \( x = (x, y, z) \), and the basis functions \( b \) are placed on a 3D grid with \( N \) grid points. The set of parameters \( \mu_i \) are the coefficients of expansion which describe the function \( \tilde{f} \) relative to the chosen basis functions \( b(x - x_i) \). Following Lewitt [69] in this work, the Kaiser-Bessel basis functions [68] 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 [76]. Blobs as basis functions have many advantages compared with simple cubic voxels, e.g. their appearance is independent of the source position [68].

The main goal of iterative CT reconstruction is to find the optimal set of coefficients \( \mu_i \) that minimizes the difference (or ratio) between the measured \( p_j \) and calculated \( \tilde{p}_j^{(n)} = \sum_{i=1}^{N} A_{ji} \mu_i^{(n)} \) projections, where \( A_{ji} \) are the elements of the system matrix, \( n \) is the iteration number, and \( j = (1, 2, \ldots, D) \) are the detector pixels.

For the iterative ROI reconstructions presented in this chapter, an ECG-gated aperture weighted Simultaneous Algebraic Reconstruction Technique (SART) [4] is applied. The SART method is a modified version of the ART [25], which increases the speed of reconstruction. Here an entire cone-beam projection is back projected into the image. The update formula used during the backprojection step of the ECG-gated aperture weighted SART method (gated AWSART) can be written as

\[
\mu_i^{(n+1)} = \mu_i^{(n)} + \frac{\lambda_n}{\sum_{j \in S_m} a_{ji} w_j^c w_j^a} \sum_{j \in S_m} p_j - \tilde{p}_j^{(n)} \frac{\sum_{i} a_{ji} w_j^c w_j^a}{\sum_{i} a_{ji} w_j^c w_j^a}.
\] (5.13)

Here, \( a_{ji} \) indicates a backprojection weight [147], and \( w_j^c \) represents a cardiac gating window weight, which is introduced for each projection \( p_j \) in the reconstruction algorithm in order to select data belonging to the same heart phase. The effect of various gating function shapes on the images quality has been previously studied [86]. For the 3D reconstructions presented in this work, a rectangle with smooth edges (bump) shape is used for the cardiac-gated iterative reconstructions [86].

In helical CT the object points can enter and leave the cone, which can lead to artifacts in the reconstructed images. Empirically, it was found that these artifacts can be reduced by adding an aperture weighting function \( w_j^a \), for each detector pixel, \( j \), in the back projection formula [57, 149]. For the reconstructions presented in this work, a \( \cos^2 \) aperture weighting function is used [39, 57, 149].

One update of the ECG-gated SART algorithm requires to sum simultaneously over all the projections in one subset \( S_m \). The projections of one subset are selected at equal angles and the order is determined randomly. A random sequence is used because it was found to perform very similar to more sophisticated ordering schemes [28].

The relaxation parameter, \( 0 < \lambda_n < 2 \), controls the speed of convergence. Based on empirical evaluation, \( \lambda_n = 0.8 \) is chosen, which gave reasonable results.

In this work, the MC gated AWSART method proposed by Isola et al. [39] is adopted to reconstruct the selected cardiac ROI at the chosen reference phase \( R \).

To determine the forward projection, \( \tilde{p}_j \), the \( A_{ji} \) contribution of each blob to the detector pixel, \( j \), have to be determined. In case of a divergent beam, care needs to be taken to correctly sample the blobs: e.g. blobs which are close to the source, have a different contribution to forward and back projection than more distal blobs. Ziegler et al. [147] presented a blob sampling method motivated by the acquisition geometry: due to the divergent X-ray geometry, the spherically symmetric volume elements are magnified depending on their distance to the source. The convolution of
the magnified volume elements with the sensitive detector areas defines the weights $A_{ji}$.

However, in case of MC reconstruction of a moving object (e.g. the heart, or the lungs), the motion of the blob itself and the change of its volume caused by the existence of a divergent MVF (Eq. 5.2) is neglected. Isola et al. in [39] have shown that the non-vanishing divergence of the MVF yields a non-equidistant set of grid points, and an inconsistency in the line integral calculation which produces streak artifacts in the reconstructed images. Therefore, in case of MC reconstruction, a modified forward and back projection model was proposed which adapts the individual blob volume and its relative footprint on the detector in such a way that the representation of the image becomes more homogeneous. Phantom simulations have shown that this approach improves MC reconstruction quality [39]. An initial validation of the method on clinical data is presented in the subsection 5.3.6.

Iterative reconstruction is associated with high computational costs, especially in case of high resolution image reconstructions over the entire FOV and multiple time phases. Usually, in many clinical cases, the ROI is smaller than the volume that is irradiated, e.g. in coronary CT angiography, the ROI is often restricted to only one or more of the coronary arteries. Hence, an ROI reconstruction can be an efficient solution to increase the speed of iterative or analytical image reconstructions. For filtered back-projection (FBP) reconstruction methods [9, 51, 128], an ROI reconstruction is possible without additional efforts. To the contrary, an iterative reconstruction requires that an FOV has to be reconstructed that covers the whole volume, which contributed to the absorption. Only then the forward projections can be identical to the raw measurements. In this work, in order to recover the sinogram of only the ROI from the complete clinical raw measurements, a four-steps method as proposed by Ziegler et al. in [149] is adopted. This method consists of four consecutive steps and it is briefly described in the following. The first step includes an analytical FBP reconstruction of the whole FOV. In the second step the ROI is removed from the image of the previous step by setting the corresponding grid values to zero and performing a reprojection through this image on the same trajectory and detector geometry as the measurement. The sinogram, which results of the reprojection, is subtracted from the measurement data set in a third step. These processed projections contain the projections of the ROI only, which are taken for the iterative ROI reconstruction in a fourth step [149]. In case of MC gated iterative volume reconstruction, the last step can be replaced with an MC iterative ROI reconstruction method.

5.3 Experiments and results

To evaluate our MC reconstruction method a series of experiments was performed. First, a method validation on a dynamic cardiac phantom is given. Second, a consistency check of the estimated MVF, and a qualitative evaluation of the reconstructed images for human cases are presented. Subsequently, coronary artery reconstructions of three patients are shown. Finally, a clinical validation of the blobs volume-adaptation method proposed in [39] is given for the MC iterative reconstruction of the LV of a fourth patient.
5.3 Experiments and results

5.3.1 CT scanning and reconstruction settings

The phantom data were simulated for a scanner with 16 detector rows of 0.75 mm projected height and a helical scan with a relative pitch of 0.2. All the human data sets were acquired on a Brilliance 40(64) CT scanner (Philips Healthcare, Cleveland, OH, USA). In order to perform ECG-gated reconstructions, an ECG of the patients was recorded simultaneously with the CT acquisition. Approximately 10 heart beats are expected in the full scan of each patient. Further scanning and reconstruction parameters are listed in Table 5.1.

<table>
<thead>
<tr>
<th>Cases</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>Phantom</th>
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<td>Pitch [mm]</td>
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<td>0.625</td>
<td>0.625</td>
<td>0.75</td>
<td>2.4</td>
</tr>
<tr>
<td>Relative pitch</td>
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<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td>Collimation</td>
<td>40×0.625 mm</td>
<td>64×0.625 mm</td>
<td>16×0.75 mm</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rotation time [s]</td>
<td>0.42</td>
<td>0.42</td>
<td>0.42</td>
<td>0.42</td>
<td>0.42</td>
</tr>
<tr>
<td>Tube voltage [keV]</td>
<td>120</td>
<td>120</td>
<td>120</td>
<td>120</td>
<td>120</td>
</tr>
<tr>
<td>Anode current [mA]</td>
<td>333</td>
<td>333</td>
<td>333</td>
<td>333</td>
<td>119</td>
</tr>
<tr>
<td>Minimum heart rate [bpm]</td>
<td>53</td>
<td>54</td>
<td>65</td>
<td>73</td>
<td>64</td>
</tr>
<tr>
<td>Maximum heart rate [bpm]</td>
<td>58</td>
<td>59</td>
<td>71</td>
<td>83</td>
<td>64</td>
</tr>
<tr>
<td>ROI radius [mm]</td>
<td>25</td>
<td>33</td>
<td>29</td>
<td>37</td>
<td></td>
</tr>
<tr>
<td>Gating win. width [%RR]</td>
<td>40</td>
<td>40</td>
<td>40</td>
<td>40</td>
<td>40</td>
</tr>
<tr>
<td># Subsets</td>
<td>300</td>
<td>205</td>
<td>192</td>
<td>274</td>
<td>363</td>
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<td># Views x subset</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td># Iterations</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>λ</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
<td>0.8</td>
</tr>
<tr>
<td>Cubic grid size [mm]</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
<td>0.3</td>
</tr>
</tbody>
</table>

5.3.2 Phantom study

For the simulations performed in this work, a dynamic cardiac phantom modelled with ellipsoids and two tori to simulate coronary arteries was used. The heart size was modified dynamically according to a model ventricular volume curve derived from clinical cases [140] (Fig. 5.4). This volume curve was applied to every cardiac cycle of the phantom with a constant rate of 64 bpm.

The first step of this phantom evaluation was the 4D image data set reconstruction. The AWCRT method was performed at phase points \( P \) within the range 0 to 100% RR in steps of 5% RR with an optimized gating window width [74]. The systolic phase point \( R = 40\% \text{ RR} \) was selected as reference reconstruction phase. This rapid motion phase corresponds to the minimum of the ventricular volume curve in Fig. 5.4(b). Consequently, here a significant temporal cubic-spline interpolation error should occur. Thus, it is interesting to investigate how much this error can actually degrade the final MC reconstruction.

In order to apply the registration process, a subset of volumes reconstructed at slow motion phases \( Q \) located in the regions between [20,35]% RR and [50,60]% RR was selected. Among these quiescent phases a temporary reference phase \( R^T = 30\% \text{ RR} \) was chosen. Therefore, six 3D-3D registrations were performed between the tem-
Figure 5.4. The dynamic cardiac phantom and the ventricular volume curve (see [140]). In (a), the red dashed vertical lines indicate the R-peaks, and the blue dots represent values from the model. In (b), the same volume curve values at the corresponding cardiac phases in one beating cycle are given. Here, the red and green dots indicate the systole (40% RR) and diastole (75% RR), respectively. While, in (c) a volume rendered image of the dynamic cardiac phantom is shown.
5.3 Experiments and results

Figure 5.5. Phantom’s axial (a), coronal(b) and sagittal (c) views. In order, the ground truth synthetic images at 40% RR (first column), the static (second column) and dynamic (third column) cardiac phantom’s gated AWSART and the dynamic cardiac phantom’s MC gated AWSART (fourth column) reconstructed images at phase point 40% RR with gating window width of 40% RR are shown. (after 10 iterations, Level=-200 HU, Window=1000 HU).

porary reference phase $R^T$ and all the other quiescent phases $Q$ (for the registration settings see the following subsection 5.3.3). A cubic-spline interpolation was applied to fill the MVF estimation gap at the strong motion phases 40% and 45% RR. Finally, the MVF were shifted to the actual reference phase $R = 40$ %RR following all the remaining steps explained in the subsection 5.2.4. Given the estimated MVF, an MC gated AWSART reconstruction was performed at phase 40% RR with a fixed gating window of 40% RR. For the sake of comparison, gated AWSART reconstructions of the static and dynamic heart phantom were performed at identical phase point and gating window width. These reconstructions are presented in Fig. 5.5, while quantitative image similarity measures are given in Table 5.2.

As shown in Fig. 5.5 (third column), the gated AWSART reconstruction performed at 40% RR with a gating window of 40% RR leads to an image where the ventricle shape and the coronary arteries are strongly blurred. To the contrary, the MC gated AWSART reconstruction in Fig. 5.5 (fourth column) produces a sharp
Table 5.2. Image similarity measures. The MAD and the normalized correlation coefficient (NCC) between the cardiac phantom ground truth images and the gated AWSART reconstructed images of the static and dynamic cardiac phantom, and the MC gated AWSART reconstructed images of the dynamic cardiac phantom in Fig.5.5 are presented. Moreover, the ventricle volume of each reconstructed heart phantom is given.

<table>
<thead>
<tr>
<th>Method</th>
<th>Motion state</th>
<th>MAD [HU]</th>
<th>NCC [%]</th>
<th>Volume [ml]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground truth</td>
<td>Static</td>
<td>0.0</td>
<td>100.0%</td>
<td>50.0</td>
</tr>
<tr>
<td>gated AWSART</td>
<td>Static</td>
<td>4.5</td>
<td>99.5%</td>
<td>49.9</td>
</tr>
<tr>
<td>MC gated AWSART</td>
<td>Dynamic</td>
<td>33.5</td>
<td>92.0%</td>
<td>53.5</td>
</tr>
</tbody>
</table>

image where the ventricle shape and the vessels are well defined. By analysis of the image similarity measures in Table 5.2, it can be observed that the MC reconstruction presents better MAD and NCC values compared to the gated AWSART reconstructed image. The ground truth phantom ventricle has a volume of 50 ml at 40% RR, while in the MC reconstruction its measured volume is of 53.5 ml. This slightly bigger volume is due to the temporal cubic-spline interpolation error which has shifted the reference phase from 40% to 41% RR.

5.3.3 Cardiac motion estimation

In order to generate an MM a 4D ROI data set was required, hence an AWCR method was performed at phase points $P$ within the range 0 to 100% RR in steps of 5% RR with an optimized gating window width [74]. Then, the mean absolute difference (MAD) was calculated between the subsequent reconstructed images of the 4D ROI data set. The determined $MM$s for all the clinical cases are shown in Fig. 5.6. The fast cardiac motion phases $R = 50\%, 50\%, 60\%$ and $20\%$ RR (red points in Fig. 5.6) were chosen as reference reconstruction phases for the cases A-D, respectively. In order to apply the registration process, a subset of volumes reconstructed at quiescent phases $Q$ was selected (red intervals in Fig. 5.6). Generally, suitable cardiac slow motion phases $Q$ are located in regions between $[0,5]\%$ RR, $[35,45]\%$ RR (end systole) and $[65,85]\%$ RR (diastasis). Among these quiescent phases a temporary reference phase $R^T$ was selected. The phases $R^T = 70\%, 70\%, 75\%$ and $30\%$ RR (red stars in Fig. 5.6) were chosen for the cases A-D respectively. For the EIR step a 3-level multi-resolution approach was applied, and in each level the deformation field B-spline knot spacing $h$ was empirically chosen every 12 blobs. Since no a priori knowledge was available about the deformation, according to Chun et al. in [12], the topology-preserving regularization parameters were chosen symmetrically. The regularization parameter $\gamma$ in Eq.5.5, for all the four clinical data sets was set experimentally to $\gamma = 0.001$. For the RM optimizer, at each multiresolution level, the gain factor $\rho_n$ in Eq.5.10 was calculated using the same following parameters ($a = 3500$, $A = 51$, $a = 0.602$), it was iterated for 5000 iterations, and in each iteration a different random subset of 5000 image voxels was selected which are members of a Halton sequence for computing the similarity criterion. A number of 3D-3D registrations between the
5.3 Experiments and results

Figure 5.6. The MM of the four clinical cases A, B, C and D. The mean absolute differences ((a)-(d)) are presented. For a smoother representation of the MAD curves, a cubic-spline interpolation was used. Moreover, the selected actual (red points) and temporary (red stars) reference phases, and the intervals of quiescent motion phases (red intervals) used for the image registration process are shown.

previous temporary reference phases $R^T$ and all the other selected quiescent phases $Q$ were executed. Each registration took approximately 6 minutes on a 2.8 GHz AMD Opteron. As an example, in Fig.5.7 the registration results achieved for the case B are shown. A cubic-spline interpolation was used to achieve a temporal continuous MVF $m(x_i(R^T), R^T, P)$ from the temporary phase $R^T$ and all the other arbitrary phases $P$ in the entire RR interval. Given the $m(x_i(R^T), R^T, R)$ a fixed-point-based iterative approach [11] was used to recover the inverse MVF from the actual strong motion to the temporary quiescent reference phase $i m(x_i(R), R, R^T)$. Here, to determine the $i m(x_i(R), R, R^T)$ it was iterated for 10 iterations which took approximately 3 minutes. After performing all the remaining steps previously described in section 5.2.4 the final MVFs $m(x_i(R), R, P)$ were achieved.
5.3.4 Consistency study of the estimated motion vector fields

In clinical applications, due to the absence of ground truth evaluating the accuracy of estimated MVF is a complex issue. In this contribution, the current gold standard AWCR reconstruction [57] with the narrowest gating window width was considered as the best representation of the ground truth. This reconstruction was compared with the MC AWCR reconstruction [136]. Fig. 5.8 presents the reconstruction results (top), and the mean absolute difference (MAD) between the AWCR reconstructions with a gating window width of 22% RR and the MC AWCR reconstructed volumes with gating window widths of 22%, 40%, 60% and 80% RR, performed at each phase within the RR interval with step of 10% RR.

A common way to evaluate the consistency of an MVF estimation methodology can be to determine the cumulative MVF over a closed motion sequence, which should ideally be equal to zero. For the method described in this chapter, the EIR was applied only between volumes imaged at cardiac rest phases. Therefore, it makes sense to perform the EIR consistency check, over one of the selected region of quiescent phases within the RR interval. Chosen a starting phase point $P$, the cumulative MVF of a
5.3 Experiments and results

Figure 5.8. MVF consistency study. In order in each column (top) the AWCR reconstructed images with a gating window width of 22% RR (first row), and the MC AWCR reconstructed images with a gating window width of 22, 40, 60, and 80% RR (second-fifth rows) at five different phase points within the RR interval are shown (case A, cubic grid size = 0.3 mm, Level=0 HU, Window=500 HU). At the bottom, the corresponding MAD curves are presented.
closed sequence \( m(\cdot, P, P) \) can be determined by

\[
m(\cdot, P, P) = \sum_{i=0}^{L-1} m(\cdot, P + \nu i, P + \nu (i + 1)) + \sum_{i=L-1}^{0} m(\cdot, P + \nu (i + 1), P + \nu i),
\]

(5.14)

where \( \nu = 1, 2, \ldots \) is the step, and \( L = 1, 2, \ldots \) represents the number of subsequent MVFs considered to build the closed MVF sequence. For the consistency check performed in this chapter, \( P = 65\% \) RR, \( \nu = 5\% \) RR, and \( L = 4 \) are used for all the clinical cases. In Table 5.3, the mean and the standard deviation (STD) values of the cumulative MVF \( m(\cdot, 65\% RR, 65\% RR) \)’s components are determined over all image voxels. Moreover, the percentages of voxels with MVF components within four different inconsistency bins are shown (Table 5.3). From both the re-

Table 5.3. Closed sequence consistency check. The mean and the STD of the MVF \( m(\cdot, 65\% RR, 65\% RR) \)’s components values determined over all image voxels are presented. Moreover, even the percentages of image voxels with MVF’s components inconsistency within different inconsistency bins are shown.

<table>
<thead>
<tr>
<th>Case</th>
<th>( m(\cdot, 65%, 65%) )</th>
<th>Mean [±STD]</th>
<th>&lt; 0.3 mm</th>
<th>[0.3-0.6] mm</th>
<th>[0.6-1.2] mm</th>
<th>&gt; 1.2 mm</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>MVF_x</td>
<td>-0.01[±0.27] mm</td>
<td>93.65 %</td>
<td>4.78 %</td>
<td>1.39 %</td>
<td>0.18 %</td>
</tr>
<tr>
<td></td>
<td>MVF_y</td>
<td>-0.02[±0.30] mm</td>
<td>92.13 %</td>
<td>5.60 %</td>
<td>1.88 %</td>
<td>0.39 %</td>
</tr>
<tr>
<td></td>
<td>MVF_z</td>
<td>0.06[±0.33] mm</td>
<td>90.77 %</td>
<td>4.91 %</td>
<td>2.79 %</td>
<td>1.62 %</td>
</tr>
<tr>
<td>B</td>
<td>MVF_x</td>
<td>0.08[±0.44] mm</td>
<td>91.51 %</td>
<td>5.40 %</td>
<td>2.50 %</td>
<td>0.59 %</td>
</tr>
<tr>
<td></td>
<td>MVF_y</td>
<td>-0.06[±0.42] mm</td>
<td>93.84 %</td>
<td>3.65 %</td>
<td>1.78 %</td>
<td>0.73 %</td>
</tr>
<tr>
<td></td>
<td>MVF_z</td>
<td>0.09[±0.45] mm</td>
<td>90.26 %</td>
<td>4.45 %</td>
<td>3.41 %</td>
<td>1.88 %</td>
</tr>
<tr>
<td>C</td>
<td>MVF_x</td>
<td>-0.10[±0.48] mm</td>
<td>90.51 %</td>
<td>7.35 %</td>
<td>1.39 %</td>
<td>0.15 %</td>
</tr>
<tr>
<td></td>
<td>MVF_y</td>
<td>0.04[±0.44] mm</td>
<td>87.34 %</td>
<td>8.11 %</td>
<td>2.65 %</td>
<td>1.90 %</td>
</tr>
<tr>
<td></td>
<td>MVF_z</td>
<td>0.09[±0.40] mm</td>
<td>86.10 %</td>
<td>8.25 %</td>
<td>3.22 %</td>
<td>2.43 %</td>
</tr>
<tr>
<td>D</td>
<td>MVF_x</td>
<td>-0.01[±0.23] mm</td>
<td>97.79 %</td>
<td>1.66 %</td>
<td>0.54 %</td>
<td>0.07 %</td>
</tr>
<tr>
<td></td>
<td>MVF_y</td>
<td>-0.02[±0.33] mm</td>
<td>98.59 %</td>
<td>1.09 %</td>
<td>0.29 %</td>
<td>0.03 %</td>
</tr>
<tr>
<td></td>
<td>MVF_z</td>
<td>-0.01[±0.26] mm</td>
<td>98.59 %</td>
<td>1.07 %</td>
<td>0.33 %</td>
<td>0.01 %</td>
</tr>
</tbody>
</table>

sults presented in Fig. 5.8 and the MM shown in Fig. 5.6(a), it can be observed that consistent motions are estimated in the regions of slow cardiac motion ([30,45]% and [65,85]% RR). Indeed, here the MC AWCR reconstruction with the narrowest gating window of 22%RR present a very good quality which is comparable with the quality of AWCR reconstruction (Fig. 5.8, blue curve). Moreover, despite the increased gating window width, in these phases even the MC AWCR performed with a gating window width of 40%, 60%, and 80% RR still remove the residual motion blurring artifacts (Fig. 5.8, bottom, red, green, and magenta MAD curves). Clearly, at the phases of strong motion the strength of the MC reconstruction can be observed. In the regions between [0.25%], [50,60%], and [90,100]% RR excellent MC AWCR reconstructions are achieved. Here, all the MAD curves show higher values due to the strong motion blurring artifacts which are present in the AWCR reconstructed images, but removed in the MC AWCR results. Furthermore, as can be observed in the curves at he bottom in Fig. 5.8, the MAD values never exceed 30 HU in the interval of strong cardiac motion, and 20 HU in the phases of slow cardiac motion. Since very high absorption values are present in regions filled of contrast agent (e.g. the Aorta, the left ventricle
and the RCA and LCA), these very low maximum values of the MAD prove that a
very good global overlap was achieved between the volumes reconstructed with the
AWCR and the MC AWCR methods.

Finally, from both the images and the MAD curves shown in Fig. 5.8 can be
observed as MC reconstructions overcome the quality of non-compensated reconstruc-
tions in the whole RR interval.

Similar conclusions are achieved for the quantitative consistency check results
presented in Table 5.3. In accordance with the qualitative observations discussed
above, the presented results show as for the all clinical cases the determined cumu-
lative MVFs’s components have mean values close to zero, and STD values about the voxel size. For the 90% of voxels, a subvoxel precision
is achieved for the cumulative MVF components, and in the 95% of them the MVF
inconsistency never exceeds two times the voxel size. In conclusion, this final quanti-
tative study confirms as the EIR method can be an efficient solution to carry out a
reliable MVF estimation between volumes reconstructed at quiescent phases.

5.3.5 MC iterative coronary ROI reconstructions in patient
data

The proposed MC iterative ROI reconstruction was used to reconstruct the coro-
nary arteries of three different clinical cases. A suitable ROI was selected that was
large enough to contain the LCA and RCA of the three patients (Table 5.1). The
images were reconstructed at the strong cardiac motion reference phases $R= 50\%,$
50\%, 60\% RR for the case A, B and C, respectively. For all image reconstructions a
gating window width of 40\% RR was used. Finally, the gated AWSART and the MC
gated AWSART reconstructed volumes produced after 10 iterations and the relative
3D volume rendered images, are shown in Fig. 5.9,5.10 and 5.11 for the case A, B,
and C, respectively. Here, for reasons of comparison, even the gated AWSART recon-
structions at the quiescent phase of 75\% RR with a gating window width of 40\% RR
are presented.

For the clinical case A, an RCA was reconstructed. The gated AWSART recon-
struction leads to blurred images (Fig. 5.9(a)-(i) (left)), whereas the MC gated
AWSART reconstruction produces significantly better images quality, where the Aorta,
the RCA’s ostium, the interventricular posterior branch, the whole RCA, and its
right conal and marginal acute branches are clearly visible (Fig. 5.9(a)-(i) (right)).
The same improvements are observable in the 3D volumes rendering in Fig. 5.9(j),
where for the MC gated AWSART a very long RCA segment is recovered and visible
(Fig. 5.9(j) (center)). Due to the residual strong cardiac motion, the gated AWSART
dergogram is blurred and an inconsistent ghost RCA is obtained (Fig. 5.9(j) (left)).

An RCA is shown for the clinical case B. Even here, the MC reconstructed im-
ages of the RCA (Fig. 5.10(a)-(c) (right)) and the Aorta (Fig. 5.10(a)-(b) (right)) look
sharper than the corresponding non-compensated gated reconstructions (Fig. 5.10(a)-
(c) (left)). The 3D volumes rendering presented in Fig. 5.10(d) confirms as the pro-
posed MC gated AWSART method (center) allows to strongly reduce the motion
blurring artifacts which degrade the quality of the standard gated reconstruction
(left).
Figure 5.9. The axial (a)-(e), coronal (f) and sagittal (g)-(i) views and the corresponding 3D volume rendering (j). In order, the gated ASWART (left column) and the MC gated ASWART (right column) reconstructed images at phase point 50% RR with a gating window width of 40% RR are shown. In (j) the corresponding 3D volume rendering of gated ASWART reconstruction are presented (left and center) and a gated ASWART reconstruction at 75% RR with a gating window width of 40% RR is shown (right). (Case A, 10 iterations, ROI’s radius=25 mm, Level=0 HU, Window=700 HU)
Figure 5.10. The sagittal (a), axial (b) and coronal (c) views and the corresponding 3D volume rendering (d). In order, the gated AWSART (left column) and the MC gated AWSART (right column) reconstructed images at phase point 50% RR with gating window width of 40% RR are shown. In (d) the corresponding 3D volume rendering are presented (left and center) and a gated AWSART reconstruction at 75% RR with a gating window width of 40% RR is shown (right). (Case B, 10 iterations, ROI’s radius=33 mm, Level=0 HU, Window=500 HU).
Elastic registration-based motion estimation for MC iterative cardiac CT

Figure 5.11. The axial (a)-(b), sagittal (c) and coronal (d)-(e) views and the corresponding 3D volume rendering (f). In order, the gated AW-SART reconstruction at 75% RR with a gating window width of 40% RR is shown (j)(right). (Case C; 10 iterations, ROI's radius=29 mm, Level=800 HU in (a) and Level=320 HU, Window=900 HU in (b) and Level=320 HU, Window=800 HU in (c) and Level=320 HU, Window=850 HU in (d) and Level=320 HU). The corresponding 3D volume renderings are presented (left and center) and a gated AW-SART reconstruction at 75% RR with a gating window width of 40% RR are shown. In (j) the corresponding 3D volume renderings at phase point 60% RR with the gated AW-SART (left column) and the MC gated AW-SART (right column) reconstructed images at phase point 60% RR are shown. In order, the axial (a)-(b), sagittal (c) and coronal (d)-(e) views and the corresponding 3D volume renderings (f).
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Excellent results are achieved even for the LCA’s ROI reconstruction of the clinical case C. In Fig. 5.11(a) the *left main* and its two main branches, the *left anterior descending* and the *left circumflex artery* are clearly visible in the MC gated AWSART reconstruction (right), but practically invisible in the gated AWSART image (left). In the MC images in Fig. 5.11(b) (right) the *aortic valve* is very sharp and visible, instead in its counterpart non motion-corrected gated image the same valve is strongly blurred (Fig. 5.11(b) (left)). The same conclusions can be given for the MC results presented in the coronal and sagittal views in Fig. 5.11(c)-(e), where the LCA vessel, and the *aortic valve* are well visible. The 3D volumes rendering in Fig. 5.11(f) (center) show as even in a phase of strong cardiac motion, the MC iterative reconstruction leads to an image where not only the LCA’s main branches, but even the secondary vessels as its *first diagonal branch* and its *first marginal branch* are recovered and noticeably visible.

Finally, it is interesting to observe as in all cases presented the MC gated AWSART reconstructions at strong motion phases produce coronary arteries that are consistent with those obtained with a standard gated AWSART method at a quiet phase of 75% RR (Fig. 5.9(j)(right), 5.10(d)(right), 5.11(f)(right)). Despite the impressive results, the ECG-gated reconstructions at phases of slow cardiac motion present an higher image sharpness compared to that achieved using the proposed MC approach at strong motion phases.

5.3.6 Validation on clinical data of the blobs volume-adaptation for MC iterative reconstructions

In this subsection an investigation of the performance of the efficient projection model for blobs in MC iterative cone beam CT reconstruction [39] on clinical data is presented. Due to the characteristic divergent pumping motion of the chambers of the heart, the comparison between the MC gated AWSART reconstructions with and without the proposed blobs-volume scaling, is shown for the LV reconstruction of the clinical case D.

The gated AWSART and MC gated iterative reconstructions with (MC gated AWSART) and without (MC gated AWSART$_{nv}$) the proposed blob volume scaling are performed by using the settings listed in Table 5.1. In Fig.5.12 the relative reconstructed images are shown. Furthermore, in Fig.5.13 the absorption profiles along the red and green lines in the images in Fig.5.12(b) and Fig.5.12(c) are presented.

In Fig. 5.12(a) (left) the gated AWSART reconstructed images are strongly affected by the motion blurring artifact. This makes impossible to perform a preventive analysis of the cardiac condition of the LV, the *ventricular myocardium*, the *left atrium*, the *ascending Aorta*, and the *aortic and mitral valves*. In Fig. 5.12(a) (middle) the MC gated AWSART reconstructed images performed using the estimated MVFs and the proposed volume-dependent blob-footprint adaptation look sharper and the motion blurring artifact is strongly reduced. The same enhancement is clearly visible in Fig. 5.12(b)-(c) (middle). Here, the *pulmonary artery*, the *ascending Aorta* and the *aortic valve* are well defined. Moreover, even a section of the LCA vessel which was strongly blurred and almost invisible in the non-compensated iterative reconstruction, in the MC images it looks sharper and well visible. For reasons of
Figure 5.12. Axial (a) and coronal (b)-(c) views of the gated AWSART (left column), the MC gated AWSART (middle column), and the MC gated AWSART 
(right column) reconstructed images are shown. (Case D, at phase point 20% RR, 
gating window width of 40 % RR, 10 iterations, ROI's radius=37 mm, Level=150 
HU, Window=650 HU).
Figure 5.13. Absorption coefficients of the gated AWSART, the MC gated AWSART, and the MC gated AWSART\textsubscript{nvs} image reconstructions performed for clinical case D, respectively, along the red lines indicated in Fig. 5.12(b), and along the green lines indicated in figure Fig. 5.12(c).

comparison, in the right column in Fig. 5.12(a)-(c), even the MC gated AWSART\textsubscript{nvs} reconstruction images performed using the same estimated MVFs are shown. Even in this case the motion artifacts are reduced, but the quality of the images is clearly degraded. Here, due to the divergent pumping motion of the LV chamber, the blobs are locally moved in different directions and an irregular reconstruction grid is produced. If any volume-dependent blobs-footprint adaptation is performed, several gaps are generated among the blobs of the irregular grid. These yield a non-homogeneous image representation and degrade tremendously the quality of the reconstructed images. In different areas of the LV, of the myocardium, and of the ascending Aorta, a strong reduction of the absorption coefficients produces several dark stains that can induce to an erroneous or practically impossible diagnosis of the LV (Fig. 5.12(a)-(c) (right)). The proposed volume-dependent blob footprint adaptation shows to avoid this strong reduction of the absorption coefficients, by taking into account the variation of the blobs volume caused from the divergent MVF of the LV. This is confirmed even from the absorption coefficient profiles shown in Fig. 5.13(a)-(b). Here, for the MC gated AWSART\textsubscript{nvs}, even if it is completely filled of contrast agent, the absorption coefficients inside the LV are so reduced that they become comparable with the absorption coefficients of the myocardium. Instead, with the MC gated AWSART and the proposed blob-volume adaptation an higher contrast between the LV and the myocardium absorption coefficients is recovered.

5.4 Discussion

In this chapter, the use of a fast elastic image registration method for fully automatic local cardiac motion compensated gated iterative coronary artery reconstruction was presented and evaluated. The evaluation included a validation on a dynamic cardiac phantom, an MVF consistency check, a qualitative inspection of reconstructed image
quality, and a clinical validation of the method proposed in [39] for volume-dependent adaptation of the footprint of the blobs in case of MC iterative reconstructions.

The ECG-gated CT reconstructed images are strongly affected by the chosen phase of reconstruction. In this work, subvolumes of the heart of different patients have been reconstructed in fast cardiac motion phases. Here, the ECG-gated iterative reconstructions, even if the smallest possible gating window width is used, fail to generate motion artifact-free images. This hampers the interpretation of coronary segments which could contain suspicious structures.

From the MC gated iterative reconstruction results presented in Fig. 5.5, 5.9, 5.10, 5.11, and 5.12, it is noticeable that adding a reliable object motion model inside the iterative reconstruction framework can lead to excellent reconstructed images with reduced motion blurring. After the clinical validation study, the efficient projection model proposed in [39] reduced the strong artifacts caused by the change of the blobs volume, when a divergent MVF is applied for MC iterative reconstructions.

Compared with local improvements obtainable with other landmarks- or coronary centerlines-MVF estimation methodologies [5, 43, 95], here the improvement of the MC reconstruction is visible uniformly inside the ROI. Future research should be focused on the application of the proposed method on whole heart MC iterative reconstruction. Here, further investigations are required to verify if accurate cardiac MVFs can be achieved.

The calculation of the temporal resolution of an MC reconstruction with the proposed motion model is not straightforward and no recipe to calculate temporal resolution known from the literature includes motion compensation. The interval of possible values for the temporal resolution varies from the time required to measure a single projection at the selected phase point (ideal MC reconstruction) to the temporal resolution of a data set reconstructed with an ECG-gated reconstruction method using all projections inside the gating window. Apparently the temporal resolution is improved when using an MC reconstruction method, but the exact quantification remains an open area of research.

Despite the promising results, some method limitations are not negligible. First, since the image registration estimates the unknown cardiac MVF at the quiescent motion phases, future work should address the challenge to estimate the MVF even at fast motion phases. It is important to stress that a non-equidistant phase sampling is to the cost of interpolation errors between phases where rapid cardiac motions take place. A linear or cubic-spline temporal interpolation of the MVF might not capture the real motion of the heart. Registering the images reconstructed at fast motion phases could provide important spatial information of the heart at these phases. A possible solution to use the cardiac strong motion phases during the registration step, could be to add a temporal smoothing term to the combined criterion in Eq. 5.5 in order to produce a smoothed version of the motion trajectory of each image voxel. In this case, care should be taken in order to properly tune the corresponding regularization parameter, since a strong temporal regularization could lead to non-optimal solutions with poor images spatial alignment. An alternative approach is surface-model-based segmentation [96, 138] together with image registration in order to extrapolate the cardiac MVF.

Second, one requirement to this approach is having accurate initial reconstruc-
5.5 Conclusions

The frequent presence of image artifacts can affect the real MVF which describes the heart motion. A 2D-3D non-rigid registration [99] can be a potential solution for a more accurate cardiac motion estimation. Here, the 3D MVF is determined by aligning only one initially ECG-gated reconstructed volume to a series of ECG-gated projections.

Third, the proposed MC iterative method consists of two passes. Initially, the cardiac MVF is estimated by image registration, subsequently, this motion information is used to perform an MC iterative reconstruction. To increase the method’s speed and accuracy, single-pass methodologies may permit the determination of the MVF during the reconstruction process [114].

5.5 Conclusions

In conclusion, a fully automatic local cardiac motion compensated gated iterative method with volume-adapted blobs as basis functions is proposed. The method leads to excellent MC gated iterative reconstructed images which outperform the quality of the images reconstructed with a classical gated iterative method. In clinical cases, a volume-dependent blobs-footprint adaptation proves to be a good solution to take care of the change of the blobs volume caused by a divergent MVF. Though the image quality of reconstructions at cardiac phases of fast motion is increased significantly, a gated reconstruction in the cardiac resting phase remains superior in image quality at moderate heart rate.