A knowledge-based cone-beam x-ray CT algorithm for dynamic volumetric cardiac imaging

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With the introduction of spiral/helical multislice CT, medical x-ray CT began a transition into cone-beam geometry. The higher speed, thinner slice, and wider coverage with multislice/cone-beam CT indicate a great potential for dynamic volumetric imaging, with cardiac CT studies being the primary example. Existing ECG-gated cardiac CT algorithms have achieved encouraging results, but they do not utilize any time-varying anatomical information of the heart, and need major improvements to meet critical clinical needs. In this paper, we develop a knowledge-based spiral/helical multislice/cone-beam CT approach for dynamic volumetric cardiac imaging. This approach assumes the relationship between the cardiac status and the ECG signal, such as the volume of the left ventricle as a function of the cardiac phase. Our knowledge-based cardiac CT algorithm is evaluated in numerical simulation and patient studies. In the patient studies, the cardiac status is estimated initially from ECG data and subsequently refined with reconstructed images. Our results demonstrate significant image quality improvements in cardiac CT studies, giving clearly better clarity of the chamber boundaries and vascular structures. In conclusion, this approach seems promising for practical cardiac CT screening and diagnosis. © 2002 American Association of Physicists in Medicine. [DOI: 10.1118/1.1494989]

Key words: x-ray computed tomography (CT), spiral/helical CT, multislice/cone-beam CT, dynamic volumetric imaging, cardiac imaging, electrocardiogram (ECG), multiphase/state reconstructions

I. INTRODUCTION

It is widely known that cardiac diseases are of paramount importance in health care, and the number one killer in the USA. Over half of the individuals who die of a coronary attack have no recorded symptoms (http://www.americanheart.org/statistics/index.html). There is an important and immediate need for early screening and accurate diagnosis of cardiac diseases. In this aspect, noninvasive imaging techniques are invaluable. The imaging modalities available today are not fully satisfactory, including cardiac angiography, ultrasound, magnetic resonance imaging (MRI), electron-beam CT (EBCT), and spiral CT.1 Cardiac angiography, being the gold standard, is invasive. Ultrasound, as a cost-effective method, suffers from poor image quality. MRI, as a powerful modality, fails to detect calcification, and is subject to various artifacts. EBCT,2 with the fastest speed, is not widely available and suffers from limited spatial and contrast resolution. Although they are most promising, current spiral/helical CT scanners, even with ECG gating, often cannot accurately depict boundaries of the cardiac structures, nor quantify small amounts of calcium reliably, especially when the heart rate is high.

Multi-slice spiral CT (MSCT) has attracted increasing interest since its recent introduction.3,4 Compared with single-slice systems, MSCT scanners allow faster data collection, thinner slices, and wider coverage. With the rapid development of MSCT technology, cone-beam CT (CBCT) should be the future of medical x-ray CT.5 In the near future, the small cone angle will be expanded to medium cone angles by adding more detector rows. Eventually, large cone angles will very likely be used. CBCT has a great potential for dynamic volumetric imaging, with cardiac CT studies being the primary example.

There are important dynamic imaging algorithms in the literature. The idea of gating for imaging of periodically varying structures was reported in the early 1980s.6–8 The gating scheme measures an indicative periodic motion function. “This signal is used to identify a quiescent period in the periodic motion so that the acquisition of projection data may be coordinated to be centered within the quiescent period.”9 Ohnesorge et al. performed a systematic phantom experiment to study ECG-gated CT images.6 “Stop-action” reconstructed images revealed two types of artifacts: (a) pinwheel artifacts near high-contrast moving objects; and (b) streaks corresponding to missing views. Joseph and Whitley utilized the ECG to select the phase of the cardiac cycle being imaged.7 Their technique assesses the diagnostic utility...
of images reconstructed from a limited number of projections within a cardiac region of interest. To reduce artifacts due to periodic variation in reconstructed images, Glover and Pelc developed a method for transforming an indicative periodic motion function into that distributing events more evenly over the motion period. Ritchie et al. studied respiratory motion artifact reduction and developed a pixel-specific filtered backprojection algorithm. In their algorithm, in-plane motion is corrected by performing the reconstruction with a coordinate system specific to each pixel. The coordinate system moves according to the in-plane motion in the section at the time the projection is acquired. Their study was mainly evaluated for lung reconstruction with incremental CT. However, cardiac motion is much more difficult to model than respiratory motion, and incremental CT, though useful for some prospectively gated applications, can only image one phase of the cardiac cycle with limited spatial resolution. Wang and Vannier considered rigid and in-plane motion artifact reduction in spiral CT. Willis and Bresler reported their work on reconstruction of objects with temporal variation. They formulated the problem as signal recovery from time-sequential samples of a spatially and temporally band-limited signal, where one angular-independent view can be taken at a time. This requirement cannot be met by current MSCT/CBCT. Spiral CT was recognized quite early as having a significant advantage in imaging moving anatomy. With spiral MSCT, the heart can now be scanned within a single breathhold with excellent spatial resolution. Much investigation has been done into optimizing the scanning protocols and reconstruction algorithms using ECG-gating information. Taguchi and Anno developed a MSCT algorithm for imaging rapidly moving organs, such as the heart and adjacent pulmonary vessels. The proposed algorithm performs the interpolation of raw projection data based on the acquisition time. Nevertheless, their algorithm assumes no knowledge about periodic organ motion. Kachelriess et al. described two ECG-gated MSCT algorithms for cardiac imaging that improve image quality compared with the standard nongated commercial reconstruction algorithms, but their approach does not take into account any anatomical knowledge of the heart as a function of time in the cardiac cycle. In addition, MSCT currently still requires an extended breathhold time. The most consistent images are achieved for lower heart rates (approximately 70 bpm or less) while selecting the “optimal” phase within the heart cycle.

We are committed to advancing the state of the art of spiral MSCT/CBCT, and developing it into a vital tool for clinical cardiac imaging. We hypothesize that a well-designed MSCT/CBCT algorithm can significantly improve image quality in cardiac studies, providing an accurate assessment of heart function, extent of coronary stenosis, and quantification of coronary calcification. In this paper, we develop a knowledge-based approach for dynamic volumetric cardiac CT. The technical motivation is to effectively estimate and utilize temporal and spatial information of the beating heart, exploit all raw projection data, and reconstruct the heart with the highest possible clarity in any state of the cardiac cycle. These unique characteristics are achieved by optimizing the strategy for selecting and merging segments of raw data based on the relationship between the cardiac status and the ECG. In other words, data segments are collected when the heart (or a component of the heart, for example, the left ventricle) is in a consistent state (for example, in similar volumes) so that image reconstruction produces the best quality for any specified state.

In the following, we first provide some basics on the heart and cardiac motion, and formulate our dynamic volumetric MSCT/CBCT scheme, with an emphasis on the cardiac motion modeling and MSCT/CBCT data selection/interpolation strategy. Then, we describe mathematical phantoms and numerical simulation. Also, we apply our algorithm in patient studies. Finally, we discuss several related issues as further research directions.

II. METHODS AND MATERIALS

A. Cardiac motion model

The heart, consisting of two synchronized “pumps,” is the key organ of the circulatory system. The right pump pushes the blood through the lungs, while the left pump forces the blood through the peripheral organs. Each pump has two chambers: an atrium and a ventricle. The atrium moves the blood into the ventricle. The ventricle propels the blood through either the pulmonary or peripheral circulation. Special mechanisms control the heart rhythm by transmitting action potentials throughout the heart muscle.

The cardiac cycle is associated with the heartbeat, which is initiated by an electrical potential in the sinus node. This potential travels rapidly through the atria into the ventricles. The cardiac cycle is featured by a period of relaxation called diastole and a period of contraction called systole. Figure 1 illustrates the different physiological events in the cardiac cycle. The top three curves show the pressure changes in the aorta, left ventricle, and left atrium, respectively. Most importantly, the fourth curve depicts the volume change of the left ventricle, the fifth curve the ECG. Also, of potential value is the sixth curve, a phonocardiogram that records sounds produced by the heart.

Being of great clinical significance, without loss of generality, and to the first order of approximation, the volume of the left ventricle can be used to represent the instantaneous anatomical status of the heart, which is well correlated to the ECG. As shown in Fig. 1, major ECG wave forms are referred to as the P, Q, R, S, and T waves, respectively. They are electrical voltages generated by the heart and recorded from the surface of the body. The P wave is caused by the spread of depolarization through the atria, and followed by atrial contraction. Shortly after the P wave, the QRS waves appear due to depolarization of the ventricles, which initiates the ventricular contraction. Finally, the T wave indicates repolarization of the ventricles, and occurs slightly before the ventricular relaxation.

To model the motion of the left ventricle mathematically, we let $v = f(t)$ represent its volume as a function of the instantaneous cardiac phase $t$, which can also be regarded as...
the percentage time in a cardiac cycle. Our basic assumption is that $f(t)$ is a bounded, continuous, periodic function with the unit period. To simplify our model and without loss of generality, we assume that $f(t)$ can be expressed as follows:

$$f(t) = \begin{cases} f_s(t), & \text{for } 0 \leq t \leq a, \\ f_d(t), & \text{for } a < t \leq 1, \end{cases}$$

for a constant $0 < a < 1$, where $f_s(t)$ corresponds to the systole period, and $f_d(t)$ the diastole period. As it will become clear later that while a strict monotonic assumption on $f_s(t)$ and $f_d(t)$ is clinically valid and convenient for analysis, more general forms of $f_s(t)$ and $f_d(t)$ can be similarly treated.

One specific model $f(t)$, which was designed and used in our numerical simulation, is expressed in terms of the basic function $\sqrt{1-x^2}$, as shown in Fig. 2. In the figure, we divide the ECG cycle into several intervals. Let the interval $[0, a_1]$ be the region from the peak of the $R$ wave to the end of the $S$ wave, where the heart is in the isovolumetric contraction phase.
phase with the maximum isovolume. Then, let the interval \([a_1,a_2]\) be the region from the end of the S wave roughly to the beginning of the T wave, where the heart is in the ejection phase down to the minimum isovolume. Let \([a_2,a_3]\) be from the end of the ejection phase to the end of the T wave for the isovolumetric relaxation phase. Let \([a_3,a_4]\) be from the end of the T wave to the peak of the P wave, where the heart is in the rapid inflow and diastolic phase up to a large portion of the maximum isovolume. Finally, let \([a_4,1]\) be from the peak of the P wave to the peak of the next R wave, where the heart is in the atrial systole phase, allowing \(f(t)\) reaching the maximum value then falling down. Mathematically, \(f(t)\) is expressed as follows:

\[
f(t) = \begin{cases} 
  g(t;0,1,a_1,b_1,0), & 0 \leq t \leq a_1, \\
  g(t;a_1,b_1,a_2,b_2,a_2), & a_1 \leq t \leq a_2, \\
  g(t;a_2,b_2,a_3,b_3,a_3), & a_2 \leq t \leq a_3, \\
  g(t;a_3,b_3,a_4,b_4,a_4), & a_3 \leq t \leq a_4, \\
  g(t;a_4,b_4,1,1,1), & a_4 \leq t \leq 1,
\end{cases}
\]

where

\[
g(t;x_1,y_1,x_2,y_2,c) = \alpha + \beta \sqrt{1 - \left(\frac{t - c}{x_2 - x_1}\right)^2}.
\]

is the scaled and shifted version of the basic function with a symmetric axis at \(t = c\) so that \(g(x_k) = y_k\) for \(k = 1,2,\). The parameters \(\alpha\) and \(\beta\) in the above equation depend on parameters \(x_1, y_1, x_2, y_2, c,\) and are given by

\[
\beta = \frac{y_2\sqrt{(x_2-c)(x_2-2x_1+c)} - y_1\sqrt{(x_1-c)(x_1-2x_2+c)}}{\sqrt{(x_2-c)(x_2-2x_1+c)} - \sqrt{(x_1-c)(x_1-2x_2+c)}},
\]

\[
\alpha = \frac{-(y_2-y_1)(x_2-x_1)}{\sqrt{(x_2-c)(x_2-2x_1+c)} - \sqrt{(x_1-c)(x_1-2x_2+c)}}.
\]

How to obtain parameter values of the above motion model is important for an accurate estimation of the cardiac status. We have at least two ways to address this issue effectively. First, according to an individual ECG and based on data published by Stanford and others, we can quite reliably infer the cardiac status within each cardiac cycle. This method may be further improved by other physical measurements, such as ultrasound images and a phonocardiogram. Second, we can actually measure the cardiac state directly from images reconstructed either assuming an idealized cardiac dynamics or using a non-ECG-gated CT algorithm, such as that developed by Taguchi and Anno. The volume-based curve is used in this paper as one illustration; other curves, such as those specific to vascular motion, could also be used to optimally image coronary vessels. In addition, knowledge-based reconstructions can be applied iteratively, e.g., our volume-gated cardiac reconstruction results can be applied to refine the volume-phase curve for an even better volume-gated cardiac reconstruction. However, further iterations would require additional computing resources. Additionally, we mention that while our functional form of the cardiac motion model is a good choice for this feasibility study, this motion model is subject to optimization in a future study.

### B. Data selection and interpolation

First of all, we would clarify our usage of the terms “phase” and “state” as follows. By use of “phase” we mean the relative position in a cardiac cycle, while by use of “state,” or “status” in an abstract sense, we mean the absolute spatial configuration of the heart. The essence of our approach is to reconstruct the heart in multistates based on our knowledge about the instantaneous cardiac status, while existing algorithms reconstruct the heart in multiphases. In special cases, a state may just correspond to one cardiac phase. In the general case, as we will see later in this paper, a state may be related to two phases, when the heart is expanding and contracting, respectively. In other words, in our study we expect to reconstruct the heart in its anatomical state intervals to make the best use of projection data (hence, radiation dose).

Due to the geometric limitations with imaging, with each scanning turn there are only certain data segments available that are consistent to a given cardiac state interval. For ease of understanding, we first present our multistate reconstruction algorithm in the optimal case, then consider more general cases in this subsection. From now on, a cardiac state interval, or a cardiac state in brief, should be specifically understood as a left-ventricular volume interval.

Without loss of generality, we assume a constant heart rate, an adjustable source scanning speed, and a circular MSCT/CBCT scanning geometry. Let us set the x-ray source rotation period to a positive rational number \(b = m/n\) in the unit of the source rotation period, where \(m\) and \(n\) are relative prime integers, and \(b\) denotes the radio of the cardiac period over the source rotation period. By the strict monotonicity of both \(f_s(t)\) and \(f_d(t)\), we can uniquely determine \(n + 1\) volume values:

\[
v_0 < v_1 < \cdots < v_{n-1} < v_n,
\]

where \(v_0 = f_{\min}\), \(v_n = f_{\max}\), and the rest values are from \(n - 1\) intersection points \(\{v_k: k = 1,\ldots,n-1\}\) of \(f_d(t)\) and \(n - 1\) functions \(f_s(t+kb), k = 1,\ldots,n-1\). By doing so, there are exactly enough projection data for the reconstruction of all \(n\) cardiac states, which are collected after \(n\) source rotations within \(m\) cardiac cycles:

\[
[v_0,v_1],[v_1,v_2],\ldots,[v_{n-1},v_n].
\]

Furthermore, for \(1 \leq j \leq n\),

\[
\bigcup_{k=0}^{n-1} f_s^{-1}([v_{j-1},v_j]) = [0, b],
\]

and

\[
\bigcap_{k=0}^{n-1} f_d^{-1}([v_{j-1},v_j]) = \emptyset,
\]

where \(f_s(t) = f(t+kb)\) for \(0 \leq t \leq b\).

To visualize the above complicated relationship, we intro-
duce the concept of the cardiac motion map, as shown in Fig. 3, assuming \( b = \frac{1}{2} \). This cardiac motion map is nothing but a representation of all the information contained in \( f(t) \) within only one source rotation period, or equivalently within a full-scan angular range. Because the period of the source angular range is \( 360^\circ \), any angles outside the range of \([0^\circ, 360^\circ]\) can be mapped into this range. In other words, the cardiac motion map is a superposition of shifted versions of \( f(t) \) within one scanning cycle, which shows the dependence between the cardiac states and the cardiac phases within the regularized full-scan angular range.

It is critically important to interpret the cardiac motion map in the two ways shown in Fig. 3: (1) cycle overlapping view, and (2) data partition view. The cycle overlapping view shows the \( f(t) \) curve in only one full-scan angular range, where each full-scan segment, which corresponds to a scanning turn, is colored differently. The data partition view highlights the selection of data segments for the reconstruction of cardiac states. These states are naturally defined by \([v_0,v_1],[v_1,v_2],...,[v_{n-1},v_n]\). Data segments associated with each cardiac state are colored differently. As a result, we can immediately comprehend the sufficiency and necessity of projection data for the reconstruction of any cardiac state.

In reality, the period and the form of \( f(t) \) may vary significantly. As a result, the cardiac motion map may only depict a suboptimal pattern, corresponding to asymmetric/distorted data partitions. In this case, Eqs. (7) and (8) may not hold exactly. Nevertheless, these cases can be handled in the same spirit of the cardiac motion map. Actually, for any cardiac state (for example, the volume \( v_x \)) we can always numerically search upward and downward from the reference line of this cardiac state \((v = v_x)\) until a sufficient angular coverage is reached, which should be \( 180^\circ \) plus two fan angles or more. Generally speaking, we prefer having a narrower cardiac state span, a less number of data segments and smoother transitions between these segments. If it is necessary, we can use a “feathering” technique to suppress artifacts from data discontinuities.

In the MSCT situation, a special effort must be made for longitudinal data interpolation. The principle is to use data adequately close to a plane to be reconstructed. Specifically, we may request that data involved for linear/nearest-neighbor interpolation be associated with x-ray paths that are within detector collimation. The greater the permissible longitudinal range for data interpolation, the better temporal resolution, but the poorer longitudinal spatial resolution. Those data that do not meet the above requirement are considered invalid. In the case of CBCT, the pitch and the angular range corresponding to a prespecified temporal resolution define the data segments for a particular cardiac state that contribute to the volume reconstruction, and the cone-angle effect must be appropriately addressed.

C. Knowledge-based image reconstruction

Our knowledge-based MSCT/CBCT algorithm for cardiac imaging can be outlined as follows:

Step 1. Obtain the relationship between the cardiac status and the cardiac phase.

Step 2. Specify longitudinal locations of transverse slices to be reconstructed as well as cardiac states of interest.

Step 3. Find cardiac state values \( v_k \) in the cardiac motion map, where \( v_0 \) and \( v_n \) are the minimum and maximum of the cardiac state, \( v_k \), \((1 \leq k < n)\) is the solution to \( f_d(t) = f_x(t + kb) \).

Step 4. Search for the angular interval:
\[
A_k = \{ x : v_k \leq f(x) \leq v_{k+1} \};
\]

Step 5. For each transverse slice location \( z \), rearrange MSCT/CBCT data \( g_k(x) = g(x \mod b) \) for \( x \in A_k \) if they are close to \( z \), then perform data interpolation.

Step 6. Reconstruct each slice in the \( k \)th cardiac state from \( g_k \) using an appropriate reconstruction algorithm. We propose using a filtered backprojection (FB) algorithm (similar to a modified Feldkamp approach, e.g., that developed by Wang et al.\([26–28]\) but adapted to cardiac cone-beam imaging).
III. RESULTS

A. Numerical simulation

1. Dynamic performance phantom

The temporal resolution can be quantified using the temporal sensitivity profile (TSP), which is a temporal counter-

![Fig. 4. Standard reconstruction and multistate reconstructions of the dynamic performance phantom. The motion artifacts are the worst with the standard reconstruction (a), while they are suppressed in the multistate reconstructions (c)–(e) and eliminated in (b), (f).](image)

![TABLE I. Parameters of the cardiac motion model defined by Eq. (2).](table)

<table>
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<td>$a_i$</td>
<td>0.4</td>
<td>0.4</td>
<td>0.5</td>
<td>0.85</td>
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<tr>
<td>$b_i$</td>
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<td>0.0</td>
<td>0.05</td>
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<tr>
<td>$c_i$</td>
<td>0.1</td>
<td>0.1</td>
<td>0.85</td>
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part of the slice sensitivity profile (SSP). To assess the temporal resolution of our proposed approach, we used a well-known dynamic performance phantom in the literature. This dynamic performance phantom contains five sets of objects of 1000 HU, as described by Taguchi and Anno.\textsuperscript{19} It has two sets of three cylinders of diameter 3, 2, and 1 mm, respectively. Set A is stationary while set B moves in the $x$ direction. The phantom also contains three sets of three balls of diameter 3, 2, and 1 mm, respectively. Set C is stationary, set D moves in the $y$ direction, and set E moves in the $z$ direc-
tion. The cylinders are of 200 mm in length. The balls are centered at plane $z = 0$ when they do not move. The sets B, D, and E all move at the frequency of 96 cycles per minute with the amplitude of 10 mm. The sizes, shapes, and motion patterns were chosen to simulate the cardiac and pulmonary motion in the patient.

A circular CBCT geometry was simulated with 630 views and a $480 \times 168$ detector plane with height 280 mm. The source-to-center distance was set to 4000 mm. The diameter of field of view was 800 mm. A dynamic cardiac scan was simulated with five source rotations and eight cardiac cycles over the scan period. Images were constructed in $512 \times 512 \times 154$ matrices with height 240 mm, using the standard Feldkamp algorithm. Figure 4 presents a volume-rendered view of the dynamic performance phantom, which contains the standard commercial reconstruction and multistate reconstructions of the dynamic phantom. It can be observed in Fig. 4 that the motion artifacts dominate the standard reconstruction, but they are either suppressed or eliminated in the multistate reconstructions.

2. Dynamic thorax phantom

To make numerical simulation more realistically, it is desirable to provide semianthropomorphic raw data of the tho-

<table>
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<tr>
<th>Phase</th>
<th>0.0</th>
<th>12.5</th>
<th>25.0</th>
<th>37.5</th>
<th>50.0</th>
<th>62.5</th>
<th>75.0</th>
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<td>Volume</td>
<td>66.8</td>
<td>57.3</td>
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<td>34.1</td>
<td>30.8</td>
<td>30.8</td>
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For the same purpose, a dynamic thorax phantom was developed by Sourbelle, which is published on http://www.imp.uni-erlangen.de/forbild/english/results/index.htm. In our simulation, this phantom was chosen for its representative features and complete documentation. The phantom contains idealized major parts of the thorax, including lungs, heart, aorta, ribs, spine, sternum, and shoulders.

For the initial testing, a simplified time-varying “heart” was created to replace the original heart in the thorax phantom. This “heart” consists of two ellipsoidal halves with appropriately specified parameters to simulate the shape of the heart. A cardiac motion function was defined by

$$h(t) = (f(t) + 2)/3,$$  \hspace{1cm} (10)

where \(f(t)\) is defined by (2). The ellipsoidal heart was dynamically rescaled according to (10) with the model parameters listed in Table I. A CBCT scan was performed for \(b = \frac{5}{2}\) under the same conditions as in the preceding section, except that the \(z\) coverage of the detector plane was set to 180 mm, the source-to-center distance 3000 mm, and the diameter of field of view 600 mm. The reconstructed volume is of \(512 \times 512 \times 128\) of height 150 mm.

Figures 5 and 6 contain representative orthogonal sections reconstructed using the standard commercial algorithm and our knowledge-based algorithms, respectively. It can be observed that the multistate reconstructions are substantially superior to the standard reconstruction of the dynamic thorax.

Fig. 7. Cardiac volume-phase curve in the high heart-rate case.

(a) Cycle overlapping view. \hspace{1cm} (b) Data partition view.

Fig. 8. Cardiac motion map with five spiral MSCT rotations in the high heart-rate case.
phantom. Similar to what we have seen in Fig. 4, the motion artifacts are serious with the standard reconstruction, but they are significantly reduced to various degrees in the multistate reconstructions.

B. Patient studies

To demonstrate the feasibility and utility in clinical applications, we performed a number of patient studies using a state-of-the-art multislice CT scanner Mx8000 (Philips Medical Systems, Cleveland, OH, USA). The imaging protocol requires 1 mm collimation, 4 slices, 1.25 mm table increment, 0.5 s full-scan period, and ECG recording. Both the ECG-based and image-based methods, as described in Sec. II A, were used to establish the relationship between the cardiac status and the cardiac phase. Then, appropriate data segments were selected for the reconstruction of each slice of interest in all the representative cardiac states, according to the scheme described in Sec. II B. Finally, image reconstruction was performed using the algorithm described in Sec. II C.

Three comments are in order regarding the above general procedure. First, the status-phase relationship in this preliminary study takes the form of a volume-phase curve. The volume of interest at each cardiac phase was estimated from manually segmented CT images reconstructed using a half-scan algorithm. In all the cases, our cardiac motion model is
in excellent agreement with real data. Second, because of the spiral scanning nature and the limited number of detector rows, an adaptive closeness criterion was exercised in our data selection and interpolation. For example, when data are really needed, we relaxed the longitudinal range for the inclusion of data. Sometime the permissible interpolation ranges were even not symmetric with respect to the plane to be reconstructed to optimally match the asymmetric spiral MSCT geometry. Third, both full-scan and half-scan reconstruction options were implemented and used in our patient

Fig. 10. Standard reconstruction and multistate reconstructions of the high heart-rate patient. Each of the five states is defined according to the cardiac motion map, in terms of its percentage span in the full range of the volume variation.
studies. As expected, the half-scan reconstruction option was instrumental when full-scan data are unavailable.

In the following, we only present two typical examples, which are high heart-rate and low heart-rate cases, respectively.

### 1. High heart-rate case

The heart rate in this case is quite constant, about 98 beats per minute (bpm). As a result, the ratio \( b \) between the cardiac period and the full-scan period is about 1.22, which is close to

<table>
<thead>
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<th>12.5</th>
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<td>162.7</td>
<td>161.5</td>
<td>123.9</td>
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<td>80.9</td>
<td>118.0</td>
<td>128.9</td>
<td>146.3</td>
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**Table III.** Measured points on the volume-phase curve in the low heart-rate case. Both the phase and the volume are in relative terms.

![Cardiac volume-phase curve in the low heart-rate case.](image1)

**Figure 11.** Cardiac volume-phase curve in the low heart-rate case.

![Cardiac motion map with five spiral MSCT rotations in the low heart-rate case.](image2)

**Figure 12.** Cardiac motion map with five spiral MSCT rotations in the low heart-rate case.

(a) Cycle overlapping view.  
(b) Data partition view.
to \( b = \frac{3}{4} \), allowing reconstruction of 5 states. Eight data points of the volume-phase curve were determined by segmenting images reconstructed using a half-scan algorithm. These data are summarized in Table II. Then, we conducted cubic-spline fitting to generate a smooth volume-phase curve, as shown in Fig. 7. To use this information for dynamic reconstruction, the spline fitted curve was periodically extended. The cardiac motion map in this case reveals the realistic overlapping patterns of the cardiac cycles and the feasible data partitions for each of the five cardiac states, as shown in Fig. 8. Note that in the real case the cardiac motion map is indeed suboptimal, a numerical search was done to complete the data partition work according to the motion map, as we discussed in Sec. II B, “Data selection and interpolation.”

Figure 9 plots the \( z \)-position distributions of the selected data for dynamic reconstruction of the five states. Figure 10 includes a set of images reconstructed using the standard algorithm and our algorithm, respectively. It can be easily observed that our state-based reconstructions are definitely superior to the standard commercial reconstruction, because the cardiac boundaries are much better defined in all the five states. Here we would like to emphasize the cardiac volume, while optimal reconstruction of the coronary vessels can be achieved using a vessel-position-based approach, essentially similar to our volume-based approach.

2. Low heart-rate case

The low heart-rate case was similarly studied as in the high heart-rate case. The heart-rate in this case varies sub-
stantially, from 50–60 bpm. Since the source rotation period was fixed at 0.5 s, the data associated with about 60 bpm allow reconstruction of only 2 independent states. To reconstruct more states, those data segments that are associated with about 51 bpm were selected for $b = 2.32$.

Eight data points of the volume-phase curve were determined by segmenting images reconstructed using a half-scan algorithm. These data are summarized in Table III. Figure 11 is the cubic-spline representation of the data in Table III. Figure 12 includes two interpretations of the cardiac motion map, in terms of its percentage span in the full range of the volume variation.
map in this case.

As shown in Figs. 13 and 14, in this low heart-rate case the multistate reconstructions were not done at the same $z$ level, that is, states 3 and 5 were reconstructed at levels slightly different from that for states 1, 2, and 4, because the cardiac motion and the source scanning were not well synchronized to give sufficient data. However, we emphasize that even in the difficult case of this type the reconstructions were indeed of multistates with significantly better image quality of ventricular sections than the standard commercial reconstruction.

IV. DISCUSSION AND CONCLUSION

The estimation and utilization of the cardiac status-phase relationship is the key for success of our knowledge-based cardiac imaging approach. Although we have focused on the volume as the primary indicator of the cardiac status, the space of the cardiac status is evidently multidimensional. How to optimally and realistically capture the cardiac status in relation to the cardiac cycle remains an exciting topic. Our insight suggests that the most promising strategy should be toward a synergistic combination of an electronic atlas of the dynamic cardiac anatomy, various measurements of anatomical/physiological signals, as well as abundant information from raw projection data.

As a powerful tool, the cardiac motion map can be extended to represent projection data in suboptimal and even difficult cases. With a user-friendly design, additional information can be integrated into the cardiac motion map. For example, permissible data segments may be indicated using characteristic curve segments. Also, the completeness of the permissible data can be computed and visualized in a sinogram derived from the cardiac motion map. We believe that our approach should be useful in other cardiac imaging modalities as well, MRI in particular.

Much work is needed to optimize the imaging strategy for our knowledge-based cardiac imaging approach. Intrinsic interactions exist among imaging parameters, between temporal resolution and longitudinal spatial resolution, between spatial resolution and contrast resolution, between resolution and artifacts, as well as their dependencies on interpolation/reconstruction details.\(^{29-32}\) The optimality should also depend on features of interest or diseases of concern. Given the complexity of this problem, each imaging aspect needs to be addressed appropriately before the reconstruction quality of the cardiac anatomy can be optimized.

Special attention should be paid when our knowledge-based cardiac imaging approach is applied to cone-beam geometry. Although the essential idea is the same as in the multislice geometry, the intermediate or large cone angle must be rigorously compensated for to suppress image artifacts, which may be more distracting in the dynamic imaging situation than in the static counterpart. The longitudinal data truncation and the spiral scanning pattern makes the cardiac imaging even more complicated. However, because we can now utilize more specific knowledge on the cardiac dynamics, our approach is already in a better position to produce superior images than existing cardiac imaging algorithms. We are currently addressing this problem with a modified FB approach, which will be reported in a follow-up publication.

In conclusion, we have developed a knowledge-based spiral/helical multislice/cone-beam CT approach for dynamic volumetric cardiac imaging. For the first time, we have made available a methodology to tap into the geometric knowledge on the cardiac status. Even in our preliminary numerical simulation and patient studies, the knowledge-based cardiac CT algorithm has improved image quality greatly. This approach should bring immediate benefits for cardiac CT screening and diagnosis, and have a great potential in view of the rapid development of MSCT/CBCT technology. We are actively working on further development of this knowledge-based cardiac imaging approach, as well as the rigorous evaluation of diagnostic performance improvement.

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