Published in final edited form as:
Proc IEEE Int Symp Biomed Imaging. 2011 March 30; 2011: 1326–1329. doi:10.1109/ISBI.2011.5872645.

LOW-ORDER 4D DYNAMICAL MODELING OF HEART MOTION UNDER RESPIRATION

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Abstract

This work is motivated by the limitations of current techniques to visualize the heart as it moves under contraction and respiration during interventional procedures such as ablation of atrial fibrillation. Our long-term goal is to integrate high resolution models routinely obtained from pre-procedure imaging (here, via MRI) with the low resolution, sparse, images, along with a few scalar measurements such as ECG, which are feasible during the real-time procedure. A key ingredient to facilitate this integration is the extraction from the pre-procedure model of an individualized, low complexity, dynamic model of the moving and beating heart. This is the immediate goal we address here. Our approach stems from work on distributed parameter dynamical systems and uses a combination of truncated basis expansions to obtain the requisite four dimensional low order model. The method's potential is illustrated not only by modeling results but also by estimation of an arbitrary slice from the parameterized model.

Index Terms

motion compensation; interventional imaging; low order modeling

1. INTRODUCTION

The problem of motion compensation in medical imaging cuts across many applications and has been the subject of years of research and development. Here we address a particular subset of those applications, in which a low-order motion model is required to enable on-line model update and tracking during an interventional procedure based on low resolution sparse images (and potentially auxiliary data) acquired during an interventional procedure. The specific application we have in mind is MR-guided ablation procedures for atrial fibrillation, itself the subject of considerable current research. [1, 2]. During such a procedure, in current practice, the clinician typically is able to visualize a roving catheter, used for both sensing electrical activity and delivery of energy to ablate in selected spots of the heart wall, in laboratory coordinates. This visualization is presented against the background of a static model of the heart built from pre-procedure high-resolution MR imaging. Since the catheter position is known in lab coordinates, but not in anatomical coordinates, when the heart moves due to respiration, it carries the catheter along with it, so that the catheter typically appears to "jump" on the screen. Since imaging during the ablation procedures is currently carried out using fluoroscopy and/or ultrasound (intracardiac echocardiography), and there is increasing attention to development of MR imaging for this same purpose, it is reasonable to assume that low-resolution images of one or a few slices may be available to update the static pre-procedure image in an on-line fashion (or, equivalently, to estimate and compensate for the heart motion in the visualized image, in effect estimating the discrepancy between lab and anatomical coordinates with respect to the heart location). In addition, measurements of both cardiac cycle timing (*e.g.*

through ECG or pulse oximetry) and respiratory cycle timing (through a mechanical or optical measurement device or MRI micro-coils on the torso) is quite feasible. Thus what is needed is a model of heart motion that is sufficiently low-order, and appropriately parameterized, to enable updating based on a collection of such low resolution images and scalar measurements.

A further complication is that in addition to moving with respiration, the heart is also beating with timing that is largely asynchronous with respect to the respiratory cycle. Thus to factor out these two types of motion, the model has to take them both into account. The key to success will be a low dimensional parameterization of the heart model which can capture the critical dynamics of both types of motion, thus enabling efficient parameter estimation from the on-line measurements to adapt the model and track the actual motion.

In previous work we described a method to obtain low-dimensional models of the beating heart with respiratory motion held constant (*e.g.* breath-hold acquisitions) [3]. Here we describe a preliminary approach to model just respiratory motion. Once both models are fully developed, we will fuse them to jointly model both types of movement.

This type of motion compensation problem occurs in many image-guided intervention domains where tracking and compensating for physiological motion is critical, *e.g.* four-dimensional imaging for radiation planning and tumor ablations. One contemporary solution is to track changes over short time intervals, using models based on assumptions about small deformations [4]. Other approaches impose rigid rules of motion such as periodicity [5] or fixed autoregressive models [6]. Some approaches use more flexible dynamic models for tumor tracking [7] with respiratory but not contractile motion, for contractile motion plus segmentation with no respiratory motion [8], or even for cardiac tracking with both types of motion during robotic surgery [9, 10]. The latter efforts are closest to ours in approach, but without the real-time inputs to guide the animation. The key to our approach is the attempt to design and build the pre-procedure models in such a way that they can be adapted (animated) with low complexity during the procedure. We base this work on methods which are well established in dynamical system theory, using slowly-varying dynamical models based on low-order basis expansions. The models are tailored to allow direct adaptation of the control parameters that determine the exact time-varying motion by an observer whose inputs are the spatial and temporal signals available during the procedure, and in a computationally efficient fashion. The key is that the complexity and effort go into the design and construction of the pre-procedure models to allow the required computationally cheap updates.

In this report we present our initial model for respiratory motion along with a proof-of-concept example of how the model can be used to find the contours of the heart given respiratory phase and the definition of an arbitrary plane through the heart. The latter effort models the “forward” problem of identifying an image contour given both the geometry of an arbitrary image plane in lab coordinates and the respiratory phase. This is the required preliminary step to solving the clinically relevant “inverse problem” in which the image contour and geometry are known and the the phase and heart position, in anatomical coordinates, need to be identified.

2. METHODS

In the pilot study of respiratory motion presented here, the available data were a set of saggital images from a volunteer, acquired by our collaborators at University of Utah in a slice by slice fashion without ECG gating and without any respiratory synchronization across slices. We acquired several respiratory cycles for each image. Since there was no

respiratory phase synchronization between slices, we also acquired a low resolution navigator signal from the diaphragm to be able to identify the phase point of each image. Thus the first step in our approach was to extract the cycle profiles from the navigator images, smooth them, and then relabel, normalize, and interpolate them to a common phase standard. In particular, as an approximation we took the maximum excursion of the navigator in each direction as markers for full inspiration and full expiration. We then normalized all phase points to run from −1 to 1, and noted both the phase stamp and phase direction (inhalation or exhalation) for each acquired image in each slice.

We performed a user-supervised segmentation of the outer boundary of the heart in each slice, using a simple snake algorithm, manually corrected using the segmentation package Seg3D [11]. Using the phase stamps acquired from the navigator signals as just described, we interpolated these boundaries for each slice to a regular sampling of respiratory phase (10 points each for inspiration and expiration). Once this procedure was done, we had achieved synchronization across slices.

The next step was to build a single heart model which could then be driven by translation and rotation models to model respiratory motion. In brief, we determined the trajectory of the center of the heart, first from the slices and then across slices. Using this trajectory we were able to consolidate all contours to a common spatial and phase reference. We then averaged all interpolated translational- and phase-referenced contours which were at the same position in space. Doing so created a sequence of heart models, once for each sampled phase point. Finally to achieve a low-order model we fit each such model by a truncated 4D basis expansion, using a time series of spherical harmonic bases. We note that we explored several classes of basis functions for this fit, including principal components and polynomial splines, but have had the best success to date with spherical harmonics.

We then modeled the translation motion as the trajectory of the centroid of this set of model hearts. Once translation motion was identified, we could “untranslate” the heart models to a common center. This allowed us to model rotation of the heart using an SVD approach. The largest singular value was identified as the long axis of the heart. Since the other two singular values were comparable in magnitude, extra care was taken to ensure that we did not “jump” axes by simply tracking the singular values by magnitude alone.

3. EXPERIMENTAL RESULTS

To give the context for the respiratory modeling work we first illustrate the results of our modeling of contractile motion [3, 12]. The data for this experiment was from ECG-gated axial MRI images of the ventricles. We segmented smoothed models of each slice using a simple *ad hoc* algorithm. Given these rough segmentations, the epicardial and endocardial surfaces were initially represented by parameterized contours at each slice, resulting in time series of coefficients with no dynamic model. We then used a four-dimensional (three space and one in time) Cartesian spline fit to enforce spatio-temporal consistency. We designed this algorithm for the epicardium, then tested its robustness on both LV and RV endocardial surfaces, with similar results. Animations of the beating heart were qualitatively realistic in terms of their ability to capture the sharp bursts of twisting motion that characterize cardiac contraction. Results of this approach are shown in Fig. 1.

Figure 2 shows results from our pilot study of respiratory motion. Again we used a simple segmentation scheme to achieve a quick set of contours at each frame of each slice. We followed the procedure described above to identify respiratory phase, construct a 4D model of a rigid body heart moving under translation and rotation, and thus parameterize the respiratory motion. We note that since these images were not ECG gated, contractile motion

of the heart added noise to the results. The left most panel, **A**, shows the spherical harmonic heart model at one phase point with its phase-specific coordinate system as identified by the SVD. The next panel shows the translation of the heart model centroids, with phase-locked coordinates shown at four sample points along the cycle. We note that the inspiration and expiration half-cycles followed distinct trajectories. Panel **C** shows the singular values of the model, as a function of phase, that were used to track motion; the four phase points shown in panel **B** are marked by dots in corresponding colors. Finally, panel **D** illustrates the procedure for extracting phase stamps from a given slice and then interpolating the image sequences in phase. The solid curve shows the smoothed navigator signal, which was extracted directly from the image sequence and then smoothed using a truncated Fourier expansion. We note that the upper and lower limits of the plot (normalized to 0 and 1 respectively) are not achieved on any given cycle, thus allowing for flexibility in the face of cycle-to-cycle variation. The points marked * on each curve mark the interpolation points used to align across slices in phase coordinates to thus permit a 4D model of the heart to be constructed despite the lack of any slice-to-slice synchronization in the acquisition procedure.

Finally, we illustrate the “forward” step of our planned phase recovery / motion tracking procedure in Figure 3. The lower panel shows the desired plane, specified as input to the algorithm by the length and angle of a normal vector, inside the heart model. The top panel shows both the nearest points to the desired contour as found by a search procedure and the contour of the projection of those points onto the spherical harmonic surface.

4. DISCUSSION AND CONCLUSIONS

Our results illustrate the first two stages of the implementation of our approach, separately modeling cardiac contraction and respiratory motion of the heart. The common theme is the search for a low order four dimensional fit using truncated basis expansions. Slowly time-varying parameters of such expansions will allow us to modify our parameterizations in the future based on acquisition of on-line information from low dimensional images and scalar auxiliary signals. Thus the update problem will be reduced to a low-dimensional parameter estimation. As an illustration of the potential of this approach we demonstrated that the spherical harmonic parameterization allowed us to easily extract a cardiac contour not present in the original images, simply by specifying a desired respiratory phase point and a desired plane through the heart.

The heart model used in the respiratory modeling is rather coarse, due both to unmodeled contractile motion (since the acquisition was not ECG-gated) and the use of a simple segmentation algorithm. We are currently in the process of analyzing an ECG gated dataset and anticipate improved results. Another limitation of the current model is that we do not vary the respiratory cycle trajectory itself as the cycle length changes. Thus, for example, in effect we “jump” from one point on the inhalation trajectory to a point on the exhalation trajectory. In the future we will make the trajectory path itself adaptive to more closely follow the underlying respiratory motion. The next major step in our approach will be to integrate both respiratory and contractile motion into the model. We anticipate that the relatively large difference in cycle period will allow us to use truncated harmonic expansions of each motion with sufficient separation in temporal frequency.

Acknowledgments

The last author was supported in part by the NIH/NCRR BTRC Center for Integrative Biomedical Computing (CIBC), 2 P41 RR 012553 - 12

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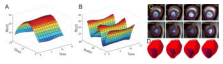

Fig. 1.

Parameterized model of cardiac contractile motion. Panel A shows the identified variation of the ventricular radius as a function of MRI slice number and time while Panel B shows radius variation across the nodes of the epicardial shape, also as a function of time. Panel C contains two sets of 4 images containing the original MRI slices at two levels with the parameterized contours for epicardial (red) and left ventricular endocardial (blue) surfaces superimposed. Panel D contains a visualization of the parameterized surfaces for these same time instants. Taken from work reported in [3, 12].

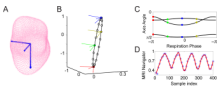

Fig. 2.

Parameterized model of respiratory cardiac motion. Panel A shows a model of the heart with heart-locked coordinate system. Panel B shows the trajectory of the geometric center of the heart during a single respiratory cycle with colored arrows indicating 4 points in the cycle. Panel C shows the parameters that describe the motion as a function of respiratory phase for the same breath. The colored dots correspond to the colors of the arrows in Panel B. Panel D shows the navigator signal extracted from the sequential MRI imaging and illustrates the variability in diaphragm motion during 4 respiratory cycles which the proposed method compensates for.

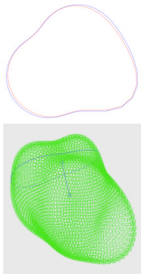

Fig. 3.
The figure shows a curve which is the estimated intersection of the parameterized model of the heart with an arbitrary plane, as specified the vector from the origin which is normal to the plane.