Series of 4D adult XCAT phantoms for imaging research and dosimetry

Jason Bond[a,b], Jack Frush[b], Sylvia Hon[a,b], Chris Eckersley[b], Cameron H. Williams[c], Jianqiao Feng[f], Daniel J. Tward[f], Tilak J.T. Ratnanather[f], M.I. Miller[f], D. Frush[c], E. Samei[a,b,c,d,e], and W.P. Segars[a,b,c,d]

[a]Medical Physics Graduate Program, [b]Carl E. Ravin Advanced Imaging Laboratories, [c]Dept. of Radiology, [d]Dept. of Biomedical Engineering, [e]Dept. of Physics, Duke University, Durham NC;

[f]Center for Imaging Science, The Johns Hopkins University, Baltimore MD

ABSTRACT

Computerized phantoms are finding an increasingly important role in medical imaging research. With the ability to simulate various imaging conditions, they offer a practical means with which to quantitatively evaluate and improve imaging devices and techniques. This is especially true in CT due to the high radiation levels involved with it. Despite their utility, due to the time required to develop them, only a handful of computational models currently exist of varying detail. Most phantoms available are limited to 3D and not capable of modeling patient motion. We have previously developed a technique to rapidly create highly detailed 4D extended cardiac-torso (XCAT) phantoms based on patient CT data [1].

In this study, we utilize this technique to generate 58 new adult XCAT phantoms to be added to our growing library of virtual patients available for imaging research. These computerized patients provide a valuable tool for investigating imaging devices and the effects of anatomy and motion in imaging. They also provide the essential tools to investigate patient-specific dose estimation and optimization for adults undergoing CT procedures.

Keywords: Computerized phantoms, simulation, CT, dose

1. INTRODUCTION

Computational phantoms and simulation techniques are set to play a critical role in CT imaging research. Given radiation concerns with patients and the expense of physical phantoms, computational phantoms provide the only practical technique with which to optimize CT applications and protocols. Combined with accurate models of the imaging process, phantoms can be used to simulate imaging data as if they were actual patients. They can be imaged repeatedly under many different scanning conditions and parameters without any fear of radiation exposure. Effects of acquisition parameters, physical processes and patient anatomy and motion can all be separated out (holding other parameters constant) and studied or compensated for independently. With a limited number of physical phantoms available, computational phantoms also have the greatest potential to estimate patient-specific organ and effective dose in CT by providing a library of anatomically diverse models from which to best derive these values.

With their great potential in CT research and dosimetry, many different computerized phantoms are currently being developed. In order for computerized phantoms to be useful, they must be very realistic or the data simulated from them will not be indicative of what would occur in live patients. To date, the most realistic phantoms are based on the segmentation of patient imaging data, typically MRI or CT [1]. Segmentation of patient data is a time-consuming process that can take many months to a year to complete. As a result, only a handful of realistic computational models currently exist, most being limited to 3D and not modeling patient motion. In order to more closely mimic a clinical study or trial, a large population of phantoms is needed that includes a range of anatomical variations representative of the public at large.

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We developed the 4D extended cardiac-torso (XCAT) phantom [2] with the purpose of applying it to high-resolution CT research to optimize 3D and 4D CT applications in terms of image quality and radiation dose. The 4D XCAT consists of whole-body adult male and female models which contain an unmatched level of detail and anatomical realism (Fig. 1). The male and female anatomies were based on the Visible Human anatomical imaging data. The XCAT includes parameterized models for the cardiac and respiratory motions based on gated patient imaging data. The XCAT phantoms are extremely realistic, containing thousands of anatomical structures. Like other computational phantoms, however, a drawback to the XCAT is that it is limited to just a few anatomies, in this case the adult male and female.

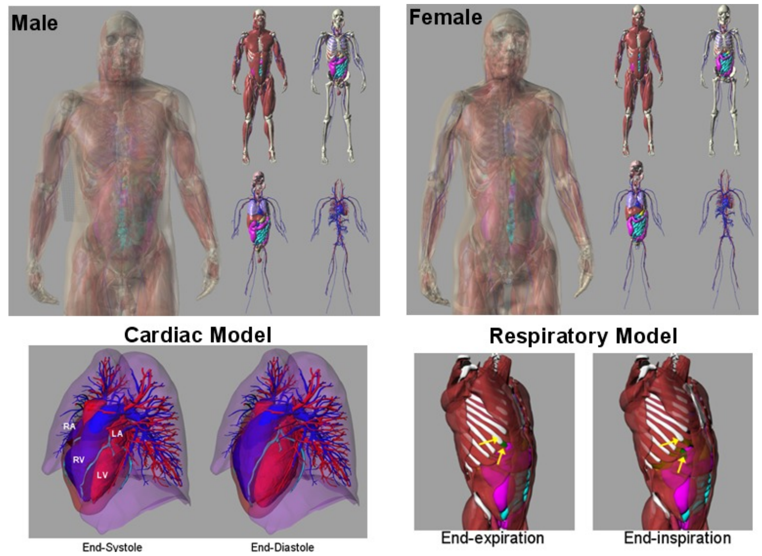

Fig. 1. 4D XCAT phantom. The male and female anatomies are shown above. 3D renderings of the male phantom are shown to illustrate the cardiac and respiratory motions.

In previous work [3], we developed an innovative method to efficiently create highly detailed, full-body patient-specific phantoms by morphing the XCAT phantom to match patient imaging data. We used this method to create 42 pediatric XCAT phantoms ranging in age from 8 weeks to 12 years old. In this work, we apply the same method to create a new series of 58 adult XCAT models of varying body-mass-indices (BMI). Combined with the pediatric models, we now have a population of 100 phantoms for use in imaging research.

2. METHODS

There are four steps to building a patient-specific XCAT phantom; segmentation, building an initial base model, calculating and applying the Large Deformation Diffeomorphic Metric Mapping (LDDMM) transform from the XCAT to the patient framework, and finalization. First, patient datasets were collected from the Duke University CT imaging database. Chest-abdomen-pelvis (CAP) datasets were obtained to represent a wide range of body types for both adult males and adult females as determined by the body mass index (BMI) (Fig. 2). Manual segmentation of selected organs was performed using ImageSegment, a custom graphical application developed in our laboratory (Fig. 3). The segmentation was performed on a tablet monitor with a light pen to make it easier to segment and define critical structures.

The initial patient model was constructed by fitting 3D polygon mesh surfaces to the segmented organs and structures (e.g. body surface, backbone, ribs, lungs, liver, heart, stomach, spleen, gallbladder, bladder, etc.). Within ImageSegment, each segmented structure was outputted as a 3D polygon model using the marching cubes algorithm from the Visualization Toolkit (VTK), www.vtk.org. The polygon models were imported into the Rhinoceros NURBS modeling software, www.rhino3d.com, and cubic NURBS surfaces were fitted to them creating an initial NURBS-based patient model. This initial model only covered the chest, abdomen, and pelvis region. To complete the phantom, we manually added on the head, arms, and legs using an existing male or female full-body XCAT template model selected to best match the age and anatomy of the patient.

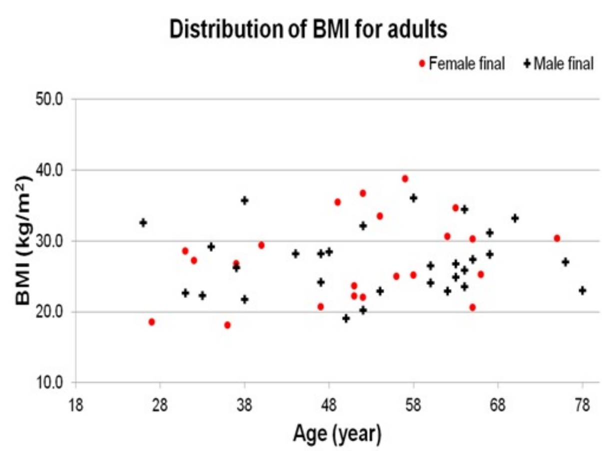

Fig. 2. BMI and ages of the patients used in developing XCAT phantoms.

Once the initial patient model was constructed, the LDDMM framework [4-6], developed by Dr. Michael Miller's group in the Center for Imaging Science at the Johns Hopkins University, was used to fill in the rest of the anatomy by transforming the selected template XCAT phantom (Visible Human-based male or female) to match the limited framework defined for the target patient model.

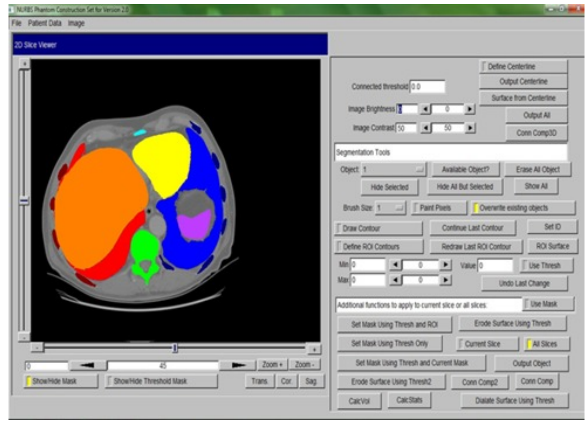

Fig. 3. ImageSegment (bottom), a GUI developed in our lab, allowed for manual segmentation of critical structures.

To calculate the LDDMM transform, images of the XCAT template and the patient target are required. The template and target images for each case were created by voxelizing the template and target models into 3D images covering the whole body. Structures from the patient model were assigned a unique integer ID in the target image to drive the LDDMM transform. The template model was set to contain the same structures and intensities as the target so the models have a 1:1 correspondence. Landmarks were defined using the template and target skeletons. Corresponding landmarks were placed on the endpoints of bones such as the ribs, arm/leg bones, and sternum. The spinal processes also served as landmarks. Given the selected landmarks and the template and target models, the LDDMM method calculated the high level transform to map the whole-body template (XCAT) to the target (patient framework). Figure 4 summarizes the steps to calculate the LDDMM transform.

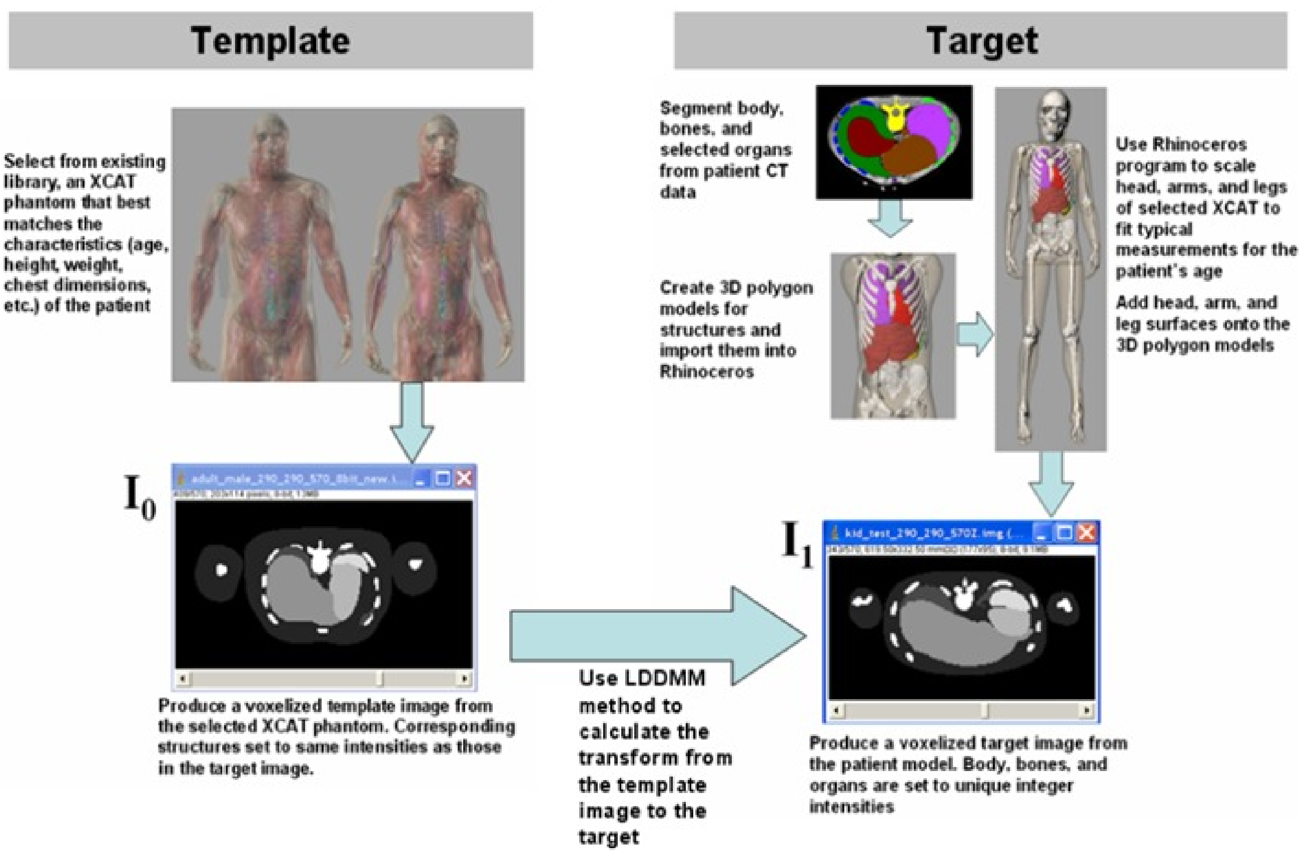

Fig. 4. Procedure for calculating the LDDMM transform. To calculate the LDDMM transform, template and target images are required. The above steps are performed to create these images.

Once the transform was determined, it was applied to the template XCAT to create the patient-specific XCAT phantom containing all anatomical structures (Fig. 5). The LDDMM transform was also applied to the base 4D cardiac model [2] of the XCAT to implement it in the new anatomy. The respiratory motion was modeled in each new phantom based on similar mechanics to that of the original XCAT [2].

Finally, each new phantom was refined by checking for anatomical accuracy via visual inspection of the 3D models. If needed, minor adjustments were made. Using these methods, phantoms of multiple body types and sizes were created.

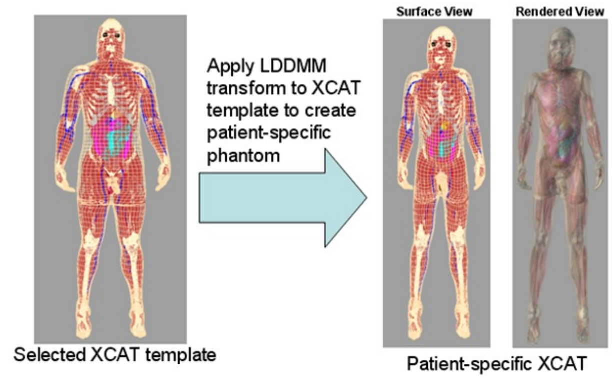

Fig. 5. The LDDMM transform is used to transform the template XCAT phantom to define the detailed anatomy of the patient.

3. RESULTS

Using our methods, we created a series of computerized phantoms with thousands of anatomical structures and modeling cardiac and respiratory motions. We created 58 (35 male and 23 female) anatomically variable phantoms in total, Fig. 6. These phantoms can be combined with existing simulation packages to simulate realistic imaging data. Figure 7 shows simulated CT data from 4 anatomically variable females. Clearly, these phantoms provide a means to obtain realistic-looking data. The advantage of having multiple shapes and sizes from an XCAT database allows for patient variability that would be common of a clinical trial.

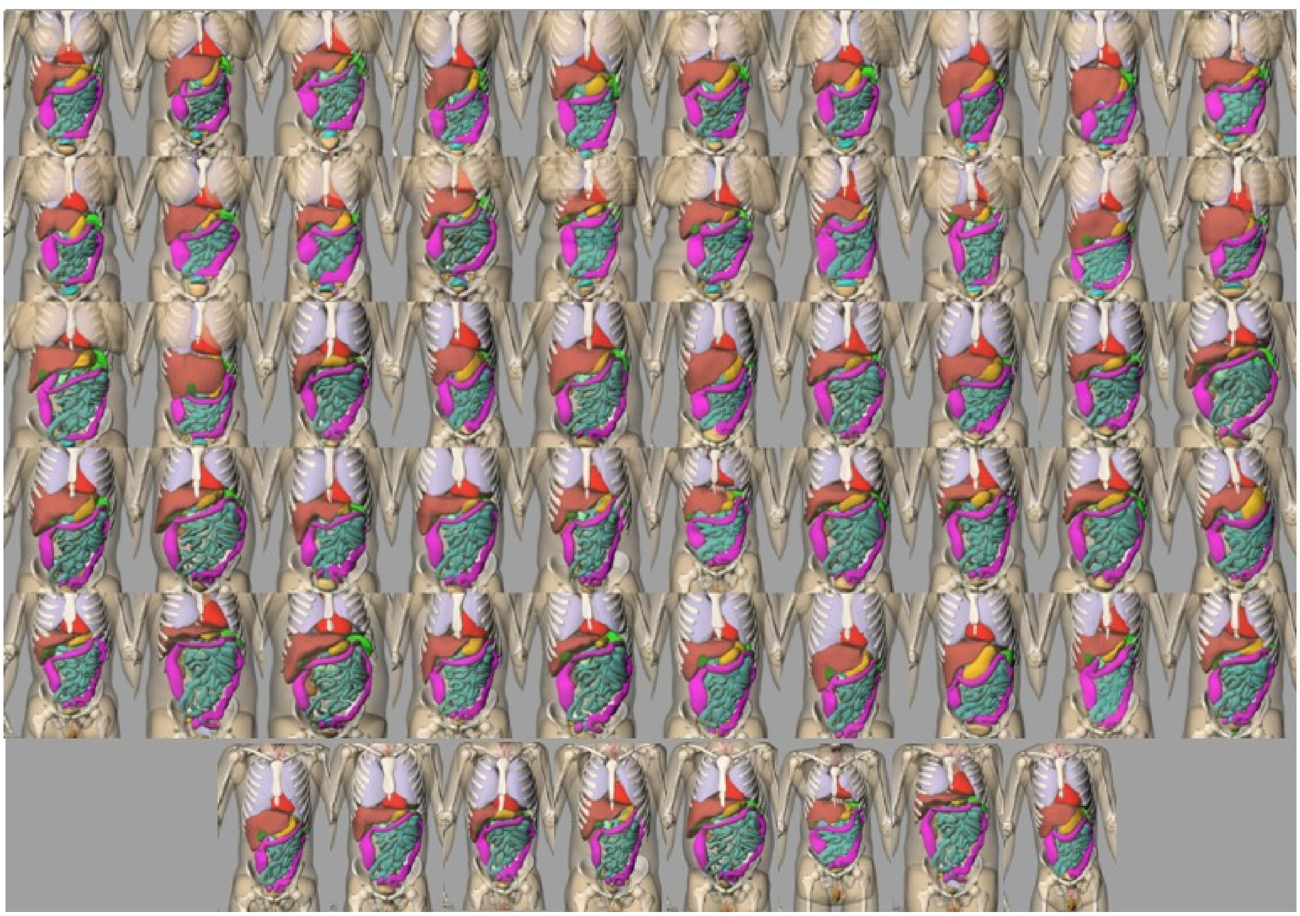

Fig. 6. Collage showing the 58 new adult anatomies.

This work provides a new population of 58 adult computerized phantoms for medical imaging research. Combined with previously developed pediatric phantoms, the XCAT library now has 100 models. Each phantom contains thousands of structures and is capable of modeling normal and abnormal variations in the cardiac and respiratory motions. Future work will provide anatomical texture features to the phantoms.

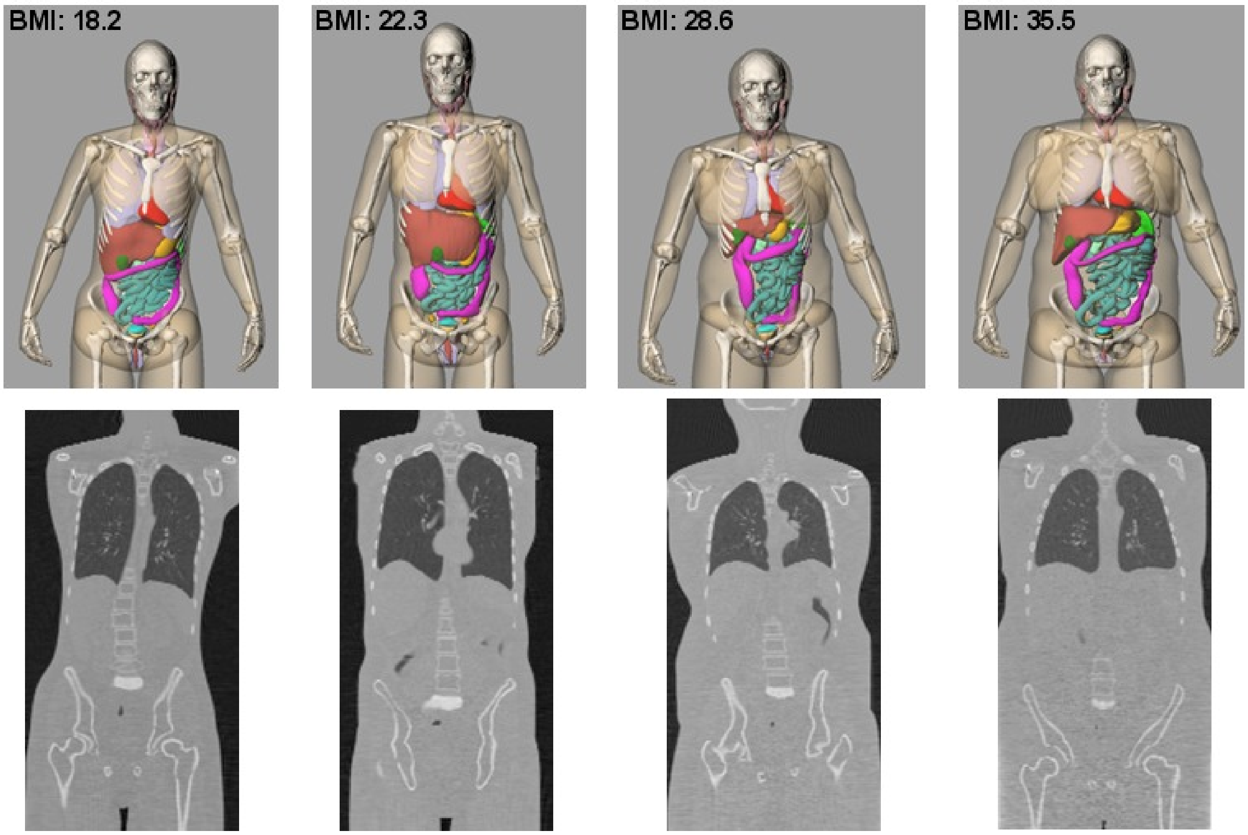

Fig. 7. Four adult female XCAT phantoms (top) with CT simulation results (bottom).

4. CONCLUSIONS

The phantoms developed in this work will provide useful tools in medical imaging research. With recent advances towards more volumetric and dynamic imaging, the phantoms have enormous potential to study the effects of anatomical, physiological, physical, and instrumentational factors on imaging and to research new image acquisition strategies, image processing and reconstruction methods, and image visualization and interpretation techniques. Combined with accurate Monte Carlo dose estimation programs, the phantom series will also provide the necessary foundation to optimize clinical CT applications in terms of image quality and radiation dose and to enable patient-specific estimation of CT dose and radiation risk.

5. ACKNOWLEDGEMENTS

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