Anatomy Registration via Patient Sensing for Chest X-ray Digital Tomosynthesis

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ABSTRACT

Chest X-ray is one of the most commonly performed radiologic procedures for respiratory diseases. Digital tomosynthesis (DTS) provides volumetric anatomic information at lower cost and dose compared to computed tomography (CT). However, current DTS system provides insufficient patient positioning feedback and requires a large number of reconstructed slices in order to ensure imaging the entirety of targeted anatomy. We propose an anatomy registration prototype using measurements from RGB-D cameras to 1) assist acquisition workflow, 2) provide individual-specific anatomical information to improve tomosynthesis reconstruction. Our experiments show that anatomy registration can provide real-time feedback of patient 2D position and body thickness. Our reconstruction simulations show that the anatomy and body information can speed up DTS reconstruction, reduce the number of redundant tomosynthesis slices, and help reduce image interpretation time.

Keywords: Anatomy registration, patient sensing, X-ray tomosynthesis

1. INTRODUCTION

X-ray is widely used in the hospital general wards and intensive care units (ICU), and chest radiography is the most commonly performed imaging study in the United States.[1] Chest X-ray examinations are performed to monitor patients' respiratory progress, check catheters and lines, especially when patient transportation to CT examinations is counter indicated.[2] In chest radiography, digital tomosynthesis (DTS) is a technology that enables volumetric anatomic information at cost and dose on par with regular 2D X-ray examination. A major difference from the 2D X-ray system is that chest DTS system includes a computer-controlled gantry for the X-ray tube, which allows the tube to tilt at various angles and thus acquire multiple views when sweeping over a predefined path. For patients with respiratory diseases or clinically suspected infections, chest X-ray images from a DTS system have better image quality for pulmonary infiltrates, nodules, and thus can provide better detection, diagnostic and monitoring outcomes.[1,3] The improved image quality and visualization could also obviate the need for multiple retakes and transport outside the ICU for further imaging, and thus reduce the time, cost and infectious risk of patient transport to the radiology department.

Despite the advantages over conventional radiography, DTS has limited depth resolution due to the limited sweep angle range. It is more sensitive to motion, and thus long breath holds are often required for patients in order to reduce motion artifacts. DTS also produces a larger number of slices, which means a longer interpretation and review time than 2D chest radiography, e.g., 200 seconds vs. 120 seconds on reported average.[4] Finally, DTS is only currently available for fixed-room environments where mechanical registration is provided. For future mobile DTS system design, the X-ray tube and the portable detector need to be positioned relative to patient anatomy, e.g., lungs, as best as possible during chest X-ray examinations of bed-ridden patients. In this work, we propose to estimate individual-specific anatomical structure information for optimizing the acquisition parameters, e.g., dose, source to object distance, and to deal with the limitations of chest X-ray DTS.

As cameras become adapted with imaging systems in a secure hospital environment, there is an opportunity for low-cost, vision techniques to provide cost-efficient solutions for various human sensing applications, e.g., human detection,[5] pose estimation[6] and body segmentation.[7] In addition, recent deep neural network-based algorithms

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has achieved high accuracy and begun to exceed human performance in many tasks, with the help of large training datasets, e.g., ImageNet.[8] In addition, researchers in the augmented reality and virtual reality communities have developed prototypes to project anatomical structures and annotations over the human body for cloth fitting, garment production and education purposes.[9,10] However, there has been less effort in integrating anatomical information for automating the medical imaging workflow. While researchers in the medical imaging community have been actively applying deep learning techniques in creating new reconstruction and image processing algorithms,[11] in this work we propose a framework to apply deep learning algorithms to obtain patient-specific anatomical and body information, e.g., lung location and chest thickness, to obtain optimal parameters for existing DTS reconstruction algorithms.

Specifically, we propose to use an RGB-D camera as a peripheral device in a DTS system, and apply the state-of-the-art human detection and pose estimation algorithms[6,7] to detect body keypoints from the camera's RGB images. One example is shown in Figure 1. Based on the detected keypoints, we perform 2D anatomical registration by mapping patient keypoints with those from human anatomical models.[12] For patients with postero-anterior (PA) chest views, we combine our 2D registration results with depth measurements to estimate the chest thickness of the patients. The 2D anatomy registration will provide real-time feedback of patient body positioning, ease workflow operation, and reduce the chance of retakes. The body thickness information can be used to optimize DTS acqusition and reconstruction parameters, e.g., dose, reconstruction matrix size, etc. The number of DTS slices can be significantly reduced, considering the large variation in adult thorax thickness, e.g., up to 11 cm.[13] That is, the adapted DTS reconstruction volume parameter can lead to less image interpretation time for doctors and radiologists. Our reconstruction simulation further shows that personalized anatomy and body information can significantly reduce DTS reconstruction processing time, e.g., by 41%, compared with the filtered back projection (FBP) algorithm without using any anatomy information.

To summarize, the contribution of this paper is to provide a framework to infer anatomy information from camera view to achieve optimized DTS acquisition and reconstruction. We develop an anatomy registration prototype with RGB-D cameras for the PA chest X-ray use case. We demonstrate that our anatomy registration provides real-time feedback to assist patient body positioning. We also perform reconstruction simulation to evaluate the impact of using anatomical and body information on reducing the reconstruction time and the number of redundant tomosynthesis images. The rest of the paper is organized as follows. Section 2 describes the anatomy registration prototype, DTS reconstruction and system simulation. Section 3 presents our experiments, registration results and their impact on DTS reconstruction. We conclude in Section 4.

2. METHODS

In this section, we first present our anatomy registration, body thickness estimation algorithms. Then we describe DTS reconstruction and possible ways to incorporate anatomy and body information.

2.1 Anatomy registration

We propose to use RGB and depth images to 1) register 2D anatomical structure, i.e., lung of a person with a canonical human anatomy model, and 2) estimate chest thickness in the postero-anterior (PA) chest X-ray scenario. The overall pipeline of the anatomy registration and chest thickness estimation algorithm is shown in Figure 2, and we explain all the components in detail next.

First, we apply the state-of-the-art 2D pose estimation algorithm[6] to detect a person's body part keypoints, such as shoulders, knees, etc. Then we select four keypoints: right and left shoulders, right and left hips, which are the closest joints to the chest, as shown in Figure 1. Assuming the person is standing and facing away from the camera that is mounted on the X-ray tube, we perform a rigid transformation to estimate the position of the lung by registering the detected keypoints to keypoints on a canonical human anatomy model, e.g., the male Duke model, or the female Ella model.[12] The lung image from the anatomy model is then superimposed on the camera view, so that the X-ray operator can properly assess whether the patient is properly positioned. Examples of our anatomy registration results are shown in Figure 4. Note that four keypoints are required in our registration for the PA view, and for the lateral view, we may have fewer keypoints available. We can perform body segmentation to obtain additional information, but we leave it as future work and focus on the PA view use case in this work.

Figure 1. Depth image (left) and RGB image with detected joint keypoints (right) from D435 camera (blue annuli indicate our selected keypoints in anatomy registration).

While the 2D anatomy registration is achieved by using images from the RGB camera, we obtain the depth view of the scene from the depth camera. After an RGB and depth alignment, we map our estimated lung image to the depth measurements to obtain the depth profile for the lung area. For a fixed room DTS system, the position of the X-ray detector is known; thus we can calculate its 2D position in the camera view and obtain the depth of the detector as well. Comparing the detector depth with the lung depth profiles, we can calculate the body thickness of the lung area. Specifically, we define *chest thickness* as the maximum body thickness of the lung area, and we calculate it by subtracting the peak value of the lung depth profile from the X-ray detector depth. Note that we smooth the depth profiles by averaging measurements during a time window when the human body is stationary, since the depth data from an RGB-D camera can be noisy in varying environment conditions. Also note that a 3D lung registration is possible by further applying registration on the depth profile. However, we only estimate the chest thickness instead of the lung thickness, considering the large variations in human anatomy, clothing condition, deformation issue and depth measurement noise, which we discuss in Section 3.3.

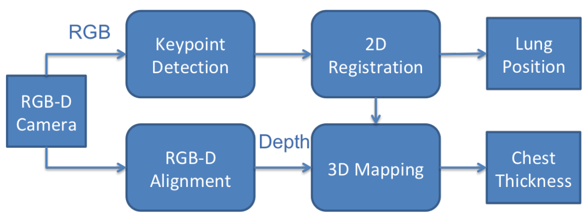

Figure 2. Flow chart of the anatomy registration and chest thickness estimation algorithm.

2.2 DTS Acquisition and Reconstruction

Before incorporating our registration results in DTS acquisition and reconstruction, we describe the DTS system, reconstruction algorithm, and numerical phantom model used in this paper. First, we assume the X-ray detector in the DTS system has a standard size of 40cm by 40cm, the X-ray tube has a sweep angle of ±20 degrees, and the source to image distance (SID) is 100cm.[14] For DTS reconstruction, we use the filtered back projection (FBP) algorithm to reconstruct radiation measurements into DTS slices. Considering an adult anterior-posterior thickness range of 19.4cm to 30.8cm,[13] we set the maximum reconstruction volume dimensions to be $L_x = 40cm$, $L_y = 40cm$, and $L_z = 32cm$, where L_x, L_y are the XY dimensions to cover the full detector area, and L_z represents the Z dimension to cover all possible human body thicknesses. That is, the reconstruction volume matrix size is set to be 40cm by 40cm by 32cm, without incorporating anatomy and body information. Thus, if the DTS slice depth interval d_z is set to be 0.2cm, our DTS reconstruction will produce 160 slices. Finally, we use the virtual family anatomy Duke model[12] to create our chest numerical phantom model, on which we can apply DTS reconstruction in our evaluation. The lateral and PA views of the Duke model are shown in Figure 3.

Now we propose the following ways to incorporate estimated person anatomy and body information in the DTS acquisition and reconstruction processes. First, we combine our anatomy registration results with the position of the X-ray detector to assist DTS acquisition workflow. For a fixed room X-ray system, the position and orientation of the X-ray detector is precisely controlled. Thus, we can use the pose information to calculate a bounding box in the camera view. Then, we use our anatomy registration results to detect if the X-ray detector covers the lung area or not and indicate the result to the operator. That is, real-time feedback of patient positioning can be provided to the X-ray operator as to whether the estimated lung position is entirely covered.

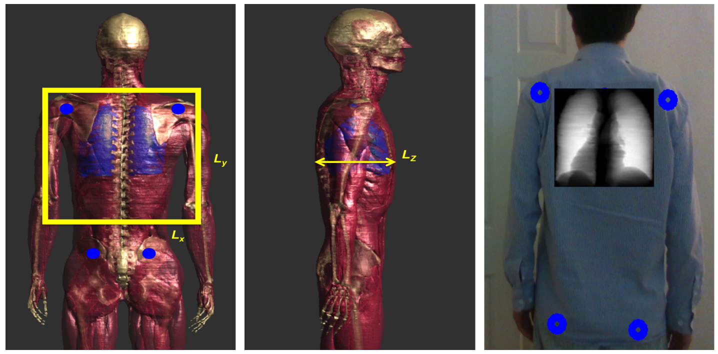

Figure 3. PA (left) and lateral (middle) views of the Duke anatomy model and the corresponding keypoints on the camera view of a person (right).

Second, the anatomy and body dimension information can be used to select optimal parameters for the DTS reconstruction algorithm. For example, instead of using a fixed volume matrix size, the length parameters in the horizontal XY dimensions L_x, L_y can be determined based on the width and length of the registered lung, and the chest or lung thickness estimation can be used to determine the L_z parameter. In this work, we choose to use the estimated chest thickness as the vertical length parameter L_z, and call this DTS reconstruction *anatomy-based filtered back projection* (aFBP). The reconstruction volume matrix parameters L_x, L_y and L_z used in aFBP are shown in Figure 3. Note that we can also adjust the radiation dose based on the body thickness information, since the attenuation from different body sizes would be very different. However, the body mass index (BMI) is widely used, and dose management is out of the scope of this work. In the next section, we perform experiments and simulations to evaluate the above two ways of using the anatomy registration in chest X-ray DTS to 1) assist acquisition workflow, and 2) improve DTS reconstruction efficiency.

3. EXPERIMENTS AND RESULTS

In this section, we perform experiments to demonstrate that our anatomy registration prototype can provide real-time feedback to assist chest X-ray workflow. We also run DTS reconstructions to investigate the improvement we can obtain by using the anatomy and body information in our reconstruction algorithms.

3.1 Workflow Assistant

We mimic the DTS chest X-ray workflow in our experiments by setting up a flat poster stand as our mock-up X-ray detector, as shown in Figure 4. We use the Intel RealSense D435 camera system to capture the RGB and depth images. We deploy the camera at various distances, e.g., 100cm, from the X-ray detector, facing perpendicularly to the detector plane. As shown in Figure 4, our anatomy registration prototype projects lungs to the camera view, and also calculates the body thicknesses at different distances, e.g., 100cm, 110cm away from the camera. If the registered lungs are inside a predefined region, i.e., the X-ray detector area, a green box is shown to indicate correct person positioning. Otherwise, a red box is shown as a warning to operator. Note that the colored bounding box is just a way to illustrate the real-time feedback function that the anatomy registration provides. In a real chest X-ray scenario, other ways of notification, e.g., audio, can be used to ease workflow operation and reduce X-ray retakes.

3.2 Improve Reconstruction

We now evaluate the impact of using anatomy and body information on DTS reconstruction. We run our reconstruction algorithm on a workstation with Intel Xeon 2.1GHz CPU (8 cores) and 64GB memory, and we record the processing time of the FBP reconstruction algorithm for various reconstruction sizes in the vertical

Figure 4. Anatomy registration and body thickness with different SID distances, 100cm (left) and 110cm (right).

Time (sec.)	18cm	20cm	22cm	24cm	26cm	28cm	30cm	32cm
$d_z = 1mm$	100.3	110.4	113.3	122.7	146.3	168.5	174.6	194.7
$d_z = 2mm$	82.1	89.0	98.6	108.8	134.3	147.0	162.7	189.7

Table 1. Reconstruction time vs. chest thickness for 1mm and 2mm slice internals.

dimension L_z. The reconstruction processing times (averaged over ten runs) for various L_z are shown in Table 1. We see that if we use our aFBP reconstruction method, i.e., FBP algorithm with chest thickness information included, the reconstruction time can be significantly reduced for a person with thin body size. For example, the chest thickness of a person is estimated as 22 cm ($\pm$1 cm) in our experiments, as shown in Figure 4. If we use it in our aFBP reconstruction, the reconstruction processing time will be reduced from 194.7 seconds to 113.3 seconds, for the 1mm slice interval case. That is a 41.8% reduction in reconstruction time. The DTS image preparation process will speed up with the help of anatomy and body information.

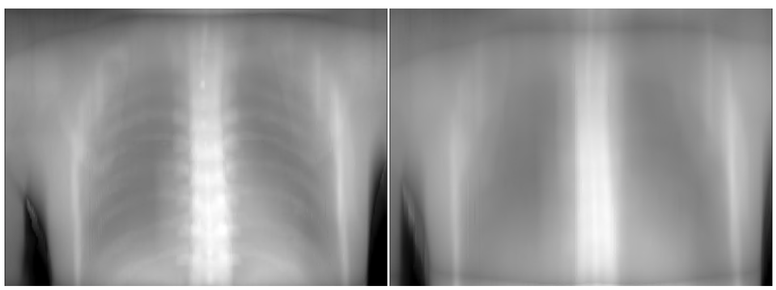

Figure 5. The first DTS slice from aFBP (left) vs. the 20th slice from FBP algorithm (right).

In addition, for a person with a chest thickness of 22cm, the aFBP reconstruction will produce 220 DTS slices while the FBP reconstruction will produce 320 slices for a 1 mm slice interval. Fewer DTS slices eliminate poorly focused slices and less time for interpretation and review by doctors and radiologists. As shown in Figure 5, we can see lung and rib structures from the first DTS slice produced by the aFBP reconstruction, but for the 320 slices produced by FBP, we still have a blurry image even after we go through the first 20 slices.

3.3 Discussions

In addition to chest thickness, additional anatomical information, e.g., lung thickness and width can be used to further refine the reconstruction region. For example, the maximum thickness of the lung region of the Duke anatomical model, as highlighted in blue in Figure 3, is 17.2cm, 4.5cm smaller than the chest thickness $L_z = 21.7cm$. If accurate lung depth can be estimated, even fewer DTS slices could be produced and more image review and interpretation time can be saved. However, additional work needs to be done to deal with large variations in human lung sizes, deformation issue, etc. We leave that as the future work. In this work, we use chest thickness as an example to show that our RGB-D camera-based sensing prototype can estimate anatomical information for DTS reconstruction in an automatic way during a chest X-ray exam.

We performed preliminary experiments to evaluate the real-time performance of the anatomy registration and chest thickness estimation algorithm. We anticipate that the accuracy of the depth estimate depends on the RGB-D camera, the distance between the person and camera and the details of the camera calibration. We plan to perform additional experiments to quantify the accuracy in a future work.

4. CONCLUSIONS

We develop an anatomy registration prototype using RGB-D cameras to assist chest X-ray acquisition workflow, and improve DTS reconstruction efficiency. Our experiments show that the 2D lung registration provides real-time feedback of patient 2D positioning. Our simulation and DTS reconstruction show that the anatomy and body information can speed up DTS reconstruction, reduce the number of redundant tomosynthesis slices, and help reduce image interpretation time.

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