Patient Specific External Respiratory Motion Modeling Using Depth Sensors

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Abstract

Human respiration induces considerable external and internal motion in the thoracic and abdominal regions. Tracking and modeling of this motion is an important task for accurate treatment planning and dose calculation during external beam radiotherapy. Inaccurate motion tracking can cause severe issues such as errors in target/normal tissue delineation and increment in the volume of healthy tis-sues exposed to high doses. Different methods have been introduced to model the respiratory motion, but most of them use wearable markers or surgical node implanting techniques, which are inconvenient to patients. In this paper, we experiment the feasibility of using commercial 3D depth sensors with Principal Component Analysis (PCA) techniques to track and model the subject-specific external respiratory motion.

1. Introduction

Radiotherapy is a widely used technique, generally as a part of cancer treatment to control or kill malignant cells. Its goal is to eradicate tumors by delivering high enough dose of radiation while sparing the surrounding healthy tissues. Inaccurate patient setup, anatomical motion and deformation, and target/normal tissue delineation errors are some of the reasons that radiotherapy cannot achieve desired goals. Respiratory-induced anatomical motion and deformation contribute significantly to errors in both the radiotherapy planning and delivery process especially in radiotherapy of thoracic and abdominal regions [1]. If the respiratory motion is not accounted correctly, severe problems can be occurred such as target/normal tissue delineation errors, dose calculation errors, expose of healthy tissues to high doses, and not receiving advocate dose coverage for clinical target volume.

Motion encompassing, respiratory gating, breath holding, and forced shallow breathing with abdominal compression are some of the traditional methods, which have been used to handle the respiratory motion during radiotherapy [2]. All of these traditional methods have drawbacks of handling patient movements, longer treatment time, patient training, and patient discomforts. Real-time tumor tracking techniques recently gained significant research interest as it can actively estimates the respiratory motion and continuously synchronizes the beam delivery with the motion of the tumor.

The Synchrony respiratory tracking system, a subsystem of CyberKnife, is the first technology which continuously synchronize beam delivery to the motion of the tumor [3]. The external respiratory motion is tracked using three optical fiducial markers attached to a tightly fitting vest. Small gold markers are implanted near the target area prior to treatment to ensure the continuous correspondence between internal and external motion. The Calypso, prostate motion tracking system integrated in Varian (Varian Medical Systems, Palo Alto, CA), implants three tiny transponders with an associated wireless tracking to eliminate the need of internal-external motion modelling [4]. The BrainLAB ExacTrac positioning system uses radiopaque fiducial markers implanted near the target isocenter with external infrared (IR) reflecting markers [5]. Internal markers are tracked by an x-ray localization system while an IR stereo camera tracks the external markers. Xsight Lung Tracking system (extension of CyberKnife system) is a respiratory motion tracking system of lung lesion that eliminates the need of implanted fiducial markers [6].

Most of these real-time systems use 4D X-ray computed tomography (CT) or magnetic resonance imaging (MRI) techniques to extract the respiratory motion, which is the reason for few problems such as slow acquisition and unnecessary ex-pose to extra dose of ionizing. In addition, most of these systems have the disadvantage of invasive fiducial marker implantation procedures that increase the patient preparation time and treatment time. In order to avoid these problems, we propose a respiratory motion tracking

(a) (b)

Fig. 1. Experiment setup in the laboratory environment. (a) Example setup of the patient and the depth sensor. (b) Asus Xtion PRO depth sensor that is used in the experiment setup.

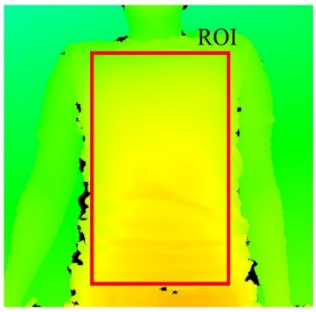

Fig. 2. Example depth image and selected ROI.

system that uses only a commercially available 3D depth sensor. Within the proposed system, an Asus Xtion PRO depth sensor is used to capture the depth images of thoracic and abdominal regions. Then a region of interest (ROI) based Principal Component Analysis (PCA) is carried out to model the patient specific respiratory motion.

2. Proposed Method

In our proposed method, an Asus Xtion PRO depth camera is used to capture continuous depth data of the patient's thoracic and abdominal region along with visual images. During the laboratory level experiments, three volunteers participated in motion data collection process. Each volunteer is advised to lay down in a supine position and the depth sensor is placed above the volunteer nearly in 75 cm distance as shown in the Fig. 1. For each volunteer, 100 consecutive depth frames are captured and an ROI covering the thoracic and abdominal area is defined to use in further processing. Fig. 2 shows an example depth image and the selected ROI.

After capturing the depth data, PCA is applied on the input data described by Equation 1, where x_i is the column matrix of the depth data on selected ROI at frame i and N is the total number of depth frames ($N = 100$).

$$X = [x_1 x_2 \ldots x_N] \tag{1}$$

Before applying the PCA, standard deviation (σ) of the depth images is calculated using Equation 2 where μ (mean) can be defined as in Equation 3. The resultant standard deviation images are shown in the first column of Fig. 3.

$$\sigma = \frac{1}{N}\sqrt{\sum_{i=1}^{N}(x_i - \mu)^2} \tag{2}$$

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{3}$$

In order to apply PCA, first the covariance matrix (K) is calculated using Equation 4. Then the eigenvalues λ and the eigenvectors e are calculated by solving Equation 5.

$$K = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)(x_i - \mu)^T \tag{4}$$

$$Ke = \lambda e \tag{5}$$

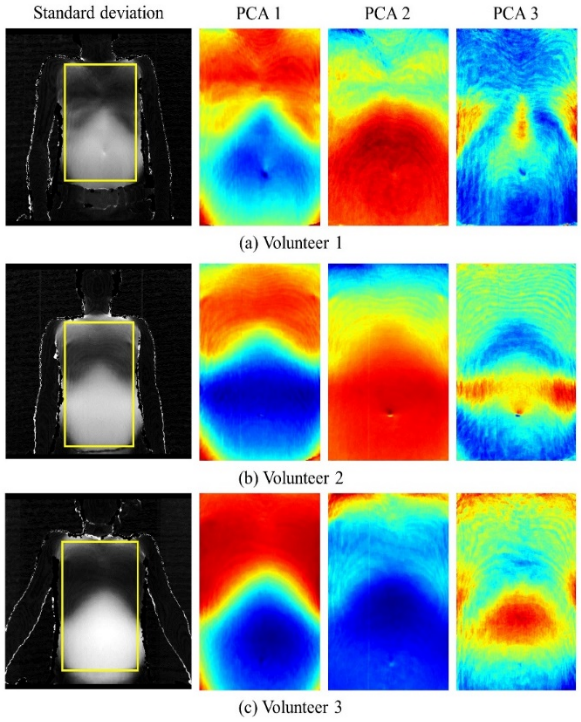

Fig. 3. PCA analysis results on 100 consecutive depth images of respiratory motion of three volunteers. First column represents the standard deviation of all depth images and next three column represent the first three Principal Components.

Eigenvectors are then arranged in descending order according to the magnitude of the eigenvalues. Each eigenvector represents principal components (PC) of the input data where only first few principal components represent the dominant variance of the motion. Fig. 3 depicts the first three principal components of each volunteer where only first and second principal components show a significant variance. By comparing the PCA results with the standard deviation images, we can conclude that PCA represents a better motion model compared to direct depth data as depth values depend on the location of the sensor.

After finding the principal components, dimension reduction techniques are applied to reduce the complexity of the depth images and represent them in fewer dimensions. Equation 6 can be used to reduce the complexity of the depth image x into k dimensions, where e_k represents the k^{th} eigenvector and a_k represents the reduced k^{th} dimension value. In the experiments, only first three principal components are considered and all the depth images are re-projected onto these three dimensions.

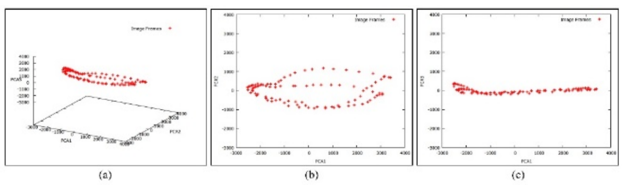

Fig. 4. Results of the dimension reduction. First principal component represents the dominant variation of the motion compared to other three. (a) Each depth frame is re-project onto first three principal components. (b) Comparison of the first PC with second PC. (c) Comparison of the first PC with third PC.

$$\left[a_1 \ldots a_k\right] = \left[x - \mu\right]^T \left[e_1 \ldots e_k\right] \qquad (6)$$

Fig. 4(a) shows an example of re-projection using the depth data of volunteer 2. Two graphs in Fig.4(b) and Fig. 4(c) compare the first principal component with second and third principal components. According to the comparison, first principal component is dominant over the other two and holds a significant amount of motion data. Hence, only the re-projection data on the first dimension is used in Fig. 5 to represent the respiratory motion model of each volunteer.

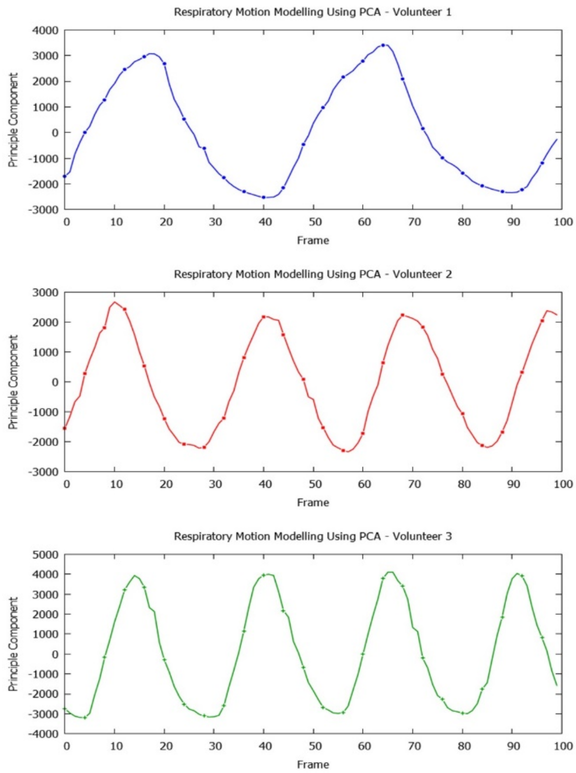

Fig. 5. Respiratory motion modelling results of the three volunteers using PCA analysis on 100 consecutive depth frames.

3. Conclusions & Future Works

This paper introduced a patient specific external respiratory motion modeling technique using commercial depth sensors. PCA is applied on 100 consecutive depth frames captured using Asus Xtion Pro depth camera and then a dimension reduction technique is applied to have a clear representation of the respiratory motion. Even though raw depth data has a considerable amount of noise, proposed method managed to find out a smooth respiratory motion model by using PCA techniques.

In the current implementation, manual ROI selection process is carried out during the PCA and we are planning to use visual coded markers in order to implement an automatic ROI selection process. Furthermore, we are planning to extend this work to find out the motion models of separate locations on the thoracic and abdominal region; as the current implementation gives only an overall motion model.

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