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Real-Time Tracking Diaphragm Motion On During-Treatment KV Cone Beam Projection Images Using ResNet50

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MO-H345-IePD-F5-02, Investigating a Real-Time Dose Calculation to Guide Multi-Target MLC Tracking: E Hewson[1]*, D Nguyen[1, 2, 3], A Le[3], J Booth[3, 4], P Keall[1], L Mejnertsen[1],(1) ACRF Image X Institute, University of Sydney, Sydney, NSW, AU, (2) University of Technology Sydney, Ultimo, Sydney, NSW, AU, (3) Northern Sydney Cancer Centre, Royal North Shore Hospital, Sydney, NSW, AU, (4) School of Physics, University of Sydney, Sydney, NSW, AU

Purpose: Differential motion of multiple tumors can result in dosimetric error for patients with locally advanced cancer. To address this issue, a multileaf collimator (MLC) tracking method that corrected dose error in real time for independently moving targets was developed. This study investigated real-time multi-target tracking optimized using a fast dose calculation and compared the dosimetric accuracy to previous treatment methods**. Methods:** A multi-target MLC (MT-MLC) tracking algorithm that optimized leaf positions in real time based on accumulated dose error was developed for moving prostate and static lymph node targets. To enable real-time dose accumulation, the dose calculation was simplified to deposit a unit of dose in the treatment volumes along the line-of-sight of the aperture at each timestep. The MLC leaves were then adapted to minimize the difference between the planned and delivered doses with motion. The MT-MLC tracking algorithm was evaluated by simulating treatment for five locally advanced prostate cancer patients and three motion traces. Delivered doses were evaluated using a clinically accepted dose calculation in a treatment planning system (TPS) (Eclipse v16.1). The performance of dose-optimized MT-MLC tracking was compared to a 2D geometric-optimized MT-MLC tracking approach, and no tracking, using a 2%/2mm gamma-pass criterion**. Results:** Dose-optimized MT-MLC tracking had the lowest error with mean gamma-failure rates of 11.5%±8.5% for the prostate and 2.2%±3.2% for the nodes, compared to 22.6%±11.6% and 3.6%±2.5% for geometric-optimized MT-MLC tracking ($p=0.02$), and 37.1%±27.8% and 23.6±3.2% without tracking ($p<0.01$). The difference in dose errors for the fast dose calculation and the TPS dose ranged between -6.6% and 5.2% for 99% of voxels. **Conclusion:** Though the fast dose calculation was simplified and did not account for all physical interactions of radiation dose in tissue, dose errors between the planned and delivered doses were sufficiently accurate to guide MLC optimization, enabling improved multi-target tracking.

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MO-H345-IePD-F5-03, Three-Dimensional Voxel-By-Voxel Motion Tracking of Mobile Phantoms Using Microwave Imaging: N Alsbou[1]*, S Ahmad[2], I Ali[2],(1) Department of Engineering and Physics, University of Central Oklahoma, Edmond, OK, (2) University of Oklahoma Health Sciences Center, Oklahoma City, OK

Purpose: To track the motion of mobile phantom manufactured from tissue equivalent materials using microwave-imaging. A motion tracking model was developed that uses the variation in the microwave signal to classify the microwave signals and extract 3D-motion trajectory on a voxel-by-voxel basis for the whole phantom volume in the microwave imaging view. **Methods:** Several microwave motion sensors were mounted in a circular ring around a mobile phantom that moves with controlled motion patterns. A sequence of 2D and 3D-microwave images were acquired and sorted in time to create the motion trajectory for of all the voxels in the tissue-equivalent phantom. The variations in the microwave intensity due to variations in phantom position, thickness and density were classified to quantify the motion parameters induced by different motion patterns that mimic variation in amplitude and frequency in respiratory motion of different patients. **Results:** The motion trajectory of a mobile phantom was reconstructed using microwave-imaging and a classification motion algorithm. The motion algorithm classified the relationship between the variations in microwave intensity and the mobile phantom positon, thickness, and composition in the imaging field of view. The variations in the position of the different voxels varied linearly with the positon of the minimal microwave intensity within 3.0mm. The minimal microwave intensity deceased nearly linearly with the increasing volume of water in the microwave imaging field. However, variations in the microwave intensity was not linear with the density of the tissue-equivalent phantom objects such as breast, muscle, liver adipose, lung and bone. **Conclusion:** Using microwave-imaging, a voxel-by-voxel motion detection technique for the whole volume of a tissue-equivalent phantom was developed. This technique has potential clinical application particularly in radiation therapy considering tracking all voxels in the image instead of tracking an external or internal-markers used in gating from the management of cancer patient motion.

MO-H345-IePD-F5-04, Real-Time Tracking Diaphragm Motion On During-Treatment KV Cone Beam Projection Images Using ResNet50: J Liang*, Q Liu, E Porter, D Yan, Beaumont Health System, Royal Oak, MI

Purpose: Diaphragm manifested on Cone Beam projection image has been used as surrogate to monitor lung tumor position. We propose a deep learning method to detect diaphragm apex position of the ipsilateral lung in real-time on KV projections acquired during Lung SBRT delivery. **Methods:** 7 hypo-lung SBRT patients with right lower lobe tumor were selected in this retrospective study. The imaging projection angle ranges from about -270 to 112 degrees. The right lung diaphragm apex was manually labeled as ground-truth on KV projections acquired during-treatment sessions with 899±167 projections per session. The backbone of our machine learning model is 50 layers convolution neural network (ResNet50). Four dense layers were added in the top layers. A weighted mean square function was used as the loss function. The model was trained on 5 patients' data with image augmentation (random shift in two dimensions) to increase 4 times of the input data. The model is then applied to the 4 during-treatment sessions of the other 2 patients. The ground-truth and the predicted output of the model from the during-treatment projections were compared. The motion in Superior-Inferior direction was evaluated in this study**.** **Results:** Absolute error for all the test projections was 1.98±2.00 mm, max error of 4.9mm for 95% projections with the largest error at the lateral projections. For the 4 individual sessions, the absolute error was 1.88±1.71, 2.07±1.72, 2.20±2.58 and 1.85±1.60mm respectively. There was no significant difference of error distribution across sessions. Predictions were generated in 18 milliseconds per projection when using one NVIDIA Quadro P6000 GPU card, well below 182 milliseconds projection image interval in Elekta XVI system. **Conclusion:** The ResNet50 model was able to track diaphragm apex position, with the uncertainty < 5mm for 95% predictions, at ipsilateral lung on all projection angles.

MO-H345-IePD-F5-05, A Deep Learning Fiducial Marker Detection Algorithm for Beam's-Eye-View Marker Tracking for Liver Cancer Patients: D Chrystall[1]*, E Hewson[2], C Sengupta[2], A Mylonas[2], T Wang[3], R O'Brien[2], Y Lee[4], P Poulsen[5], D Nguyen[2], P Keall[2], J Booth[1]</sup>,(1) Northern Sydney Cancer Centre, St Leonards, NSW, AU, (2) The University of Sydney, Sydney, NSW, AU, (3) Western Sydney Local Health District, NSW, AU, (4) Princess Alexandra Hospital, Qld, AU, (5) Aarhus University Hospital, Aarhus N, DK,

Purpose: The MV imager is an ideal real-time intrafraction motion management tool that adds no additional imaging dose, provides motion data in the frame of reference of the treatment beam, and comes with any standard-equipped linear accelerator. This study extends a deep learning framework that automatically detects fiducial markers to track intrafraction liver motion using MV images and evaluates the performance of the fully-trained convolutional neural network (CNN) classifier in segmenting liver fiducial markers. **Methods:** A CNN classifier was trained using MV images from 7 liver cancer patients (30 fractions) with implanted fiducial markers. The classifier was made of four convolutional layers and one fully connected layer. The CNN performance and marker tracking system accuracy were validated on unseen MV images from 7 patients (13 fractions). The classifier performance was evaluated using the Precision-Recall Curve (PRC), the Area Under the Curve (AUC), sensitivity and specificity. The tracking system accuracy was evaluated by calculating the geometric error in BEV co-ordinates in the x and y-directions, using the ground truth from manually labelled images. **Results:** The CNN classifier had an AUC of 0.98, sensitivity of 97.94% and specificity of 99.71%. The overall geometric tracking error (mean ± standard deviation [1st, 99th percentile]) was 0.0 ± 0.6 [-1.6, 1.6] mm and 0.0 ± 0.6 [-0.9, 1.1] mm in the x and y-directions, respectively. For frames that were manually labelled the CNN successfully tracked at least one marker in 49% (range = 22–97%) of frames for EBH patients and 15% (range = 0–66%) for FB patients**.** **Conclusion:** The first deep learning method of tracking liver fiducial markers on MV images was developed and evaluated on an unseen patient dataset. The high performance of the CNN classifier and sub-mm tracking accuracy show this is a feasible method for tracking liver fiducial markers using MV images.

Data acquired from ethics approved TROG 17.03 LARK Trial for liver SABR data (ID: NCT02984566). Funding support from the NSW Cancer Council Grant and the Cancer Australia Grant.

MO-H345-IePD-F5-06, A Smartphone-Based Surface Guided Radiation Therapy Tracking System for Respiratory Monitoring in Radiation Therapy: D Capaldi[1]*, M Axente[2], A Yu[3], L Skinner[3], N Prionas[1], E Hirata[1], T Nano[1],(1) University of California, San Francisco, San Francisco, CA, (2) Emory University School of Medicine, Atlanta, GA, (3) Stanford University, Palo Alto, CA

Purpose: Surface-guided radiation-therapy (SGRT) systems are becoming standard-of-care for patient setup and motion monitoring. However, commercial systems remain inaccessible to resource-limited clinics around the world. Alternative to current solutions, we have previously developed and evaluated the feasibility of an audiovisual feedback system that leverages depth information from the front facing TrueDepth sensor onboard iOS devices. More recently released iOS devices now have LiDAR capabilities on the back facing camera. The purpose of this study was to further develop and validate the platform using the back facing LiDAR camera**.** **Methods:** The iOS application was developed in Swift and implemented on an iPhone 13 Pro® with a build-in the LiDAR camera system. The application contains different feature, such as 1) visualizing both the depth as well as the camera video feed, 2) selecting a region-of-interest (ROI) over the area that motion will be evaluated, 3) determining the angle of the plane that the ROI makes