CBCT for Treatment Verification

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Issues with CBCT

- Low soft-tissue contrast
- All sorts of artifacts: scatter, motion, noise
- Additional imaging dose



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CBCT

Wide availability

– LINAC, proton, Gamma Knife

Adaptive RT

- Electron density

- Inexpensive compared to MRI
- Many recent advances in improving CBCT quality

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Improve CBCT HU accuracy

- Deform planning CT to CBCT geometry
 - Accurate CT number from planning CT
 - Challenge: Content change
- Scatter correction
 - Hardware based
 - Software based
 - Analytical (kernel, Boltzmann transport)
 - Monte Carlo

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Blocker based scatter correction

 Signal in blocked region attribute to scatter, signal in un-blocked region is the sum of primary and scatter



- 2D scatter fluence is estimated using interpolation of the detected signal in the blocked region.
- Static blocker: reduce imaging volume or additional measurements needed.

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Moving Blocker



Motor-controlled Blocker



https://www.youtube.com/watch?v=m71jAxiHp58 (Ouyang et al, Med. Phys., 2013, Ouyang et al, Radiother. Oncol. 2015; Chen et al, Med Phys. 2017)





CT number accuracy

	ROI1	ROI2	ROI3	RMSE
MDCT fan-beam	69	70	-58	
Normal CBCT	-214	-201	-191	239
Moving blocker CBCT with scatter correction	70	67	-42	10

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Acuros CTS

Estimate scatter by deterministically solving the linear Boltzmann transport equation (LBTE)



Synthesized CT from CBCT

Supervised Learning

- -Require paired CBCT and planning CT (pCT)
- -In reality, perfectly matched CBCT and pCT does not exist
- Unsupervised Learning is desired

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This CVPR paper is the Open Access version, provided by the Computer Vision Foundation. Except for this watermark, it is identical to the version available on IEEE Xplore.

Image Style Transfer Using Convolutional Neural Networks

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CBCT provides content (i.e., updated patient anatomy)

Planning CT provides style (i.e., accurate CT number)

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- Contextual loss: measured based on the differences between the low-level image features extracted by the kernels in the first block of the pre-trained loss network
- Perceptual loss: calculated based on the differences between the high-level image features extracted by the kernels in the second, third and fourth blocks of the loss network.

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Results



Four Dimensional CBCT (4D-CBCT)

- In 4D-CBCT, projection images are sorted to different groups according to the breathing phases.
- The number of projections at each phase is considerably smaller than 3D-CBCT from full projection dataset.
- Severe view aliasing artifacts will present in the 4D-CBCT when it is reconstructed by analytical Feldkamp-Davis-Kress (FDK) algorithm.



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Simultaneous Motion Estimation and Image Reconstruction (SMEIR) for 4D-CBCT



Motion compensated image reconstruction

Update motion model directly from projections

J. Wang et al, Med Phys, vol. vol. 40, 101912 (2013)





Incorporate Biomechanical Modeling into 4D-CBCT reconstruction





Develop a convolutional neural network (CNN) based approach to improve the DVFs accuracy inside of lung, overcoming the long <u>computational time of biomechanical modelling</u>.

□Using DVFs at lung boundary estimated by 2D-3D registration step in SMEIR as the input, we aim to use CNN to improve the DVFs inside of lung. We developed <u>two U-net based architectures</u> to estimate DVFs inside of lung.

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Results



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Results

Groun	d Truth	SMEIR	SMEIR-Bio	U-net-3C	Unet-4C	
		SMEIR	SMEIR-Bio	U-net-3C	U-net-4C (CT)	
	RMSE	87.2	73.8	67.1	49.2	
	UQI	0.67	0.81	0.80	0.84	
Ra	idiation Oncolo	ogy X. Hua	ng et al, AAPM (2	019)	UT Southwee Medica	stern I Center

Lung Tumor Tracking by Surrogate Signals

Tracking motion only at limited locations on chest wall surface:

> Motions are highly correlated

	Construct ar sample point	n observation ts.	matrix from 3D motions	s of all	
	QR decomposition with column pivoting (QCRP) to identify locations with independent motion patterns				
Patien ● ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○		Patient 2	Patient 3 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0		

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Predicting Lung Tumor Motion

Train model parameters for each vertex of lung surface from motions at selected locations





Derive tumor motion using predicted lung surface motion through biomechanical modeling

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Lung Tumor Motion Simulation Error

#Patient	TCM motion range AP (mm)	TCM motion range RL (mm)	TCM motion range SI (mm)	TCM Euclid. Range (mm)	TCM Sim. error AP(mm)	TCM Sim error RL (mm)	TCM Sim. error SI (mm)	TCM Euclid. Error (mm)
1	1.23	2.43	1.12	2.94	0.53	1.02	0.68	1.33
2	0.58	1.17	0.30	1.33	0.59	0.63	0.28	0.90
3	1.65	1.56	4.35	4.90	0.71	0.82	1.43	1.79
4	1.50	3.75	12.00	12.66	0.41	1.11	2.12	2.42
5	1.21	2.90	0.45	3.17	0.31	0.84	0.44	0.99
6	1.49	4.96	3.30	6.14	0.98	2.32	1.34	2.85
	1.38	0.87	1.50	2.21	0.36	0.78	0.51	0.99
8	1.07	1.66	5.70	6.03	0.40	0.46	1.78	1.88
9	0.85	0.70	5.40	5.51	0.39	0.52	1.21	1.37
10	0.68	2.53	14.23	14.46	0.34	1.01	2.22	2.46
Mean	1.16	2.25	4.83	5.93	0.50	0.95	1.20	1.69



Dose reconstruction for lung SBRT based on 4D-CBCT







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CT Recon w/ Human-Like Auto Parameter Adjusting

CT Recon w/ Human-Like Auto Parameter Adjusting







CNN-based metal artifacts reduction



Radiation Oncology Zhang and Yu, IEEE TMI 37(6):1370–1381, 2018 UTSouthwestern Medical Center

Conclusions

- Image quality of CBCT can be improved by both hardware- and software-based approaches, especially with help from recent advances of deep convolutional neural network.
- With improved quantification and motion modeling, CBCT and 4D-CBCT can be used for dose reconstruction and adaptive RT.
- Combined with other noninvasive imaging, 4D-CBCT can facilitate tracking tumor motion during beam delivery.

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