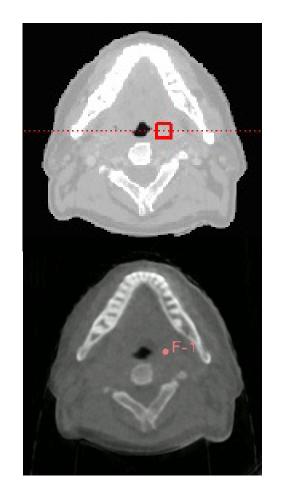
Concepts of synthetic imaging

Brian Winey, Ph.D. Medical Physicist, MGH Associate Professor, HMS Lecturer, MIT









Disclosures

Research support from Raysearch and NIH

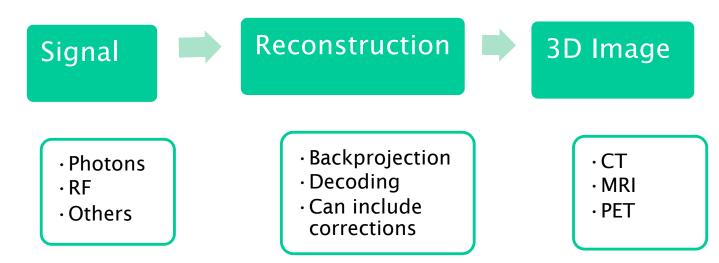






3D Imaging

Traditionally:



Ex: FDK for CBCT







3D Imaging options

CBCT:

- Varian CBCT
- IBA CBCT (x2)
- MedPhoton
- Forte









3D Imaging options

CT:In Room



J Appl Clin Med Phys. 2017 May; 18(3): 130–136.

MEVION AND MEDPHOTON BRING ADVANCED CONE BEAM CT IMAGING TO PROTON THERAPY

Mevion to integrate in-room CBCT imaging with its MEVION S250 Series; invites customers to learn more at ESTRO 36

LITTLETON, Mass., May 2, 2017 – Mevion Medical Systems, the leader in compact proton therapy, is announcing a strategic agreement with medPhoton GmbH to integrate ImagingRing, an innovative cone beam computed tomography (CBCT) system for volumetric image guidance, with





Trento

PSI

Dresden...



3D Imaging future

MR: In Room

Hoffmann et al. Radiation Oncology (2020) 15:129 https://doi.org/10.1186/s13014-020-01571-x

Radiation Oncology

Dose difference

MEDICAL SCHOOL

REVIEW

а

Open Access

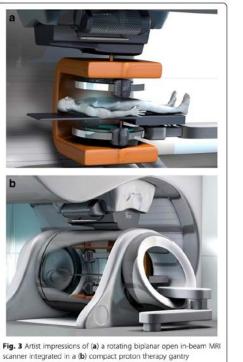
MR-guided proton therapy: a review and a preview

СТ



Aswin Hoffmann^{1,2,3}, Bradley Oborn^{4,5}, Maryam Moteabbed⁶, Susu Yan⁶, Thomas Bortfeld⁶, Antje Knopf⁷, Herman Fuchs^{8,9}, Dietmar Georg^{8,9}, Joao Seco^{10,11}, Maria Francesca Spadea^{10,12}, Oliver Jäkel¹³, Christopher Kurz^{14,15} and Katia Parodi^{15*}

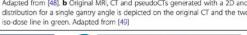
SCT



duse on CT does an sCT CT density b original MR original CT 120 100 80 1% pseudoCT Unet2D pseudoCT Unet3D 60 40 20 Fig. 5 a From left to right: HU and dose profile of a proton spread-out Bragg peak (SOBP) for a beam entering via the frontal sinus. SOBP dose and dose difference distribution in a 2D sagittal plane as planned on the sCT and then delivered on the CT using a prescribed dose of 2 Gy. Adapted from [48]. b Original MRI, CT and pseudoCTs generated with a 2D and a 3D Unet for an exemplary brain case. The SFUD proton dose distribution for a single gantry angle is depicted on the original CT and the two pseudoCTs. The generic target volume is marked in red, the 95%



RADIATION ONCOLOGY





treatment room (Image courtesy: Ion Beam Applications SA, Louvain-la-Neuve, Belgium)

Imaging Needs:

- Image Quality (registration, contouring, and dose calculations)
 - HU or SPR Accuracy
 - Soft tissue Contrast
- 4D Motion for thoracic/abdominal
- Workflow Integration





Image Quality Issues

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GENERAL HOSPITAL

RADIATION ONCOLOGY

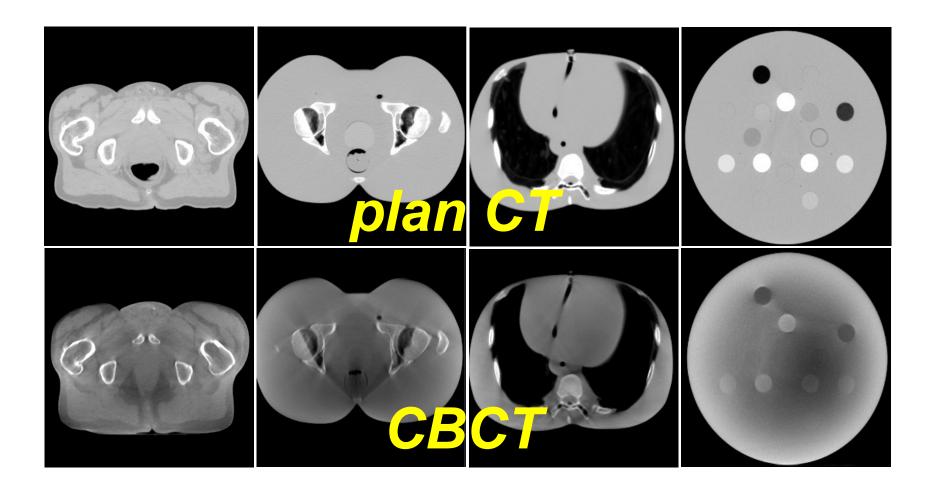
- Artifacts: streaks, scatter, beam hardening
- HU/RSP conversion (MR)
- Geometric Accuracy (MR)
- Gantry Flex/Sag
- Motion

M Zhu et al Med Phys 2014

HARVARD

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CBCT Artifacts









Synthetic Imaging

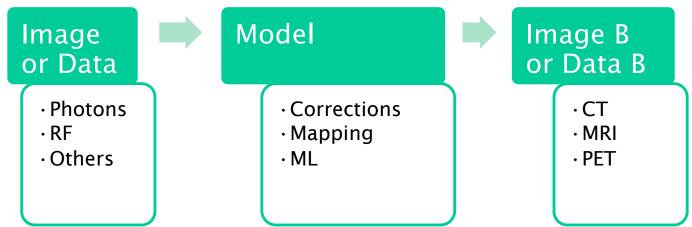
- Some Examples:
 - Patient modeling
 - Correct Image Artifacts (CBCT, MR, CT):
 - Scatter
 - Intensity
 - Motion
 - Geometry
 - Convert from type A to type B
 - Convert MR to CT/SPR
 - Multiple MR Sequences





Synthetic Imaging

- Some Examples:
 - Patient modeling
 - Correct Image Artifacts (CBCT, MR, CT):
 - Convert from type A to type B



 \rightarrow The analytic/synthetic distinction is blurry!





Synthetic Image Methods

- Model (low frequency)*
- HU Look Up Table (LUT)^
- Deform CT to CBCT^
- A priori CT scatter correction *^
- ML Models*^
- Iterative^
- * Projection Domain; ^ Reconstruction Domain







Scatter Model

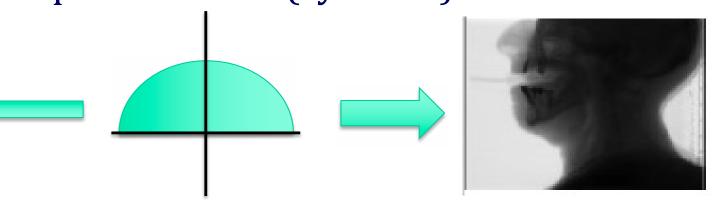
Estimate of Scatter based upon Model

Early online CBCT devices and reconstructions

Boellaard, et al., Radiotherapy & Onc, 44, 1997, 149-157.

Also, simplified model (cylinder) for scatter





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RADIATION ONCOLOGY

LUT

Basic method: Calibration

• Mapping of $I_{CBCT} \rightarrow I_{CT}$

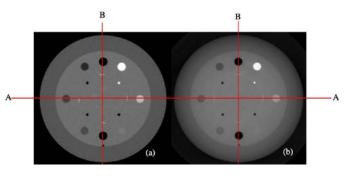
Yang, et al., PMB, 52, 2007, 685-705

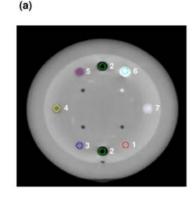
Contour/ROI

- CBCT (many studies)
 A. Richter, et al., Rad Onc, 3, 2008
 Hu, et al., Rad Onc, 5, 2010
- MR (many studies)

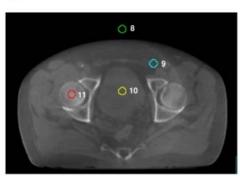
Korhonen, et al., Med Phys, 41(1), 2014





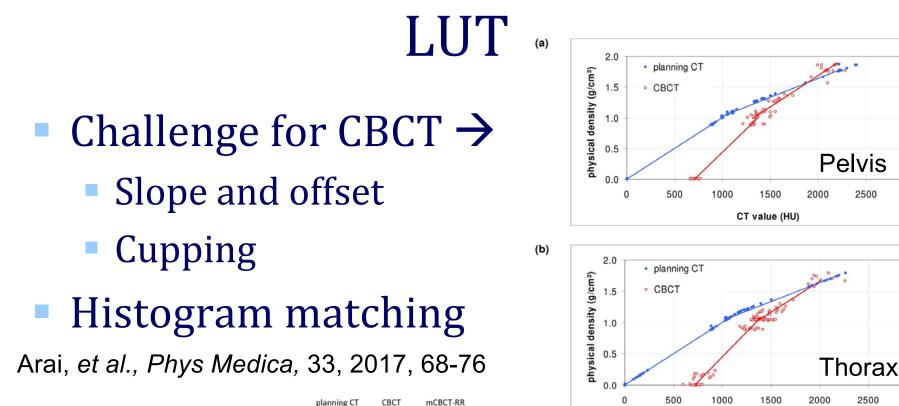


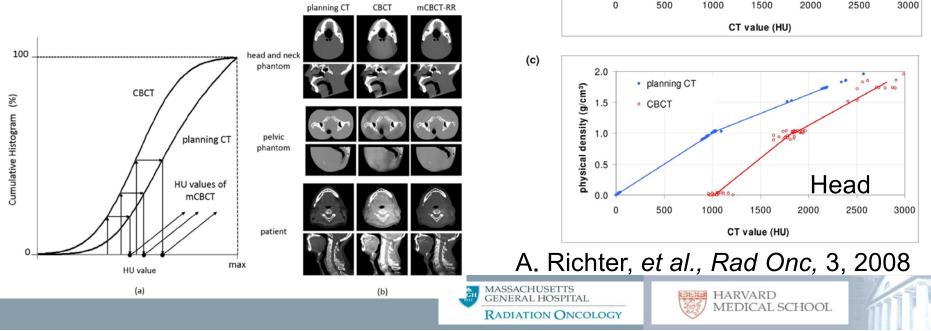
(b)



HARVARD MEDICAL SCHOOL







Deform CT

Originally proposed for photon therapy

Zhen, et al. PMB, 57(21), (2012), 6807.



Investigated for Proton Therapy

Landry, *et al. Med Phys*, 42(3), (2015), 1354-1366. Landry, *et al. PMB*, 60(2), 2015, 595-613.

- Various Additional Corrections:
 - CBCT Intensity
 - Air Cavity and Patient Contour

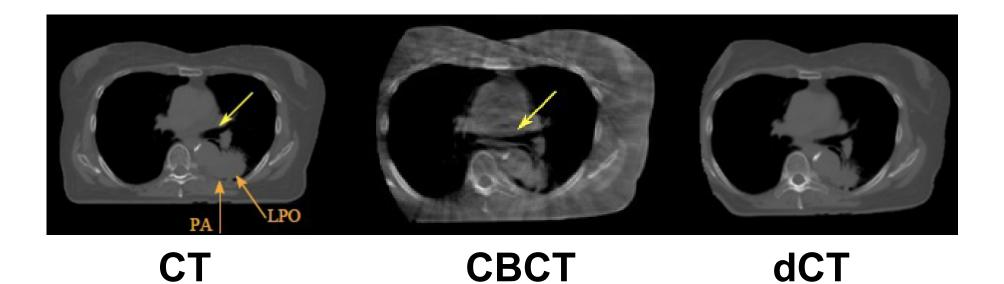






Deform CT

Clinical Data from Penn



Veiga et. al., IJROBP, 95(1) 2016, 549-559.







Correction Methods

Deform CT

 Challenges when anatomy changes too much, especially with air cavities



CT



MASSACHUSETTS

GENERAL HOSPITAL

RADIATION ONCOLOGY

dCT

Veiga et. al., IJROBP, 95(1) 2016, 549-559.





A priori Method

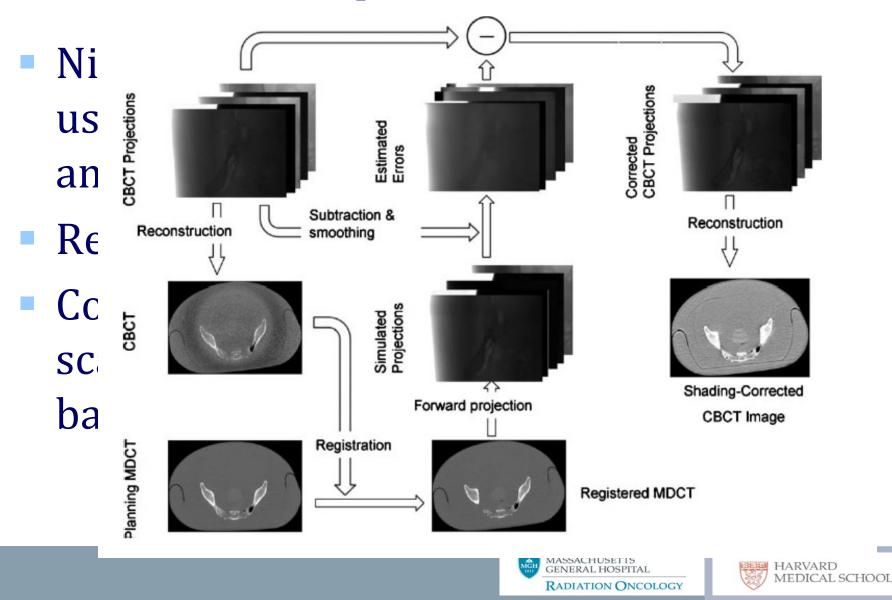
- Niu et al (Med Phys 2010) using *a priori* CT information and scatter kernel
- Reconstructions with RTK
- Compared to a uniform scatter correction model and baseline CBCT







A priori Method

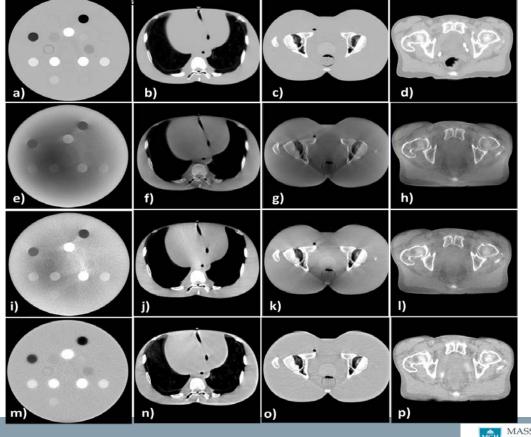


a priori Method

Proton dose calculation on scatter-corrected CBCT image: Feasibility study for adaptive proton therapy

Yang-Kyun Park,^{a)} Gregory C. Sharp, Justin Phillips, and Brian A. Winey Department of Radiation Oncology, Massachusetts General Hospital and Harvard Medical School, Boston, Massachusetts 02114

(Received 21 March 2015; revised 16 June 2015; accepted for publication 17 June 2015;



plan CT

CBCT: Simple FDK

Uniform Corr (~Elekta/Varian Gen 1)

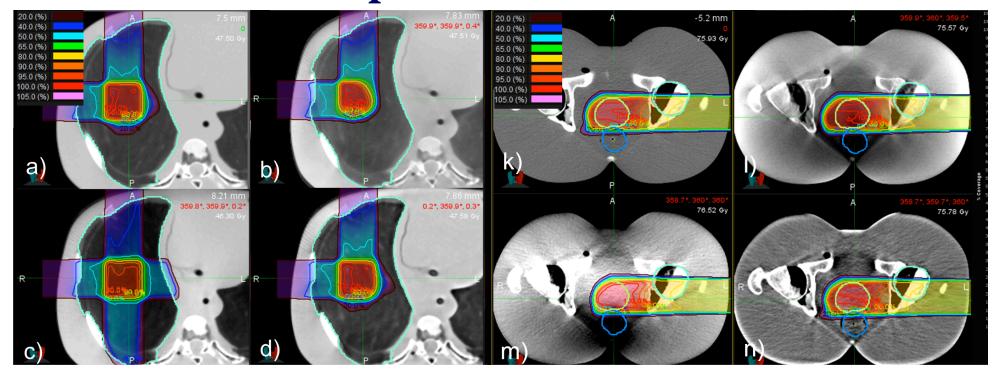
HARVARD

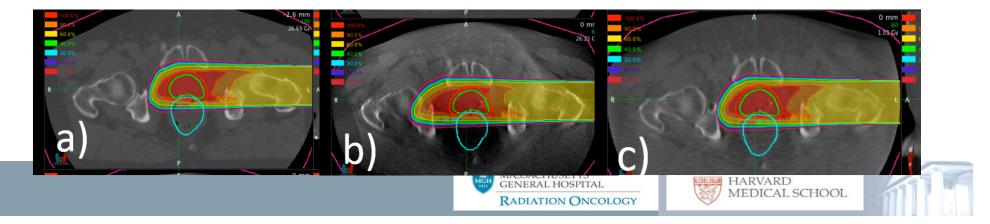
MEDICAL SCHOOL

a priori Corr



Dose Comparison: Phantoms





Investigating deformable image registration and scatter correction for CBCT-based dose calculation in adaptive IMPT

Christopher Kurz^{a)} Department of Radiation Oncology, LMU Munich, Munich 81377, Germany and Department of Medical Physics, Ludwig-Maximilians-Universität München, Garching bei München 85748, Germany

Florian Kamp Department of Radiation Oncology, LMU Munich, Munich 81377, Germany

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Christoph Zöllner Department of Medical Physics, Ludwig-Maximilians-Universität München, Garching bei München 85748, Germany

Simon Rit Université de Lyon, CREATIS, CNRS UMR5220m Inserm U1044, INSA-Lyon, Université Lyon 1, Lyon F69373, France David Hansen Department of Oncology, Aarhus University Hospital, Aarhus 8000, Denmark

Mark Podesta Department of Radiation Oncology (MAASTRO), GROW-School for Oncology and Developmental Biology, Maastricht University Medical Centre, Maastricht 6229 ET, The Netherlands

Gregory C. Sharp Department of Radiation Oncology, Massachusetts General Hospital and Harvard Medical School, Boston, Massachusetts 02114

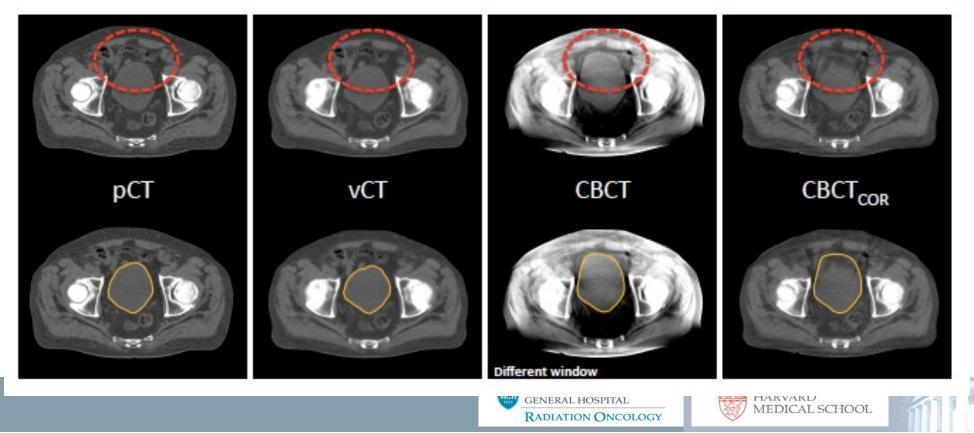
Minglun Li, Michael Reiner, Jan Hofmaier, Sebastian Neppl, Christian Thieke, Reinoud Nijhuis, Ute Ganswindt, and Claus Belka Department of Radiation Oncology, LMU Munich, Munich 81377, Germany

Brian A. Winey Department of Radiation Oncology, Massachusetts General Hospital and Harvard Medical School, Boston, Massachusetts 02114

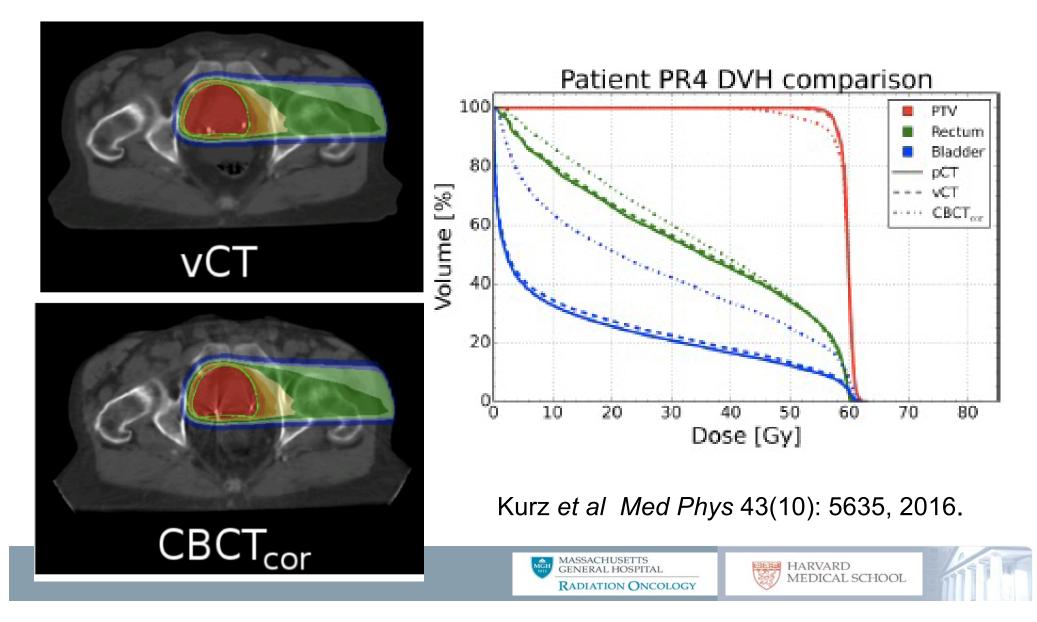
Katia Parodi and Guillaume Landry Department of Medical Physics, Ludwig-Maximilians-Universität München, Garching bei München 85748, Germany

(Received 12 April 2016; revised 30 August 2016; accepted for publication 5 September 2016; published 23 September 2016)

Deform versus a priori (LMU and MGH)



Patient Dose Calculations



A Priori Method

- Limitation was time
- Generally found to have HU accuracy and WEPL accuracy within 2-3 mm.
- Beam hardening still needs addressed
- Faster: Machine Learning or Patient Specific Scatter Kernel

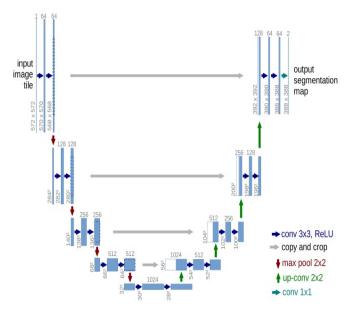


Fig. 1. U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations.







Machine Learning

- Use of ML to generate relationship between Image/Data A and Image/Data B.
- Examples:
 - MR to CT
 - CT with Artifacts to CT without
 - MR Sequence 1 to MR Sequence 2







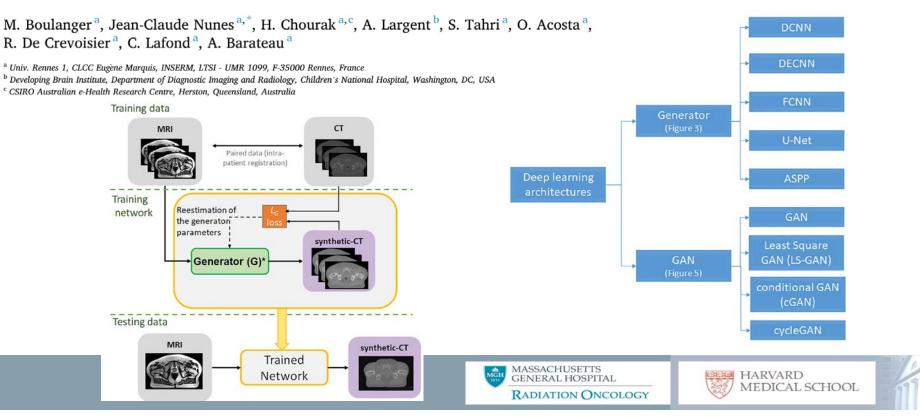
ML for MR to CT

Check for

Physica Medica 89 (2021) 265-281



Deep learning methods to generate synthetic CT from MRI in radiotherapy: A literature review



ML for MR to CT (Protons)

International Journal of Radiation Oncology biology • physics

www.redjournal.org

Physics Contribution

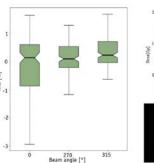
Deep Convolution Neural Network (DCNN) Multiplane Approach to Synthetic CT Generation From MR images—Application in Brain Proton Therapy

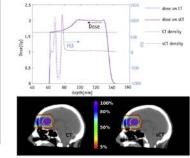
Maria Francesca Spadea, PhD,* Giampaolo Pileggi, PhD,*,[†] Paolo Zaffino, PhD,* Patrick Salome, MSc,[†] Ciprian Catana, PhD,[‡] David Izquierdo-Garcia, PhD,[‡] Francesco Amato, PhD,[§] and Joao Seco, PhD^{†,||}

*Department of Experimental and Clinical Medicine, Magna Graecia University of Catanzaro, Catanzaro, Italy; [®]Biomedical Physics in Radiation Oncology, DKFZ—Deutsches Krebsforschungszentrum, Heidelberg, Germany; [®]Department of Radiology, Athinoula A. Martinos Center for Biomedical Imaging, Charlestown, Massachusetts; [®]Dipartimento di Ingegneria Elettrica e delle Tecnologie dell'Informazione, Università degli Studi di Napoli Federico II, Naples, Italy; and [®]Department of Physics and Astronomy, Heidelberg University, Germany

Received Nov 28, 2018. Accepted for publication Jun 21, 2019.

Table 1 Air, soft ti	issues, fat, and bone HU, MA	AE, ME, and DSC compar	ison between CT and	sCT (mean \pm stand	dard deviation)
Tissue	Mean HU on CT	Mean HU on sCT	MAE (HU)	ME (HU)	DSC
Air (HU <-800)	-940 ± 14	-928 ± 18	53 ± 32	-37 ± 39	0.92 ± 0.03
FAT	-73 ± 3	-49 ± 13	44 ± 8	-4 ± 5	—
CSF	24 ± 2	28 ± 5	10 ± 3	0 ± 9	_
WM	37 ± 3	37 ± 3	6 ± 2	0 ± 4	_
GM	48 ± 4	48 ± 2	8 ± 2	0 ± 6	—
Bone (HU >200)	769 ± 71	767 ± 33	119 ± 17	20 ± 52	0.93 ± 0.02





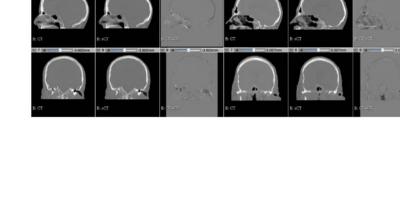
Worst case

sCT

CT-sCT

CT

Abbreviations: CT = computed tomography; DSC = Dice similarity coefficient; HU = Hounsfield units; MAE = mean absolute error; ME = mean error; sCT = synthetic computed tomography.



CT-sCT

Best case

sCT

CT







ML for CBCT to CT

ScatterNet: A convolutional neural network for cone-beam CT intensity correction

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Guillaume Landry Department of Medical Physics, Faculty of Physics, Ludwig-Maximilians-Universität München (LMU Munich), Garching bei München 85748, Germany

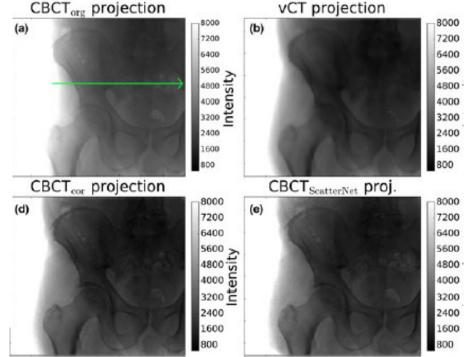
Florian Kamp and Minglun Li Department of Radiation Oncology, University Hospital, LMU Munich, Munich 81377, Germany

Claus Belka Department of Radiation Oncology, University Hospital, LMU Munich, Munich 81377, Germany German Cancer Consortium (DKTK), Munich, Germany

Katia Parodi Department of Medical Physics, Faculty of Physics, Ludwig-Maximilians-Universität München (LMU Munich), Garching bei München 85748, Germany

Christopher Kurz^{a)} Department of Medical Physics, Faculty of Physics, Ludwig-Maximilians-Universität München (LMU Munich), Garching bei München 85748, Germany Department of Radiation Oncology, University Hospital, LMU Munich, Munich 81377, Germany

(Received 1 May 2018; revised 5 July 2018; accepted for publication 29 August 2018; published 8 October 2018)



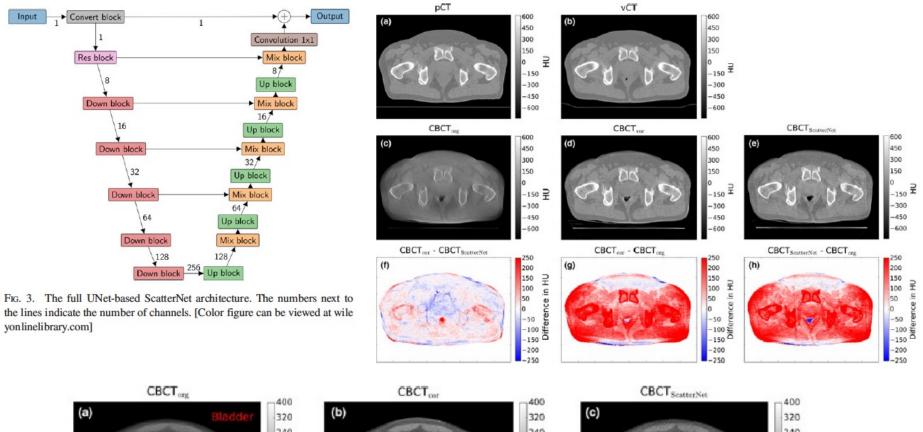
*Highlighting few of many publications. Many groups have published ML algorithms for CBCT correction, in both the projection and reconstruction domains

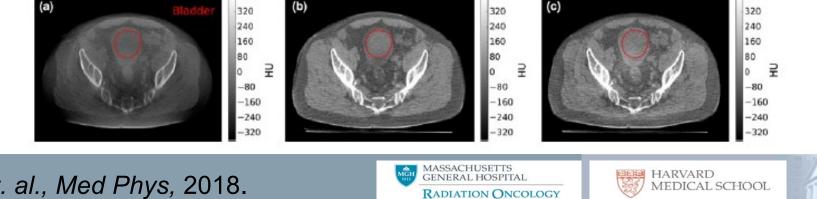
Hansen et. al., Med Phys, 2018.











Hansen et. al., Med Phys, 2018.

Dose CBCT_{coc} VMAT Dose CBCT_{ScatterNet} VMAT Dose difference VMAT 2.0 (b) (C) (a) 70 1.6 1.2 70 orNet [96] 60 60 0.8 50 [K9] asoq 50 6 0.4 0.0 -0.4 0.0 -0.4 CBC1 South 0.4 0.0 40 OG 30 30 -1.2 to -1.6 to 20 20 -2.0 Dose CBCT_{oor} IMPT Dose CBCT_{ScatterNet} IMPT Dose difference IMPT 2.0 -CBCT SouterNet [%] (e) (d) 70 70 (f) 1.6 1.2 60 60 0.8 50 [GV] 50 5 0.4 0.0 40 OG -0.8 8 30 30 -1.2 5 -1.6 8 20 20 -2.0 Dose CBCT_{ScatterNet} G90 Dose difference G90 Dose CBCT_{cor} G90 2.0 (g) (h) (i) 70 70 1.6 1.2 rNet [96] 60 60 0.8 [AS] asod 50 [K5] asoq 0.4 0.0 0.0 DBC 8.0-'n 30 50 -1.2 bg -1.6 D 20 20 -2.0

Hansen et. al., Med Phys, 2018.

MASSACHUSETTS GENERAL HOSPITAL RADIATION ONCOLOGY

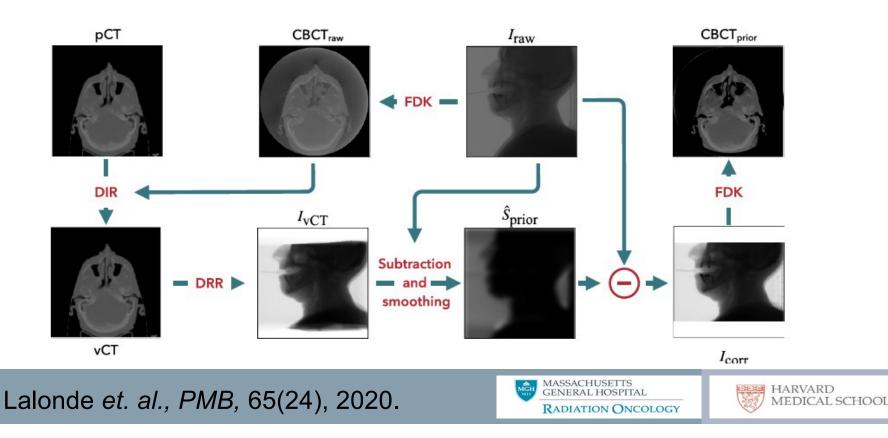




Evaluation of CBCT scatter correction using deep convolutional neural networks for head and neck adaptive proton therapy

Arthur Lalonde^(D), Brian Winey, Joost Verburg, Harald Paganetti and Gregory C Sharp Department of Radiation Oncology, Massachusetts General Hospital and Harvard Medical School, Boston, MA, United States of America

E-mail: alalonde@mgh.harvard.edu



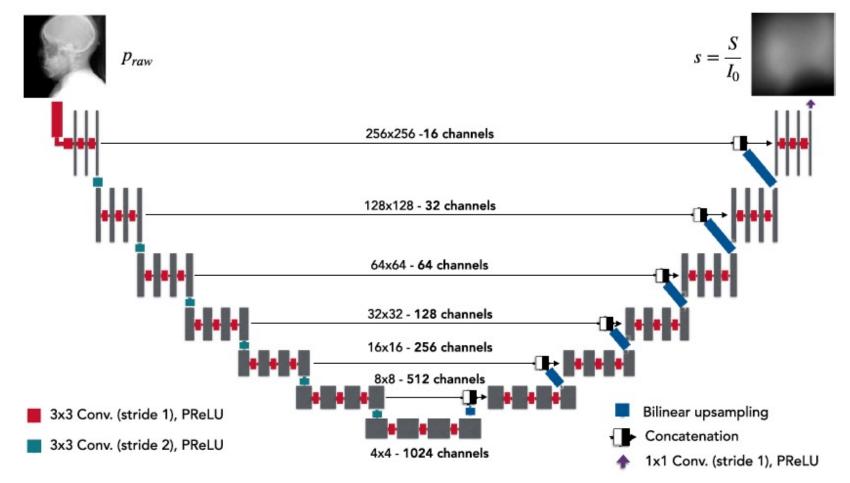


Figure 2. Deep convolutional neural network architecture used in this study.

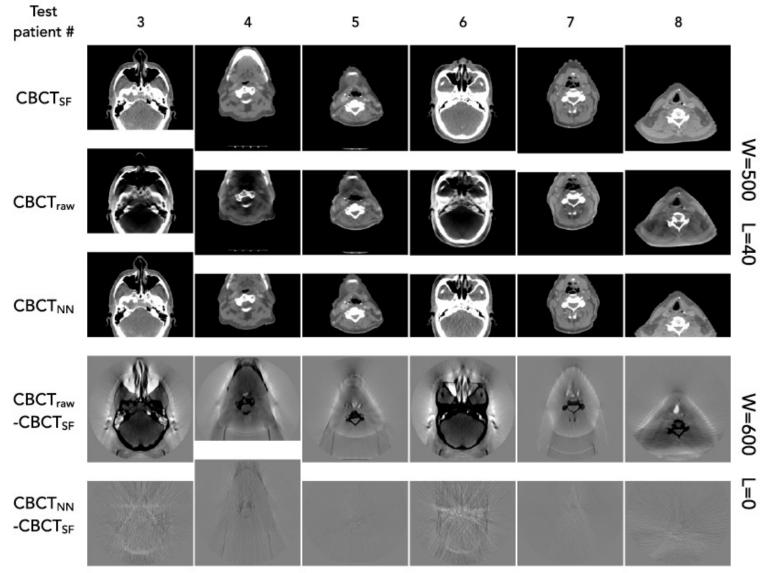
Uses the CNN to generate the scatter estimate in the projection space instead of the reconstruction domain.

Lalonde et. al., PMB, 65(24), 2020.







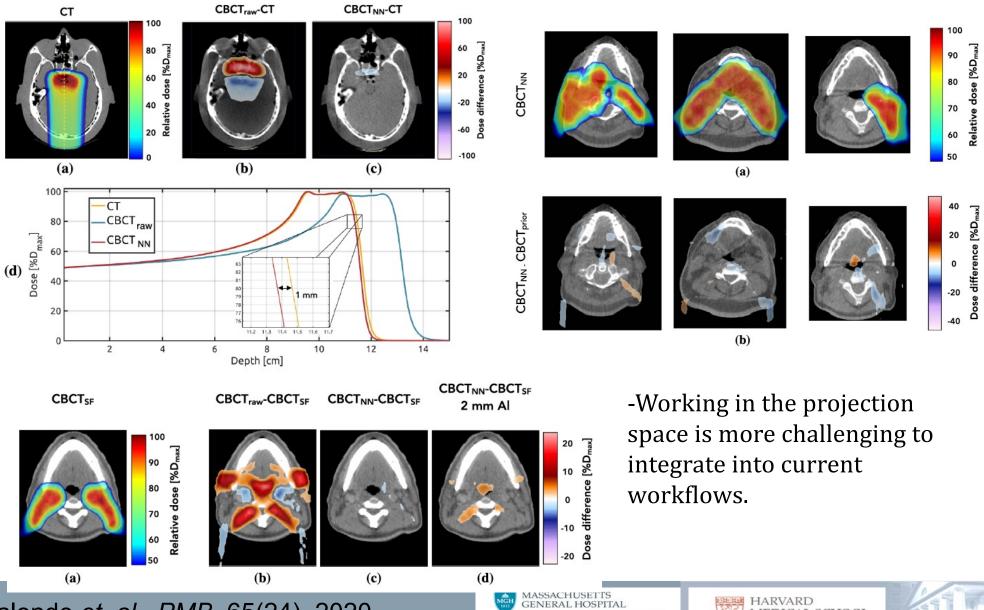


Lalonde et. al., PMB, 65(24), 2020.

MASSACHUSETTS GENERAL HOSPITAL RADIATION ONCOLOGY







RADIATION ONCOLOGY

Lalonde et. al., PMB, 65(24), 2020.

C N / MEDICAL SCHOOL



Comparisons

Phys. Med. Biol. 65 (2020) 095002

https://doi.org/10.1088/1361-6560/ab7d54

Institute of Physics and Engineering in Medicine



PAPER

Comparison of CBCT based synthetic CT methods suitable for proton dose calculations in adaptive proton therapy

Adrian Thummerer^{1,7}, Paolo Zaffino², Arturs Meijers¹, Gabriel Guterres Marmitt¹, Joao Seco^{3,4}, Roel J H M Steenbakkers¹, Johannes A Langendijk¹, Stefan Both¹, Maria F Spadea^{2,6} and Antje C Knopf^{1,5,6}

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⁵ Division for Medical Radiation Physics, Carl von Ossietzky Universität Oldenburg, Oldenburg, Germany

E-mail: a.thummerer@umcg.nl

Method	Literature	Anatomical site	Suitability for proton dose calculation
LUT based correction	Kurz et al 2015	Head and neck	_
Histogram matching	Arai <i>et al</i> 2017	Phantoms, head and neck	_
DIR	Veiga <i>et al</i> 2015, 2016, 2017, Kurz <i>et al</i> 2015, 2016a, Landry <i>et al</i> 2015b	Lung, head and neck, pelvis	++ (H&N), + (pelvis), + (lung)
Projection-based correction	Park <i>et al</i> 2015, Kurz <i>et al</i> 2016a	Head and neck, pelvis	++
Deep convolutional neural network	Hansen <i>et al</i> 2018, Landry <i>et al</i> 2019	Pelvis	+

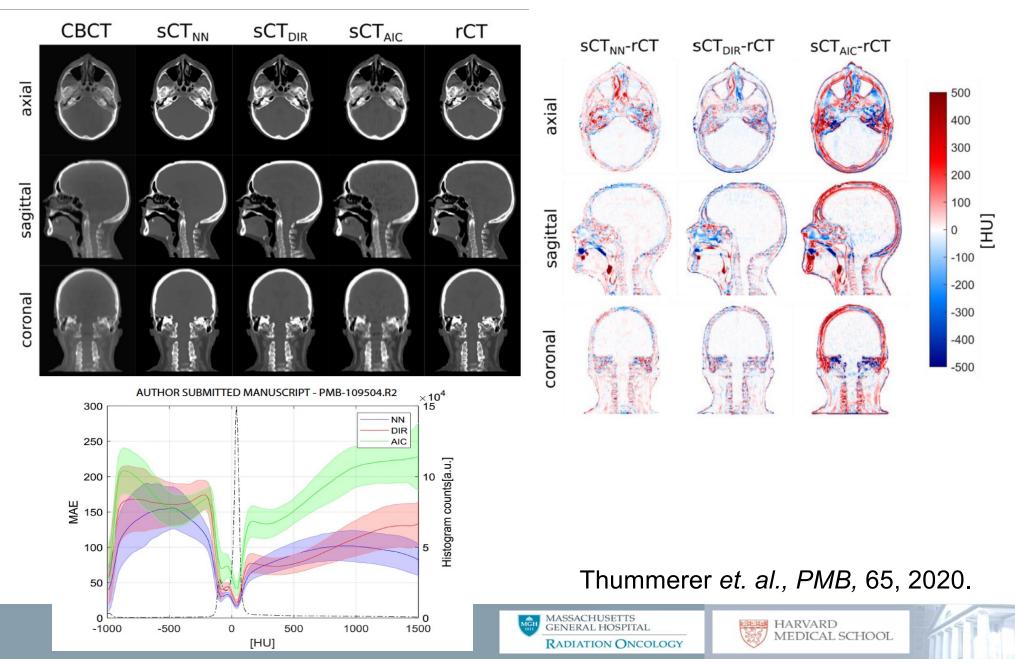
Thummerer et. al., PMB, 65, 2020.

MASSACHUSETTS GENERAL HOSPITAL RADIATION ONCOLOGY

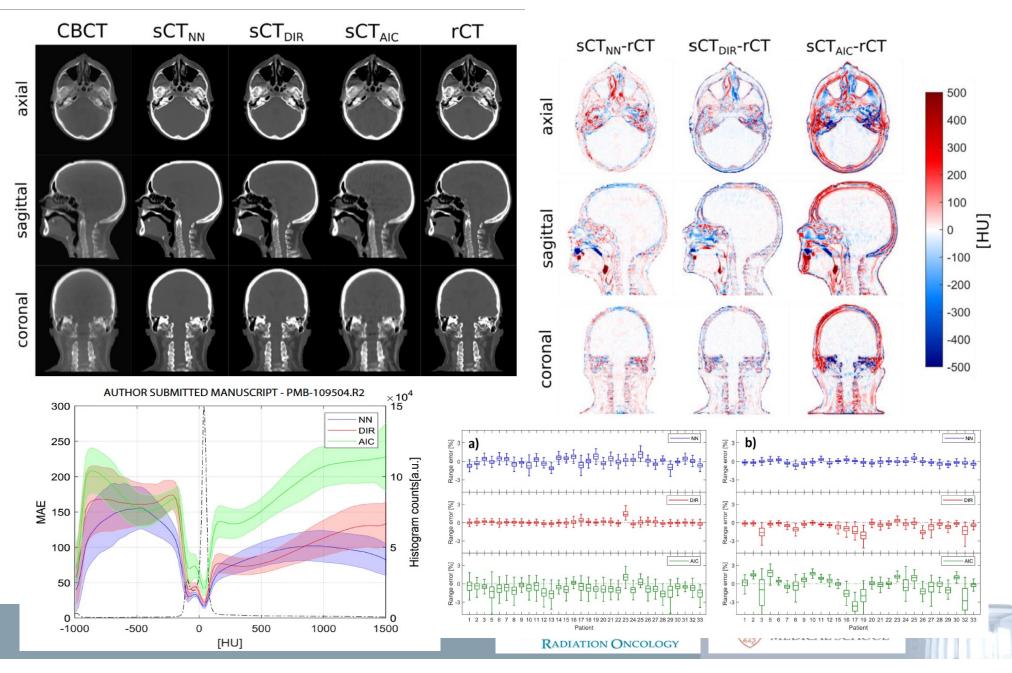




Comparisons



More Comparisons



QA of Corrected CBCT

Received: 18 February 2021 Revised: 28 May 2021 Accepted: 28 May 2021

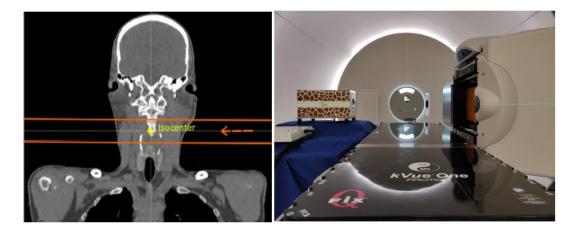
DOI: 10.1002/mp.15020

RESEARCH ARTICLE

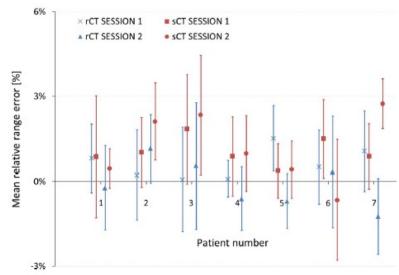
MEDICAL PHYSICS

Range probing as a quality control tool for CBCT-based synthetic CTs: In vivo application for head and neck cancer patients

Carmen Seller Oria | Adrian Thummerer | Jeffrey Free | Johannes A. Langendijk | Stefan Both | Antje C. Knopf | Arturs Meijers



1%	1%	1%	1%	1%	1%	1%	1%	0%	0%	5 -1%		0%	0%		1%	2%	29
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1%	0%	1%	1%		1%	0%	0%	4%	0%	6 0%				1%	1%	2%	3%
2%	-3%	-2%	0%	2%	1%	0%	-1%	1%	0%	5 0%	0%	1%	1%	2%	2%	2%	2%
%	0%	-3%	-3%	1%	2%	2%	1%	-1%	1%	2%	1%	2%	2%		3%	2%	2%
2%	2%	0%	-4%	-4%	-1%	3%	2%	1%	0%	5 1%	2%	2%	2%	3%	4%	3%	3%
1%	3%	3%	1%	-5%	-5%	0%	3%	3%	1%	5 1%	2%	3%	3%	4%	4%		4%
2%	2%	2%	2%	0%	-5%	-5%	1%	3%	4%	2%	1%	4%	4%	4%	5%	5%	5%









QA of Corrected CBCT

 $\Delta R_{\rm gel}$

 $\Delta R_{\rm sim}$

----- ΔR_{film}

 $-\Delta R_{\rm rec}$

80

80

80

Measurement-based range evaluation for guality assurance of CBCT-based dose calculations in adaptive proton therapy

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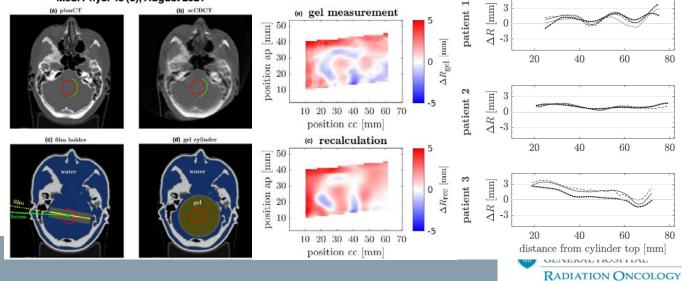
Katia Parodi

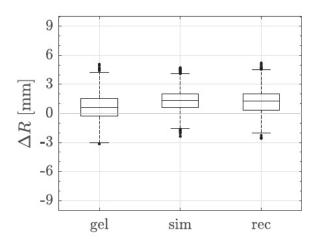
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Med. Phys. 48 (8), August 2021





5. CONCLUSIONS

A novel measurement-based evaluation of a scatter corrected CBCT workflow for online adaptive proton radiation therapy was introduced. The evaluation of CBCT image data for proton planning using gel dosimetry showed that the observed range differences agreed well with the expected values from TPS recalculations and optimizations. It is thus an interesting candidate for measurement-based quality assurance of online adaptive proton therapy. The evaluated CBCT correction method seems to be suitable for proton dose calculation. Film measurements provided an additional benchmark in dedicated slices and supported the results obtained with the gel measurements. 98.5% of the range differences observed with the gel measurement agreed with the simula*tion approach* within 2 mm. Further studies are needed to evaluate the measurement-based approach for more patients and preselected beam directions. A development of a 3D printed phantom for other body regions potentially including anatomical variations would make the method applicable for more treatment sites.

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Motion?







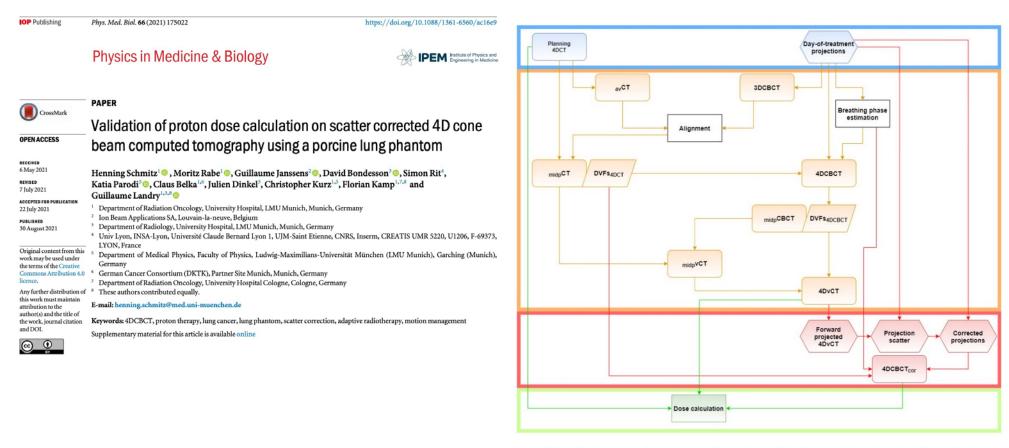


Figure 2. Sketch depicting the most important steps of the complete workflow from input (blue box), via 4DvCT (orange box) and 4DCBCT_{cor} (red box) to the final dose calculation (green box). Rounded rectangles show images, hexagons represent projections, rectangles stand for actions, and parallelograms for DVFs.





IOP Publishing	Phys. Med. Biol. 66 (2021) 175022	https://doi.org/10.1088/1361-6560/ac16e9	_	Ph0	Ph3
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OPEN ACCESS	Validation of proton dose calculation		5		
	beam computed tomography using a	porcine lung phantom	CBCT		
S May 2021	Henning Schmitz ¹ , Moritz Rabe ¹ , Guillaume Janssens ²		0	4	
IEVISED 7 July 2021 INCCEPTED FOR PUBLICATION	Katia Parodi ⁵ [©] , Claus Belka ^{1,6} , Julien Dinkel ³ , Christopher J Guillaume Landry ^{1,5,8} [©]	Kurz ^{1,2} , Florian Kamp ^{1,7,8} and			
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attribution to the author(s) and the title of the work, journal citation	E-mail: henning.schmitz@med.uni-muenchen.de Keywords: 4DCBCT, proton therapy, lung cancer, lung phantom, scatter cor	rection, adaptive radiotherapy, motion management	BC		
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Figure 4. Phase 0 (inhale), phase 3 and phase 6 (exhale) are shown with level = -300 and window = 1600 for 4DCT, 4DCBCT, 4DVCT and 4DCBCT_{cor}. Additionally, the differences 4DvCT-4DCT and 4DCBCT_{cor}-CT are displayed.



CBCT



Ph6



300 200 100

-100

-300

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(2019) 2:23

Visual Computing for Industry, Biomedicine, and Art

ORIGINAL ARTICLE

Advanced 4-dimensional cone-beam computed tomography reconstruction by combining motion estimation, motioncompensated reconstruction, biomechanical modeling and deep learning

You Zhang^{*}⁽⁰⁾, Xiaokun Huang and Jing Wang



Conventional 4D-CBCT and DVF-derivation scheme Phase grouped projections Image Reconstruction Image Reconstructio

4D-CBCT





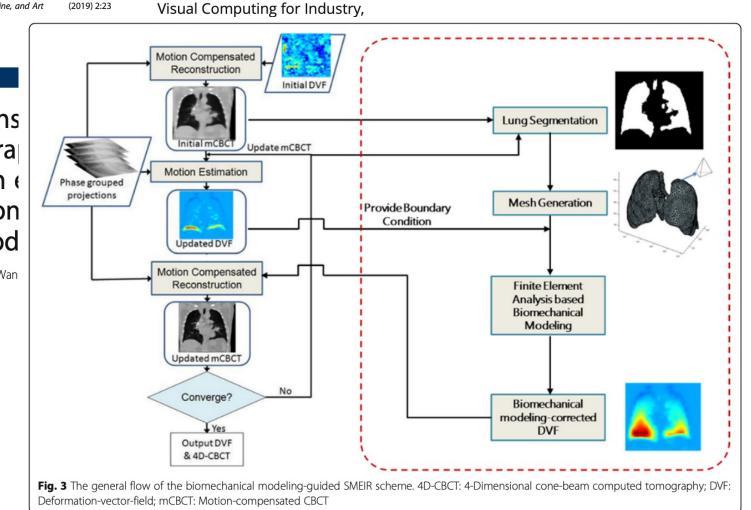


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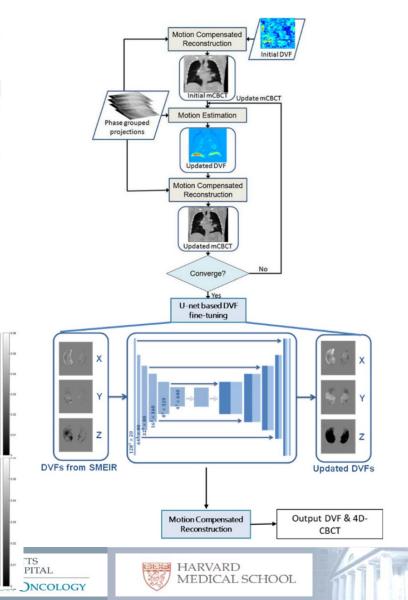
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