AAPM Grand Challenge: SPARE Sparse-view <u>Re</u>construction Challenge for 4D Cone-beam CT

<u>Chun-Chien Shieh</u> Xun Jia, Bin Li, Yesenia Gonzalez, Simon Rit, Paul Keall





AUSTRALIAN CANCER RESEARCH FOUNDATION

By the end of this talk

- Aim of the SPARE challenge
- How the challenge datasets were generated
- How image quality was quantified
- The top 4 performing teams
- Access to the full datasets



4D cone-beam CT



3D-CBCT

- 1 minute scan
- Motion blur



4D-CBCT

- 2-4 minutes
- Undersampling artifacts



4D-CBCT better predicts intrafraction motion range than **4DCT**

4D-CT

4D-CBCT



Steiner et al., WE-HI-KDBRB1-10, 1:45-3:45 pm

IMAGE X INSTITUTE

4DCBCT-based model for intrafraction motion monitoring

IOP Publishing | Institute of Physics and Engineering in Medicine

Physics in Medicine & Biology doi:10.1088/0031-9155/60/9/3807

Phys. Med. Biol. 60 (2015) 3807-3824

3D fluoroscopic image estimation using patient-specific 4DCBCT-based motion models

> S Dhou¹, M Hurwitz¹, P Mishra², W Cai¹, J Rottmann¹, R Li³, C Williams¹, M Wagar¹, R Berbeco¹, D Ionascu⁴ and J H Lewis¹

¹ Department of Radiation Oncology, Brigham and Women's Hospital, Dana-Farber Cancer Institute, and Harvard Medical School, Boston, MA, USA

² Varian Medical Systems, Palo Alto, CA, USA

³ Department of Radiation Oncology, Stanford University, Stanford, CA, USA

⁴ Department of Radiation Oncology, William Beaumont Hospital, Royal Oak, MI, USA

IOP Publishing | Institute of Physics and Engineering in Medicine

Physics in Medicine & Biology

Phys. Med. Biol. 62 (2017) 3065-3080

https://doi.org/10.1088/1361-6560/aa6393

A Bayesian approach for three-dimensional markerless tumor tracking using kV imaging during lung radiotherapy

Chun-Chien Shieh¹, Vincent Caillet^{1,2}, Michelle Dunbar¹, Paul J Keall¹, Jeremy T Booth^{2,3}, Nicholas Hardcastle^{2,4}, Carol Haddad², Thomas Eade^{1,2} and Ilana Feain¹

¹ Sydney Medical School, The University of Sydney, NSW 2006, Australia

² Northern Sydney Cancer Centre, Royal North Shore Hospital, NSW 2065, Australia

- ³ School of Physics, The University of Sydney, NSW 2006, Australia
- ⁴ Centre for Medical Radiation Physics, University of Wollongong, NSW 2522, Australia



High quality 4D-CBCT from a standard one-minute scan?

- Shorter scan time
- Lower dose
- High quality 4D-CBCT on every system

Standard 3D reconstruction



Conventional 4D reconstruction





Algorithms for reconstructing undersampled 4D-CBCT data





Algorithms for reconstructing undersampled 4D-CBCT data

- Iterative
 - Total-variation
 - PICCS
- Motion compensation
 - Projection space
 - Image space
- Prior deformed
- Hybrid

Image reconstruction in circular cone-beam computed tomography by constrained, total-variation minimization

Emil Y Sidky and Xiaochuan Pan

High temporal resolution and streak-free four-dimensional cone-beam computed tomography

> Shuai Leng¹, Jie Tang¹, Joseph Zambelli¹, Brian Nett¹, Ranjini Tolakanahalli³ and Guang-Hong Chen^{1,2,3,4}

On-the-fly motion-compensated cone-beam CT using an *a priori* model of the respiratory motion

Simon Rit, Jochem W. H. Wolthaus, Marcel van Herk, and Jan-Jakob Sonke^{a)} Department of Radiation Oncology, The Netherlands Cancer Institute-Antoni van Leeuwenhoek Hospital, Plesmanlaan 121, 1066 CX Amsterdam, The Netherlands

A novel digital tomosynthesis (DTS) reconstruction method using a deformation field map

Lei Ren^{a)}

Simultaneous motion estimation and image reconstruction (SMEIR) for 4D cone-beam CT

Jing Wang^{a)} and Xuejun Gu Department of Radiation Oncology, The University of Texas Southwestern Medical Center, Dallas, Texas 75235-8808



SPARE Challenge

<u>Spa</u>rse-view <u>Re</u>construction Challenge for 4D Cone-beam CT



Spare scan time Spare dose



- To systematically investigate the efficacy of various algorithms for 4D-CBCT reconstruction from a one minute scan.
- Provide a common dataset for future 4D-CBCT reconstruction studies.



The challenges of hosting a 4D-CBCT challenge

- Ground truth
- Realistic images
 - Patient images
 - Poisson noise
 - Scatter

IMAGE × **INSTITUTE**



NCAT phantom



XCAT phantom

 Monte Carlo simulation of real patient CTs



Patient – no scatter



Patient – scatter

Data – source volumes for simulation



4D-Lung dataset

- 20 locally-advanced NSCLC patients
- Patients had multiple 4D-CTs
- Respiratory signal
- 12 patients had at least two 4D-CTs with acceptable quality
- 32 scans in total



Prof Geoff Hugo <u>gdhugo@wustl.edu</u>

https://wiki.cancerimagingarchive.net/display/Public/4D-Lung

Data – Monte Carlo simulation

A GPU Tool for Efficient, Accurate, and Realistic Simulation of Cone Beam CT Projections

Xun Jia¹, Hao Yan¹, Laura Cerviño¹, Michael Folkerts^{1,2}, and Steve B. Jiang¹





UTSouthwestern Medical Center



Respiratory signal

Monte Carlo simulation



Data – Monte Carlo Datasets



IMAGE × INSTITUTE

- Half-fan scan
- 680 projections over 360 degrees
- No scatter
 - 40 mA; 20 ms
 - Poisson noise
- With scatter
 - 40 mA; 20 ms
 - Poisson noise + scatter
- Low dose & with scatter
 - 20 mA; 20 ms
 - Poisson noise + scatter

Data - Clinical scans

Clinical Varian Dataset





Fully-sampled

Down-sampled

- CBCT scans from the 4D-Lung dataset
- 4 minutes, 2400 half-fan projections
- Down-sample to 680 projections
- Respiratory signal: RPM
- 5 patients. 30 scans.

IMAGE XINSTITUTE

Prof Geoff Hugo

Clinical Elekta Dataset





Down-sampled

- Regular 4D-CBCT on an Elekta Versa HD
- 3 minutes, 1000 full-fan projections
- Down-sample to 340 projections
- Respiratory signal: Amsterdam Shroud
- 5 patients. 20 scans.

Dr Simon Rit

Data - overview

Datasets

Monte Carlo

9 patients, 29 scans 3 training scans

Clinical Varian

5 patients, 25 scans 5 training scans

Clinical Elekta

5 patients, 15 scans 5 training scans IMAGE X INSTITUTE Provided to participants

For each patient

PTV contour

4D-CT

For each CBCT scan

CBCT projections

Respiratory signal

Blinded from participants

Ground truth/ Reference volumes

How the challenge was conducted

- 1. Registration (Dec 2017-15 Jan 2018)
- 2. Datasets and instructions sent to participants (31 Jan 2018)
- 3. The fun began!
- 4. Deadline: 30 April 2018
- 5. Analysis completed and summarized to the participants in May
- 6. Results sent to AAPM



Participant demographics

19 participating teams







Evaluation metrics

Image similarity

Structural similarity (SSIM)



Target localization accuracy

Alignment of PTV



Results

- 19 participating teams
- 4 teams completed the entire challenge
 - with really impressive results



Let's remind ourselves this is what can be achieved with conventional FDK reconstruction...



Top 4 performing methods – Monte Carlo case#1









Top 4 performing methods – Monte Carlo case#2









Top 4 performing methods – Monte Carlo case#3





Monte Carlo case#3 – Large CT-CBCT difference



CT



CBCT



Results – Structural similarity



Ground truth



Method #2



Method #3

Method #4

Structurally, Method#2 is closest to ground truths





Results – Target localization accuracy





Method #3

Method #4

2>3>1>4





Results – target localization accuracy



Results – scatter noise and imaging dose



IMAGE X **INSTITUTE**

Results – Clinical Varian Datasets







IMAGE × **INSTITUTE**

Results – top performing teams



Simon Rit (CREATIS)



Cyril Mory (CREATIS)



Matthew Riblett (VCU) Geoffrey Hugo (Washington University)



Yawei Zhang Zhuoran Jiang Xiaoning Liu Lei Ren (Duke University)

Prior deformed

4DCT-based motion-compensation

Method #1

Motion-aware temporal regularization (MA-ROOSTER)

Data-driven motion-compensation

Method #2

Method #3





Results – top performing teams



- Good quality and accuracy
- Residual blur
- Clinically used

4DCT-based motion-compensation



- Best overall quality and accuracy
- Occasional minor artifacts

Motion-aware temporal regularization (MA-ROOSTER)



- Data driven
- Good accuracy
- Motion can be "visually" unnatural

Data-driven motion-compensation



- Best visual quality and details
- "CT-like"
- Sensitive to CT-CBCT difference

Prior deformed









MA-ROOSTER vs MC-PICCS

Ground truth



MA-ROOSTER



MC-PICCS



MA-ROOSTER vs MC-PICCS

Ground truth



MA-ROOSTER



MC-PICCS



MA-ROOSTER vs MC-PICCS





Room for improvements

- Noise and artifacts in the ground truth volumes
- Lack of beam information for projection calibration and scatter correction
- CT-CBCT alignment was not provided
- Better ways to under-sample the clinical datasets

Ahmad 2012 Med Phys





Access to the full dataset

- All the data provided to the participants
- All the ground truth & reference reconstructions
- MATLAB scripts to automatically compute evaluation metrics
- A common dataset for future 4D-CBCT reconstruction studies
- Available from Aug-Sep 2018

IMAGE X INSTITUTE

EANCER IMAGING ARCHIVE

- AAPM
- ACRF Image X Website
 - http://sydney.edu.au/medicine/image-x/
- Contact Dr Andy Shieh <u>andy.shieh@sydney.edu.au</u>

Summary

- Accurate and high quality 4D-CBCT from a one-minute scan is challenging, but possible
- The use of motion model is critical
- Each method has its own advantages
- Overall, the combination of motion compensation and iterative regularization gives the best results
- The SPARE Challenge datasets will be publicly available for future studies





