AAPM 2017 JUL 30–AUG 3
CONNECTING OUR PATHWAYS. UNIFYING OUR PROFESSION.
59TH ANNUAL MEETING & EXHIBITION | DENVER, CO

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Fast Dynamic MRI for Radiotherapy

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Disclosures

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- I receive research grants from Varian Medical Systems
- I am a co-founder of Celestial Medical Inc.

Disclaimer

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- A "*sparse*" sampling of the enormously broad topic.
- Not all relevant works are included.

Outline

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- RT applications of dynamic MRI
- Basics of fast MRI
- Recent advances in accelerated MRI acquisitions

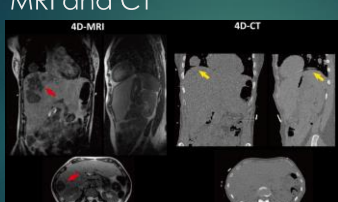
Temporally resolved CT and MR images

5

Internal organ motion is of tremendous interest to radiation therapy

Comparison of temporally-resolved MRI and CT

6



1. MR has superior soft tissue contrast
2. CT native slice orientation is limited to axial but MRI can have arbitrary slice orientation (2D dynamic MRI is more versatile than 2D CT)
3. MR does not use harmful ionizing radiation
4. MR has low lung tissue signal
5. CT has superior spatial integrity and can be directly used for treatment planning
6. Both are incapable of providing real time 3D dynamic images (more later)

First dynamic MRI for radiation therapy

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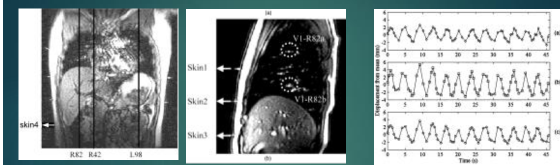


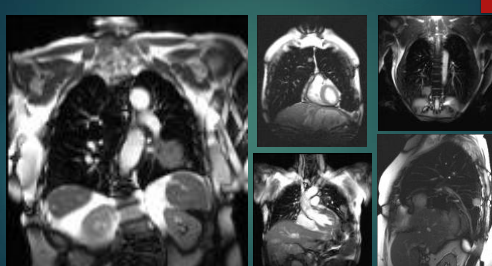
Fast gradient echo dynamic MRI on GE 1.5 T

Dynamic MRI allows simultaneous monitoring of internal anatomical landmarks and external surrogates

Koch and Liu, Int J Radiat Oncol Biol Phys. 2004 Dec 1;60(5)

Patient specific internal anatomy motion quantification

8



Modern MRI sequences using bSSFP achieves 5-10 f/s for 2D imaging

Gated Radiotherapy with MRgRT (Inspiratory breath hold)

Without coaching

With coaching

bSSFP sequence

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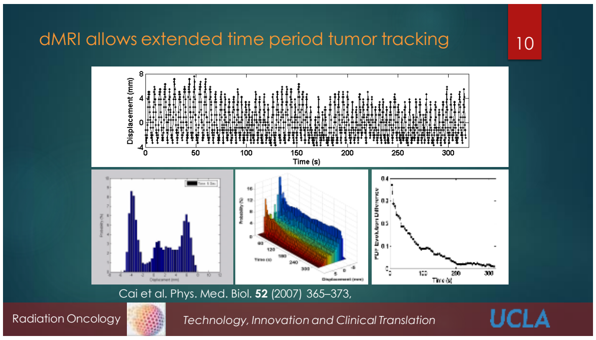
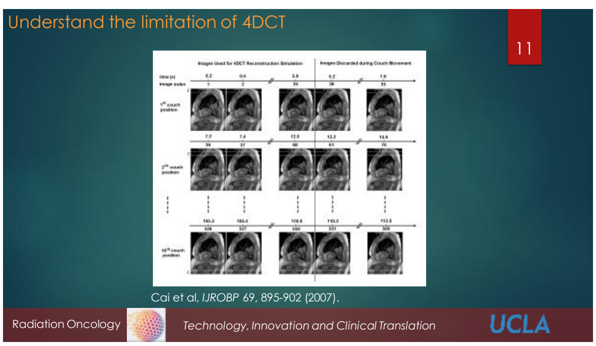

dMRI allows extended time period tumor tracking
10
Displacement (mm)
Time (s)
Cai et al. Phys. Med. Biol. 52 (2007) 365–373.
Radiation Oncology
Technology, Innovation and Clinical Translation
UCLA


Understand the limitation of 4DCT
11
Cai et al, IJROBP 69, 895-902 (2007).
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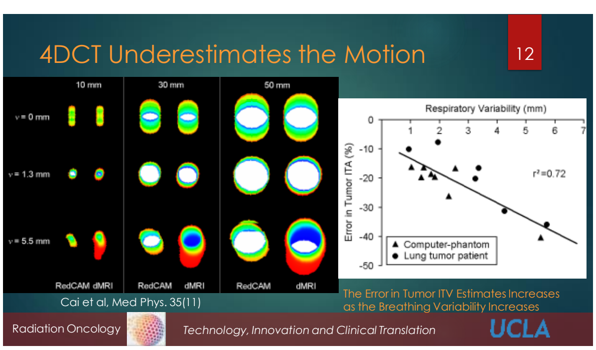
4DCT Underestimates the Motion
12
10 mm
30 mm
50 mm
RedCAM dMRI
RedCAM dMRI
RedCAM dMRI
Respiratory Variability (mm)
Error in Tumor ITA (%)
r²=0.72
Computer-phantom
Lung tumor patient
Cai et al, Med Phys, 35(11)
The Error in Tumor ITV Estimates Increases as the Breathing Variability Increases
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PDF based treatment planning

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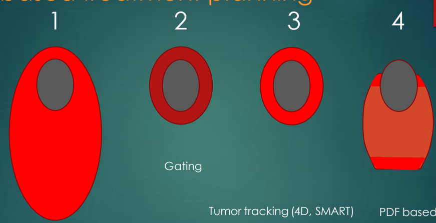

- Sheng et al. Med Phys. 33(9): 3321–3326, Trofimov et al. Med Phys. 2008 May; 35(5): 1718–1733. Sheng et al. Med. Phys., vol. 38(6), p. 3769, Watkins et al. Med Phys. 2014 Nov;41(11):111705,

Feasibility of treating PTV based on the minimal intensity projection (min-IP)

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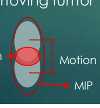
- Biologically, treating a small volume of lung to a higher dose is generally superior to treat a larger volume of lung to a lower dose.
- Utilizing the statistically stable PDF
- Min-IP is the smallest volume that can cover a moving tumor

MIP based planning

Min-IP based planning



Sheng et al, Med Phys 38 (6)

Planning practice for 10 patients

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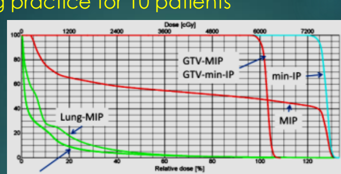

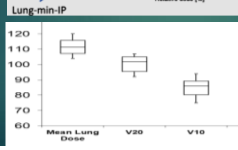

- Dosimetry of the min-IP based treatment planning as a percentage of gated radiotherapy
- Deformable registration of the lung was performed using Elastix
- Shows the feasibility of treating a smaller volume than the GTV

Limitations of 2D dynamic MRI

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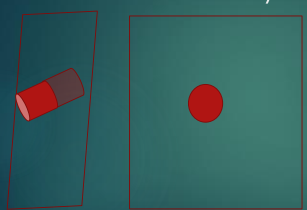

- Cannot differentiate in-plane motion from through-plane motion
- Latency in multi-slice acquisition
- Thick slices
- Non-bSSFP sequences (e.g. HASTE) have preferred contrast in certain anatomies (e.g. T2 contrast) but generally slower or lower in SNR

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Interleaved orthogonal 2D dynamic MRI

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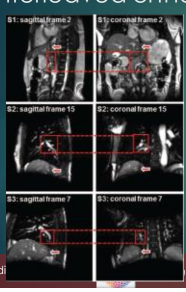

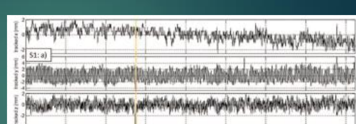

Near-simultaneous tracking of x,y,x movements of an internal object

Tryggestad et al. [Med. Phys. 2013; 40 (9): 091712]

Radi... ...ology, Innovation and Clinical Translation UCLA

Need for higher dimensional dynamic MRI

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Complex organs and targets such as the abdominal anatomies cannot be adequately localized even with orthogonal 2D dynamic MRI

Wampole et al. PLoS ONE 8(9):e75237

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4D-MRI from phase or amplitude rebinning

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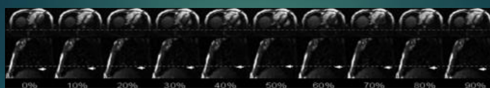

- Cai et al, Med. Phys. 38 (12)
- Tryggestad E. et al. Med. Phys. 2013; 40 (5): 051909
- Hu et al. IJROBP 2013; 86 (1): 198

- Volumetric images
- Not real-time
- Stiching artifacts
- Poor resolution in the slice direction

- Respiratory resolved 3D k-space encoding

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4DMRI with k-space rebinning

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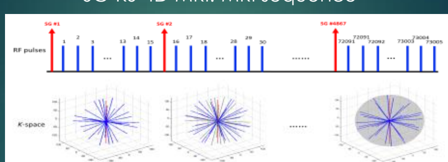
SG-KS-4D-MRI: MRI sequence



- Self-gating (SG) k-space lines collected in the superior-inferior (SI) direction at every 15 radial projection intervals
- Temporal interval of ~98ms between each SG lines
- 3D *k*-space trajectory via radial 2D golden means ordering

Deng Z et. al Magn Reson Med. 2015 May 14.

Results: Tumor motion visualization (SG-KS-4D-MRI)

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IV-contrast free SG-KS-4D-MRI shows useful pancreatic tumor tissue contrast and free of stitching artifacts despite the image noise.

Yang et al. Int J Radiat Oncol Biol Phys. 2015 Dec 1;93(5):1136-43.

ROtating Cartesian Kspace (ROCK)

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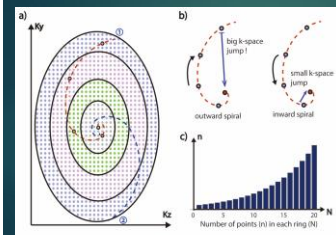

- Quasi-spiral arm rotated using segmented golden angle
- Repeatedly acquired k-space center-line for motion self-gating
- Optimal k-space sampling ordering for minimized eddy current artifact
- Efficient k-space sampling using variable density

Han et al. Med Phys. 2017 Apr;44(4):1359-1368

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ROCK 4D-MRI using low field MRI

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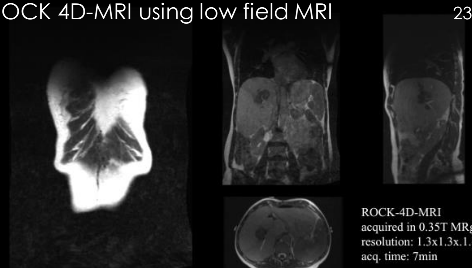

ROCK-4D-MRI
acquired in 0.35T MRgRT
resolution: 1.3x1.3x.1.8mm^3
acq. time: 7min

More on 4DMRI development

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Multi-Modality 4D Imaging: From Principles to Applications

G Hugo[1*], D Low[2*], L Ren[3*], W Yang[4*], (1) Virginia Commonwealth University, Richmond, VA, (2) UCLA, Los Angeles, AA, (3) Duke University Medical Center, Durham, NC, (4) Cedars-Sinai Medical Center, Los Angeles, CA

Presentations

7:30 AM : ***Clinical impact and applications of 4D imaging*** - G Hugo, Presenting Author
8:00 AM : ***Respiration-Correlated CT/PET: Principles, Advancements and Clinical Applications*** - D Low, Presenting Author
8:30 AM : ***4D Cone-beam CT: Developments and Applications*** - L Ren, Presenting Author
9:00 AM : ***Development of 4D-MRI for Radiation Therapy*** - W Yang, Presenting Author

MO-AB-702-0 (Monday, July 31, 2017) 7:30 AM - 9:30 AM Room: 702


Time machine

4DMRI≠dynamic MRI (real time motion information)

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Paths to real time 3D dynamic MRI and segmentation

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Retrospective k-space rebinning 4D MRI (1.5 mm iso)

300 seconds acquisition time

50-75 X acceleration

Real time 3D dMRI

4-6 seconds breathing cycle

Remarkable acceleration has to happen.

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MR acquisition speed

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- MRI was very slow
- Much of the research and development efforts were put into improving the MRI acquisition speed.

Improve the MRI sequence and k space sampling strategies + Compressed sensing + Exploiting redundant information in the spatial-temporal domain

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Improving MRI acquisition time

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Spin Echo → Turbo Spin Echo (TSE)

Single-shot TSE

1. Squeeze in more k-space read out from one excitation

Echoplanar imaging → Half-Fourier Acquisition Single-shot Turbo spin Echo imaging (HASTE)

Gradient Echo → Fast Gradient Echo (FLASH) → Steady state free precision → Balanced steady state free precision (True-FISP)

2. Push for shorter repetition time (TR)

Parallel imaging → Image domain PI (SENSE), K-space PI (GRAPPA)

3. Exploit the multicoil hardware

Selection of MRI technique

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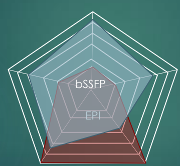
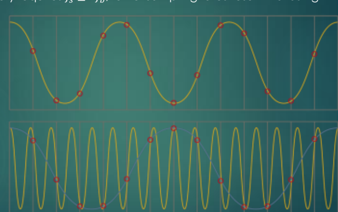


Classic sampling theorem: Nyquist's Rate

29

- Perfect recovery requires $f_s \geq 2f_b$, lower sampling rates result in aliasing artifacts.



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IEEE TRANSACTIONS ON INFORMATION THEORY, VOL. 52, NO. 4, APRIL 2006 1289

Compressed Sensing

David L. Donoho, *Member, IEEE*

Signal or image can still be recovered even if the sampling rate is lower than the Nyquist's rate, given that

1. The image has sparse representation in the transform domain (e.g. wavelet domain)
2. Incoherence between the sampling and sparsity domains to guarantee that the reconstruction problem has a unique solution (random sampling)

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Exact reconstruction using undersample k-space data

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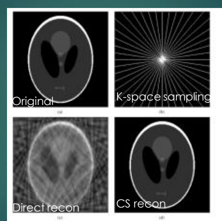

Shepp-Logan phantom was exactly recovered with only 16% of k-space samples

Candès, Romberg, and Tao IEEE TRANSACTIONS ON INFORMATION THEORY, 2006

The leap

32

	Traditional sensing	Compressive Sensing
Sampling Frequency	$\geq 2f_b$	$< 2f_b$
Recovery	Low pass filter	Convex or non-convex optimization

The optimization problem

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$$\min_u \|\Psi u\|_1 \;\; s.t. \|F_p u - d\|_2^2 < \sigma$$

Enforce sparsity Fidelity or data consistency term

- Since the optimization problem is under-determined due to the undersampling, a regularization term is used
- A popular option for the regularization term is total variation that enforces sparsity by encouraging tissue piecewise smoothness
- Compressed sensing is intricately related to parallel imaging and k space sampling trajectories

CS goes hand in hand with exotic sampling trajectories

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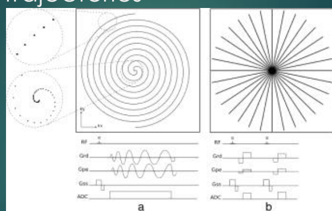

Ferreira et al. Journal of Cardiovascular Magnetic Resonance 2013, 15:41

Potential acceleration of MRI with sparse sampling and CS

35

Original

$$\arg\min_{X} \|F_p X - d\|^2 + TV(X)$$

Direct reconstruction TV reconstruction

29% under-sampling

Structured undersampling aliasing artefacts are eliminated
There is a slight increase in noise using compressed sensing

Sarma et al. IJROBP Volume 88 (3), Pages 723–731

Limitation of sparse sampling individual frames

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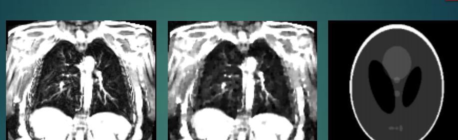

Original 12% under-sampled TV CS image

- Losing details with more aggressive under-sampling ratio
- Different from the Shepp-Logan phantom, the patient image is richer in information, and less sparse

Sail into the temporal domain

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- Same patient on the same couch with essentially the same anatomy
- There is a lot of redundant information for spatial-temporal MRI acquisition

K-space filling "tricks"

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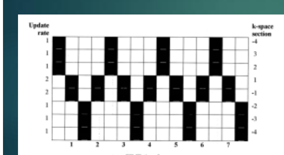
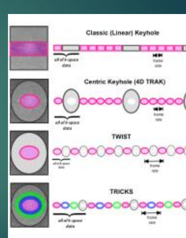
Center of the k-space more important to the image contrast



View Sharing Markl, J. Hennig / Magnetic Resonance Imaging 19 (2001) 669–676



Credit to Allen Elster

Low-rank and L1-norm regularization

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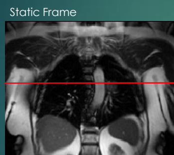
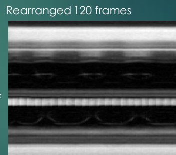
The combined sequential dynamic MRI images were assumed rank deficient

Static Frame



Rearranged 120 frames



Low Rank

Reconstruction Equation

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Generalizing x to a low-rank matrix X we have the optimization problem

$$\arg\min_{X} rank(X) \text{ such that } \|F_p X - d\|_2^2 < \sigma$$

In practice, the rank penalty is often replaced with the nuclear norm

$$\arg\min_{X} \|F_p X - d\|^2 + \lambda_1 \|X\|_*$$

Nuclear norm is further replaced by Schatten p-norm

$$\phi(X) = (\|X\|_p)^p, \; p < 1$$

k-t SLR

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Exploiting the sparse gradients of dynamic images using the TV and combining with the low-rank property,

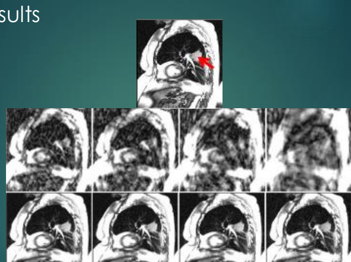
λ_1, λ_2 are regularization parameters

$$\arg\min_{X} \|F_p X - d\|^2 + \lambda_1 (\|X\|_p)^p + \lambda_2 TV(X)$$

Lingala, IEEE Trans Med Imaging. 2011 May;30(5):1042-54.

K-t SLR Results

42



Direct recon

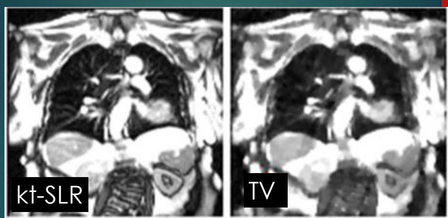
K-t-SLR

20% 15% 10% 5%

Sarma et al. IJROBP Volume 88 (3), Pages 723–731

K-t SLR compared to CS

43



10% sampling

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Evaluation of the images using tumor tracking

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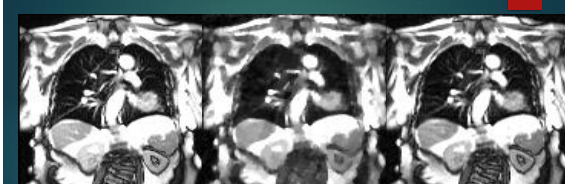

Original image

CS-TV at sampling ratio 10%

k-t SLR at sampling ratio 10%

Sarma et al. IJROBP Volume 88, Issue 3, 1 March 2014, Pages 723–731

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Evaluation of the images using tumor tracking accuracy

45

Sarma et al. IJROBP Volume 88, Issue 3, 1 March 2014, Pages 723–731

Other representative k-t methods

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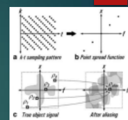
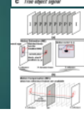
Kt-BLAST/SENSE
Exploit the reduced signal overlap in x-f space produced by interleaved k-t sampling
Tsao et al. Magn Reson Med 2003;50:1031–1042.
Kozerke et al. Magn Reson Med 2004;52:19–26.
Tsao et al. Magn Reson Med 2005;5353:1372–1382.



Kt-FOCUSS
Exploit sparsity in motion estimation/motion compensation
H. Jung, Magnetic Resonance in Medicine, 2009;61:103–116.



Deformation corrected compressed sensing (DC-CS)
Enforce sparsity on the deformable registration corrected images
Lingala et. al. IEEE Trans Med Imaging. 2015 January ; 34(1): 72–85

$$\{f^*, \theta^*\} = \min_{f,\theta} \|\mathcal{A}(f) - \mathbf{b}\|_2^2 + \lambda \Phi(\mathcal{T}_\theta \cdot f); \text{ such that } \theta \in \Theta$$

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Limitation of low rank approach

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Human anatomies do not strictly meet the low rank condition

Joint motion estimation using Primal Dual Algorithm with Linesearch (J-PDAL)

48

$$\min_{\substack{u1,\ldots,uN \\ v1,\ldots,vN \\ w1,\ldots,wN}} \sum_{i=1}^{N} \frac{1}{2} \| S_i F(I_0 + \partial_1 I_0 \otimes u_i + \partial_2 I_0 \otimes v_i + \partial_3 I_0 \otimes w_i) - b_i \|_2^2$$

Fidelity term

$$+\gamma \sum_{i=1}^{N} \| Du_i \|_1^{(u)} + \| Dv_i \|_1^{(u)} + \| Dw_i \|_1^{(u)}$$

Enforce sparsity on DVF

$$+\delta \sum_{i=1}^{N-1} \frac{1}{2} \| u_{i+1} - u_i \|_2^2 + \frac{1}{2} \| v_{i+1} - v_i \|_2^2 + \frac{1}{2} \| w_{i+1} - w_i \|_2^2$$

Enforce temporal continuity on DVF

$$\text{subject to} \quad -\varepsilon \le u_i, v_i, w_j \le \varepsilon, \text{ for } i = 1, \ldots, N.$$

Zhao, O'Connor et al, Under review

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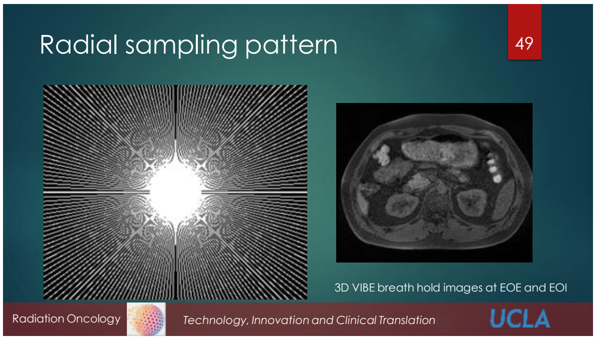
Radial sampling pattern
49
3D VIBE breath hold images at EOE and EOI
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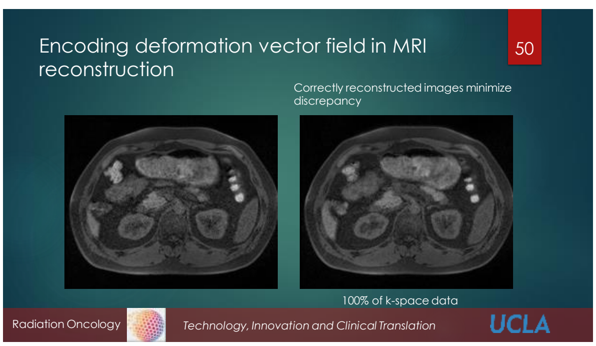
Encoding deformation vector field in MRI reconstruction
50
Correctly reconstructed images minimize discrepancy
100% of k-space data
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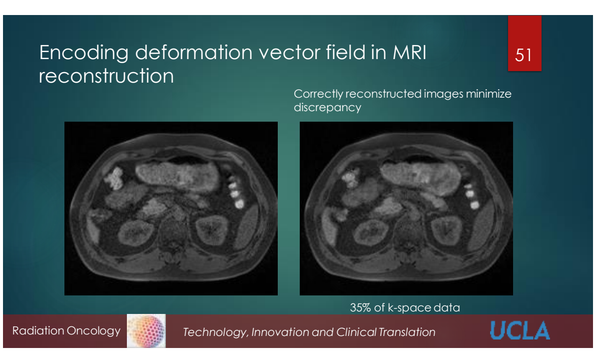
Encoding deformation vector field in MRI reconstruction
51
Correctly reconstructed images minimize discrepancy
35% of k-space data
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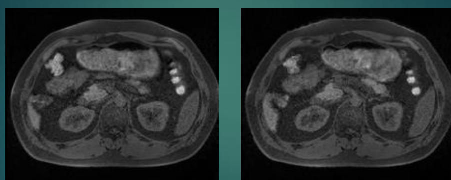
Encoding deformation vector field in MRI reconstruction

52

Correctly reconstructed images minimize discrepancy



10% of k-space data

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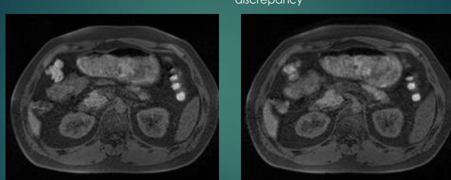
Encoding deformation vector field in MRI reconstruction

53

Correctly reconstructed images minimize discrepancy



5% of k-space data

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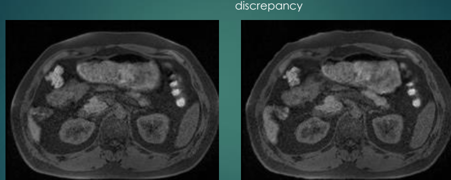
Encoding deformation vector field in MRI reconstruction

54

Correctly reconstructed images minimize discrepancy



2% of k-space data

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DVF comparison

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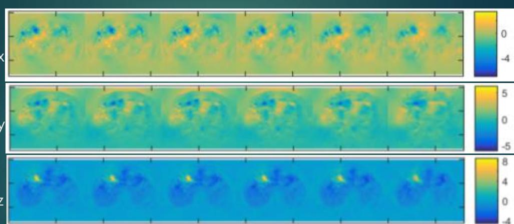

Sampling rate % 100 35 18 10 5 2

J-PDAL application on lung dMRI

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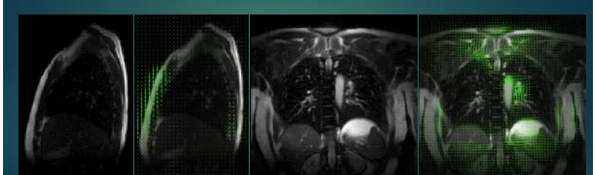

Fully sampled | 15% sampling rate | Fully sampled | 15% sampling rate

Simultaneous recovery of image and deformation vector field!

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Summary and future challenges

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- 2D real time dynamic MRI and retrospective 4DMRI have been developed to facilitate motion management in radiotherapy.
- Real time acquisition ≠ real time MRI. Most iterative reconstruction methods are slow and performed offline, OK for simulationpurposes but unacceptable for interventional radiation therapy. Acceleration of the reconstruction algorithm is equally important.
- Real time segmentation of 3D images is another challenge. Joint estimation of DVF useful.
- Still a lot of work to do for true real time 3D dMRI.

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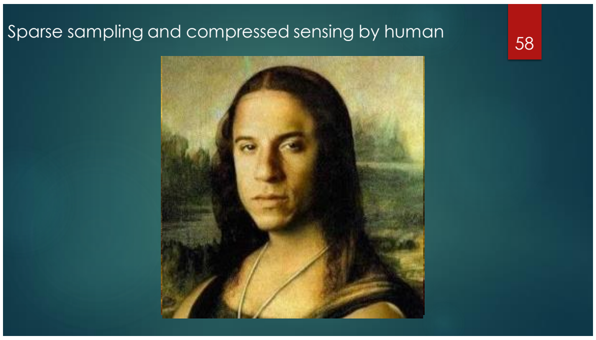
Sparse sampling and compressed sensing by human
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http://shenglab.dgsom.ucla.edu/
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