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BEYOND THE FUTURE!
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Fast and Furious: Path to Effective MRgART

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I am a founder of Celestial Medical

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MRgART: From image to treatment

Image acquisition/reconstruction
↓
Segmentation
↓
Treatment planning/optimization
↓
QA
↓
Delivery

Anatomy is faster than your "car"

Fast and Furious 1 2001

The straight story, 1999 David Lynch

MR guided adaptive RT can be slow

Process step	Median (min-max) time (minutes)
Room patient and acquire image used for re-plan	9 (5-30)
MD approval of initial setup	7 (3-18)
Adaptive re-contouring	10 (5-22)
Adjust plan and perform quality assurance (QA)	14 (8-40)
Total	54 (34-99) *

Time spent in adaptive MR guided radiotherapy
*Including ~14 minutes beam delivery time using Co-60

Lamb et al. Cureus. 2017 Aug 27;9(8)

Improving MRI acquisition time

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Spin Echo → Turbo Spin Echo (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

MRI acquisition: too much information too little time

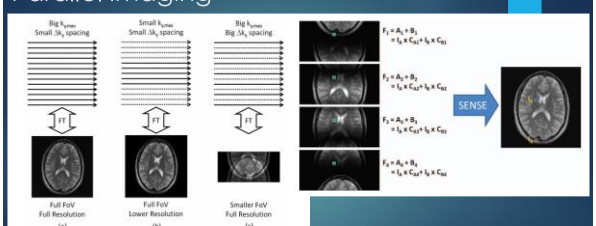
of phase encoding steps in y
SA: number of averages)

uFisp 3D sequence without

minutes

allel acquisition, improve the reconstruction

Parallel imaging



Multiple coil elements each acquires part of the k-space resulting in aliased images that are unraveled using SENSE
Frequency domain for GRAPPA, typical acceleration 2-4

Deshmane et al. J Magn Reson Imaging 2012;36:55-72.

MRI acquisition time

- Scan time = TR·Ny·N·NSA
- (TR: repetition time; Ny: number of phase encoding steps in y direction; N: number of slices; NSA: number of averages)
- Typical full field-of-view ViewRay TruFisp 3D sequence without acceleration
  Scan time = 3.37ms·334·334=6.26 minutes
- Without compressed sensing, with lower resolution, smaller FOV, parallel imaging and Partial Fourier
  Scan time = 2.9ms·180·160/(2·0.75·0.75)=23 seconds, barely fast enough for breath hold MRI

Classic sampling theorem: Nyquist's Rate

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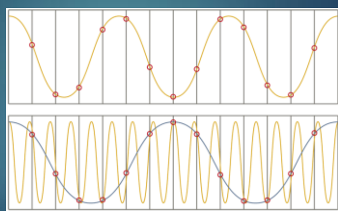
- Perfect recovery requires $f_s \geq 2f_b$, lower sampling rates result in aliasing artifacts.



The leap

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

Donoho, IEEE Transaction on Information Theory 2006

The optimization problem

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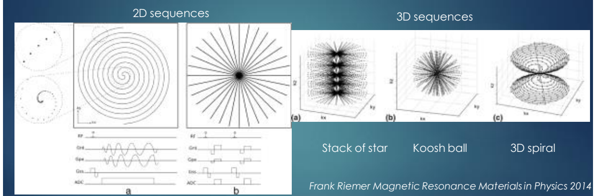
$$\min_u \|\Psi u\|_1 \quad s.t. \|F_p u - d\|_2^2 < \sigma$$

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

More Efficient k-Space Sampling



Ferreira et al. J Cardiovasc Magn Reson. 2013

Frank Riemer Magnetic Resonance Materials in Physics 2014

- Using fewer phase encoding lines to cover the k-space while minimizing the undersampling artifacts
- More heavily sample the center of the k-space where the contrast information resides.

MRI acquisition time

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- With aggressive compressed sensing: 23/8=2.875 seconds
  Speed sufficient for online adaptive RT. Image quality may show noticeable degradation
- 10X acceleration is still needed for real time 3D image
- To make this happen, capture the motion

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

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

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

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

Zhao et al. AAPM 2018 TU-GH-KDBRC-7

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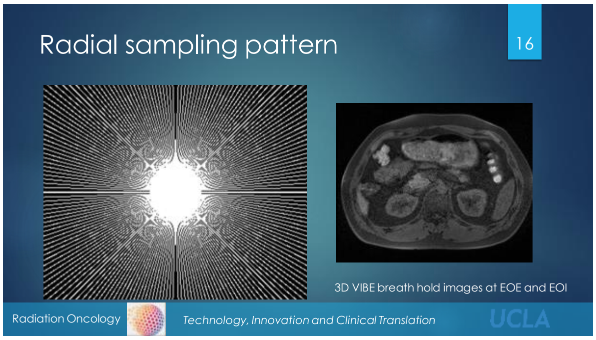
Radial sampling pattern
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3D VIBE breath hold images at EOE and EOI
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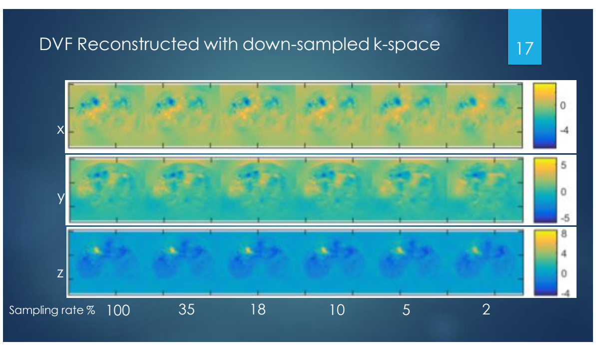
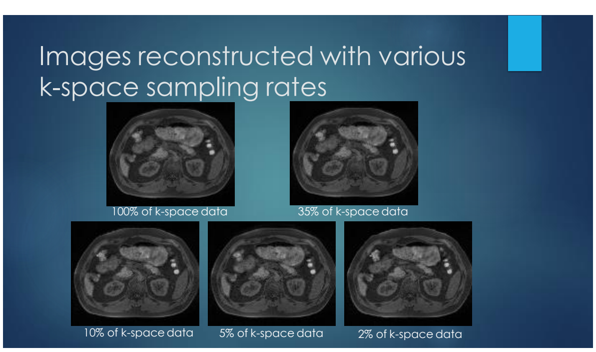
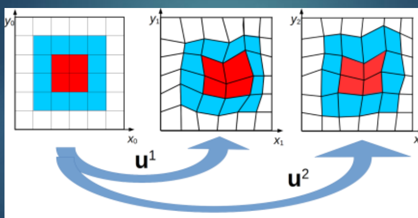

DVF Reconstructed with down-sampled k-space
17
x
y
z
0
-4
5
0
-5
8
4
0
-4
Sampling rate % 100 35 18 10 5 2

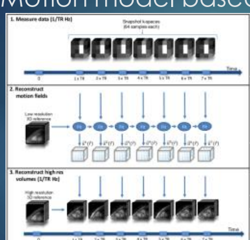

Images reconstructed with various k-space sampling rates
100% of k-space data
35% of k-space data
10% of k-space data
5% of k-space data
2% of k-space data

Motion model based reconstruction



Huttinga et al. ISMRM 2018

Motion model based reconstruction

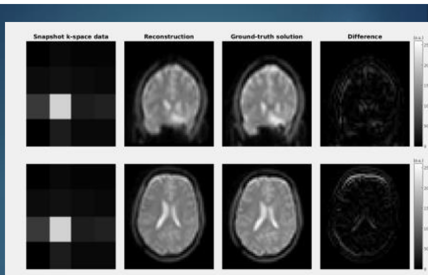


Step 1. Low-resolution snapshot data from a moving object. Using a fast single-shot readout (e.g. TR=20ms), this implies a high-resolution 3D acquisition at a rate of 1/TR=50 Hz.

Step 2. Reconstruct the desired motion-fields from the snapshots and a low-resolution reference image. Noise and small motion-artifacts will be reduced in these images, making the proposed method more robust.

Step 3. Reconstruct high-resolution 3D images by applying the reconstructed motion-fields to a high-resolution reference.

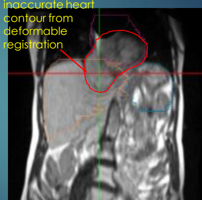
Huttinga et al. ISMRM 2018



8 volume/s, potentially accelerated to 50 volume/s

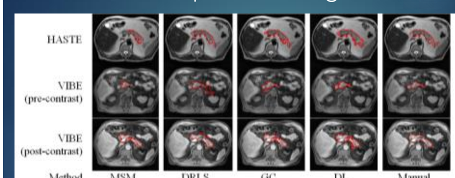
Huttinga et al. ISMRM 2018

Segmentation: a bigger time sink



- Deformable registration can carry the segmentation but the results can be inaccurate, particularly with aggressively accelerated images
- Manual contour editing is time consuming and major contributor of the slow adaptive procedures

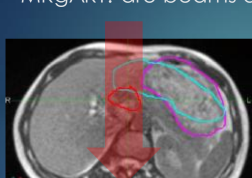
Automated MR pancreas segmentation



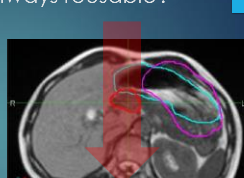
- >82% DI is achieved using a machine learning method[1]
- Comparable to manual segmentation reproducibility[2]
- Recent deep learning segmentation suggests that once the neural networks are trained, multiple organs can be segmented in <10 seconds.[3]

1. Gou et al. Adv Radiat Oncol. 2016 Jul-Sep; 1(3): 182–193.
2. Noel et al. *Med Dosim*. 2014 ; 39(3): 212–217.
3. Tong et al. AAPM 2018 TU-C930-GePD-F5-4

MRgART: are beams always reusable?



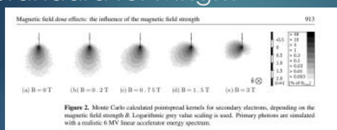
Planning MRI



Treatment MRI

- The AP beam used in the planning MRI would over irradiate the more medially distended stomach at the treatment. Patient subsequently developed stomach ulcer.
- Beam orientation or full arc optimization are needed to take advantage of the new knowledge of internal anatomy.

Monte Carlo dose calculation is standard for MRgRT



Raaijmakers et al. Physics in Medicine & Biology 2008

Model based dose calculation with B0 is fully developed.

Fast dose calculation in magnetic fields with GPUMCD

15 seconds to compute a single beamlet

Prohibitively slow for beamlet dose calculation, particularly for beam orientation optimization

Solving the fast beam orientation optimization problem

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$$\begin{aligned} \underset{x}{\text{minimize}} \quad & \underbrace{\frac{1}{2}\|(\ell - A_0 x)_+\|_2^2}_{\text{PTV}} + \underbrace{\sum_{i=0}^{N} \frac{\alpha_i}{2}\|(A_i x - d_i)_+\|_2^2 + \frac{\beta_i}{2}\|A_i x\|_2^2}_{\text{OARs}} + \underbrace{\gamma\|Dx\|_1^{(\mu)}}_{\text{smoothness}} + \underbrace{\sum_{b=1}^{B} w_b\|x_b\|_2}_{\text{group sparsity}} \quad (1) \\ \text{subject to} \quad & x \geq 0, \end{aligned}$$

Fast Iterative Shrinkage-Thresholding Algorithm (FISTA)

$$\underset{x \in \mathbb{R}^n}{\text{minimize}} \ f(x) + g(x),$$

$$f(x) = \frac{1}{2}\|(\ell - A_0 x)_+\|_2^2 + \sum_{i=0}^{N} \frac{\alpha_i}{2}\|(A_i x - d_i)_+\|_2^2 + \frac{\beta_i}{2}\|A_i x\|_2^2 + \gamma\|Dx\|_1^{(\mu)}$$

$$g(x) = \begin{cases} \sum_{b=1}^{B} w_b\|x_b\|_2 & \text{if } x \geq 0, \\ \infty & \text{otherwise.} \end{cases}$$

Solving the coplanar beam orientation optimization problem in 60 seconds

O'Connor PMB 2018

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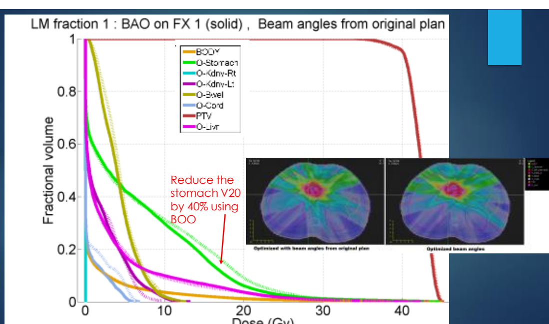
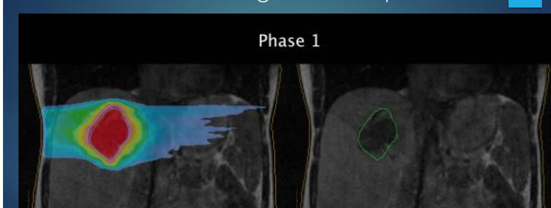


Feasible fantasy

Process	x) time (minutes)
Room p	5 min
MD appr	7 min
Adaptive	1 min
Adjust p	1 min, longer with BOO or VMAT
Total	24 min

Achievable in the near future

Ultimate form of MR guided adaptive RT



- Real time 3D images
- Real time segmentation of the tumor and the OARs
- Real time beam orientation or VMAT optimization

http://shenglab.dgsom.ucla.edu/

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2017

2018

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