

# Free-Breathing Water, Fat, $R_2^*$ and $B_0$ Field Mapping of the Liver Using Multi-Echo Radial FLASH and Regularized Model-based Reconstruction

Zhengguo Tan

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## Motivation

## Methods

Multi-Echo Radial FLASH

Regularized Model-based Reconstruction

Fat & Iron Phantom

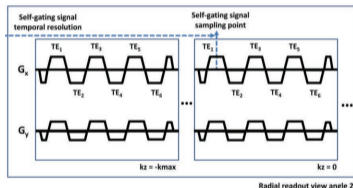
## Results

## Summary

## Appendix

# Motivation: Free-Breathing Liver Fat and $R_2^*$ Mapping

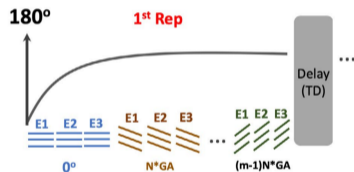
- ▶ multi-echo bipolar readout<sup>1</sup>
- ▶ self gating
- ▶ parameter fitting



- ▶ model-based reconstruction<sup>2</sup>
- ▶ calibrated coil sensitivity and  $B_0$  maps

$$\operatorname{argmin}_{\mathbf{W}, \mathbf{F}, \mathbf{R}_2^*} \sum_{c, t_n} \|E(\mathbf{W}, \mathbf{F}, \mathbf{R}_2^*)_{c, t_n} - \mathbf{Y}_{c, t_n}\|_2^2 + \lambda_W \|S(\mathbf{W})\|_1 + \lambda_F \|S(\mathbf{F})\|_1 + \lambda_{R_2^*} \|S(\mathbf{R}_2^*)\|_1.$$

- ▶ 3-point Dixon
- ▶ subspace reconstruction
- ▶ water-specific T1 mapping<sup>3</sup>



<sup>1</sup>Zhong X, et al. Effect of respiratory motion on free-breathing 3D stack-of-radial liver  $R_2^*$  relaxometry and improved quantification accuracy using self-gating. MRM (2019)

<sup>2</sup>Schneider M, et al. Free-breathing fat and  $R_2^*$  quantification in the liver using a stack-of-stars multi-echo acquisition with respiratory-resolved model-based reconstruction. MRM (2020)

<sup>3</sup>Feng L, et al. Magnetization-prepared GRASP MRI for rapid 3D T1 mapping and fat/water-separated T1 mapping. MRM (2021)

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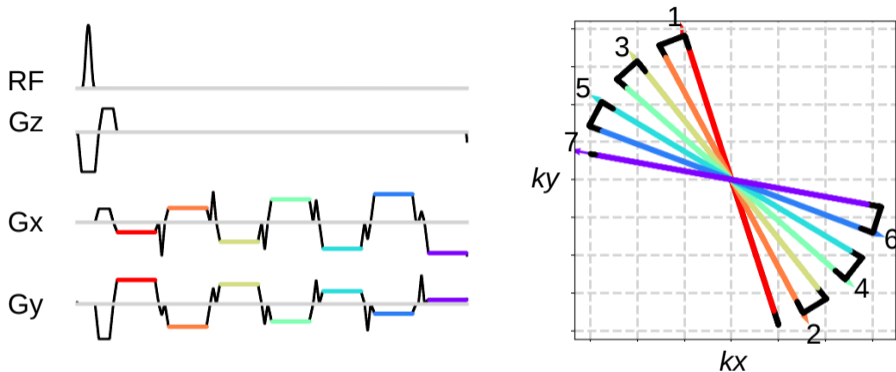
Fat & Iron Phantom

Results

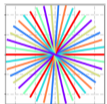
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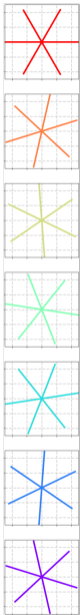
## Multi-Echo Radial FLASH Sampling



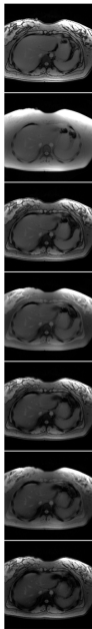
- ▶ Seven gradient echoes with different  $k$ -space spokes per RF excitation
- ▶ Echo acquisition (ADC on) is color-coded



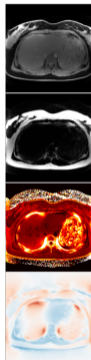
split into echoes

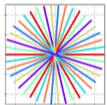


echo recon.  
e.g. pics in BART

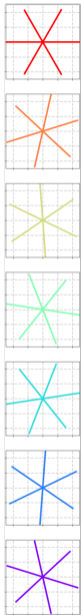


parameter fitting  
e.g. Graph Cut  
Hernando D, et al. MRM (2011)



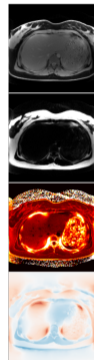


split into echoes



model-based recon.: Direct parameter mapping

Block KT, et al. IEEE TMI (2010)



# Multi-Echo Gradient-Echo Signal Modeling

- ▶ Chemical-shift and  $B_0$  field inhomogeneity encoding (WFR2S in BART<sup>1</sup>)

$$\mathcal{B} : x_p \mapsto \rho_m = (W + F \cdot z_m) \cdot e^{-R_2^* TE_m} \cdot e^{i2\pi f_{B_0} TE_m}$$

- \* 6-peak fat spectrum<sup>2</sup>:  $z_m = \sum_i \alpha_i e^{i2\pi f_i TE_m}$
- \* Inclusion of  $R_2^*$  extends the Dixon model<sup>3,4</sup>

- ▶ Given  $x = (\underbrace{W, F, R_2^*, f_{B_0}}_{x_p}, \underbrace{c_1, \dots, c_N}_{\text{coil sensitivities}})^T$ , denote the chained forward model

$$y_{j,m} = F_{j,m}(x) := P_m \mathcal{F}SB$$

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<sup>1</sup>Uecker M, et al. Berkeley Advanced Reconstruction Toolbox. ISMRM (2015)

<sup>2</sup>Hamilton G, et al. In vivo characterization of the liver fat 1H MR spectrum. NMR Biomed (2011)

<sup>3</sup>Dixon WT. Simple proton spectroscopic imaging. Radiology (1984)

<sup>4</sup>Glover GH. Multipoint Dixon techniques for water and fat proton and susceptibility imaging. JMRI (1991)



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# Regularized Model-based Iterative Reconstruction

$$\begin{aligned} & \text{minimize}_x \quad \|y - F(x)\|_2^2 + \lambda_1 \|\mathcal{W}(E_1 x)\|_1 + \lambda_2 \|\text{TV}_t(x_p)\|_1 + \lambda_3 \|x\|_2^2 \\ & \text{subject to } R_2^* \geq 0 \end{aligned}$$

- ▶ Spatial  $\ell^1$ -Wavelet regularization on  $W$ ,  $F$ , and  $R_2^*$  maps extracted by  $E_1$
- ▶ Spatial & Temporal total variation (TV) regularization on  $x_p$
- ▶  $\ell^2$  regularization on all unknowns

# Regularized Model-based Iterative Reconstruction

- ▶ Nonlinear inversion: IRGNM<sup>5</sup> with ADMM<sup>6</sup>
  1. Linearize the nonlinear objective function in each Newton iteration
  2. Solve the linearized problem with regularization via ADMM
  
- ▶ Initialization
  1. Newton-type method sensitive to initial guess, especially for  $B_0$  estimate
  2. Initialize  $W$ ,  $F$  and  $f_{B_0}$  using simplified model-based reconstruction from the first three echoes<sup>7</sup>

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<sup>5</sup>Bakushinsky AB, et al. Iterative methods for approximate solution of inverse problems. Mathematics and Its Applications (2004)

<sup>6</sup>Boyd S, et al. Distributed optimization and statistical learning via the alternating direction method of multipliers. Foundations and Trends in Machine Learning (2010)

<sup>7</sup>Tan Z, et al. Dynamic water/fat separation and  $B_0$  inhomogeneity mapping. MRM (2019)

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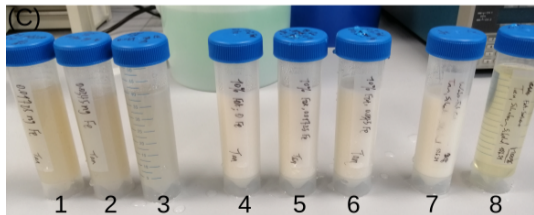
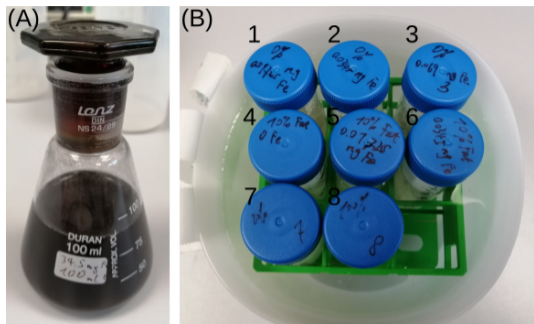
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# Fat & Iron Phantom



(A) Iron diluted in water

(B) Phantom outline

(C) Tubes

- ▶ 1 – 3: No fat, varying iron
- ▶ 4 – 6: 10% fat, varying iron
- ▶ 7: 20% fat, no iron
- ▶ 8: 100% fat, no iron

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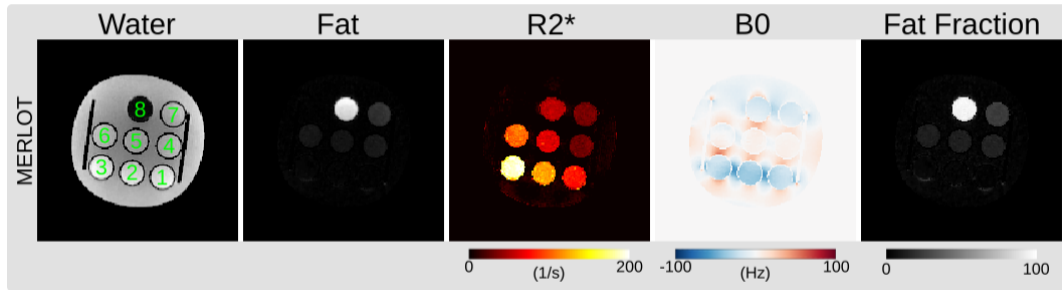
Fat & Iron Phantom

Results

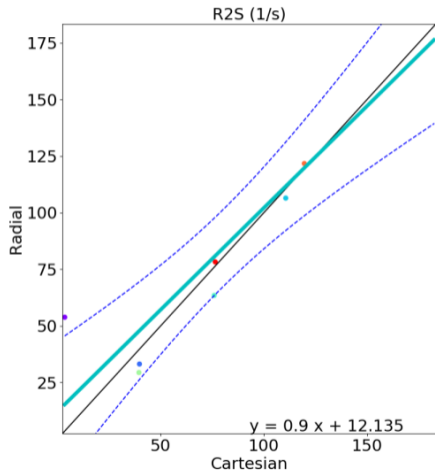
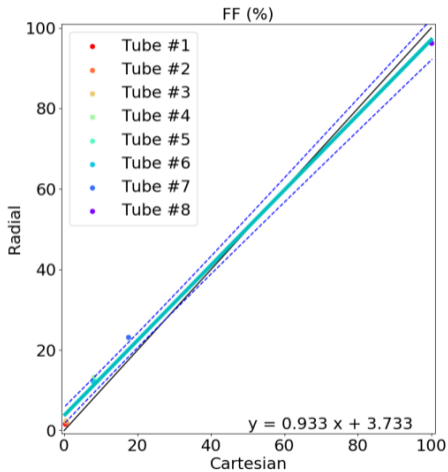
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# Results: Fat & Iron Phantom



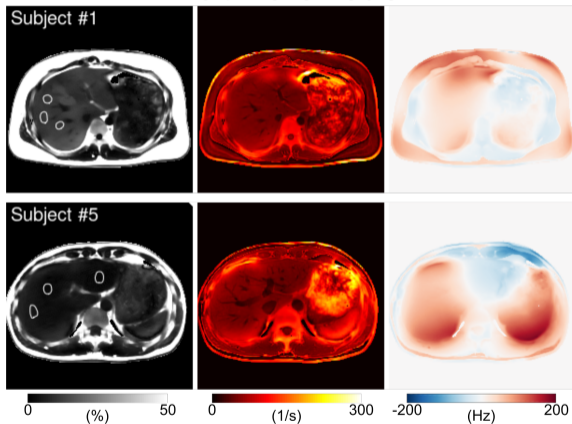
# Results: Fat & Iron Phantom



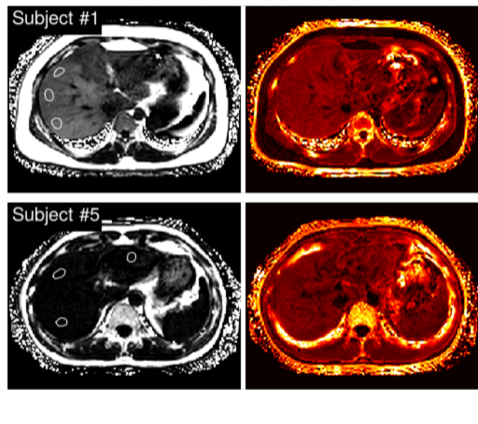


# Results: Elevated Fat Fraction in the Liver

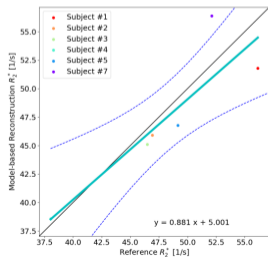
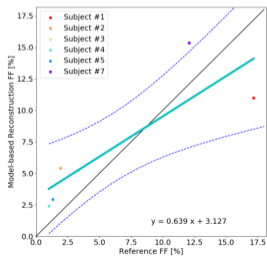
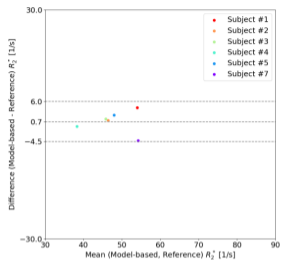
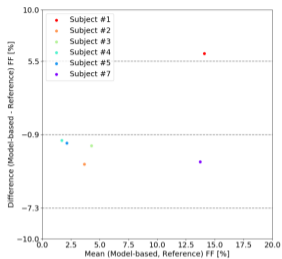
## Multi-Echo Radial



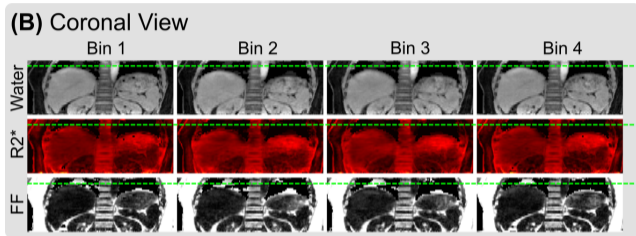
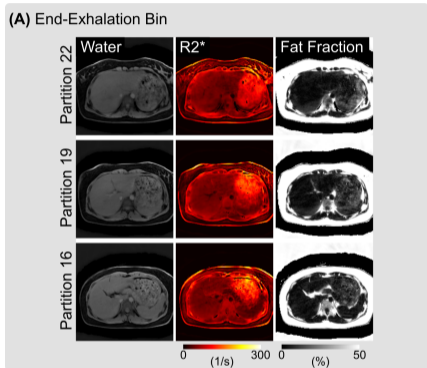
## Multi-Echo Cartesian



# Results: Quantitative Analysis



# Results: 3D Free-Breathing Acquisition in Two Minutes



- ▶ stack-of-radial multi-echo acquisition
- ▶ SSA-FARY<sup>7</sup> self gating
- ▶ multi-dimensional model-based recon.

<sup>7</sup>Rosenzweig S, et al. Cardiac and Respiratory Self-Gating in Radial MRI Using an Adapted Singular Spectrum Analysis (SSA-FARY). IEEE TMI (2020)

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- ▶ Free-breathing liver acquisition via multi-echo radial FLASH
- ▶ Multi-gradient-echo model-based recon. with advanced regularization in BART
- ▶ Good quantitative accuracy comparing with the reference method
- ▶ Associated reconstruction scripts will be updated here:  
<https://github.com/mrirecon/multi-echo-liver>

Email: zhengguo.tan@gmail.com

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## Iteratively Regularized Gauss-Newton Method (IRGNM)

- ▶ IRGNM linearizes the nonlinear forward model in every Newton step,

$$\|F(x_n) + DF(x_n)dx - y\|_2^2$$

- ▶ denote  $x = x_n + dx - x_0$ ,

$$\begin{aligned} & \|DF(x_n)(x + x_0 - x_n) - [y - F(x_n)]\|_2^2 \\ \Rightarrow & \|DF(x_n)x - [DF(x_n)(x_n - x_0) + y - F(x_n)]\|_2^2 \end{aligned}$$

- ▶ its normal equation reads,

$$\begin{aligned} & DF^H(x_n)\{DF(x_n)x - [DF(x_n)(x_n - x_0) + y - F(x_n)]\} = 0 \\ \Rightarrow & DF^H(x_n)DF(x_n)x = DF^H(x_n)\{DF(x_n)(x_n - x_0) + y - F(x_n)\} \end{aligned}$$

- ▶ with arbitrary regularization, ADMM can be used to solve it efficiently.

## Generalized $\ell_1$ Regularization via ADMM

$$\begin{aligned} & \text{minimize} \quad \|Ax - b\|_2^2 + \lambda \|z\|_1 \\ & \text{subject to} \quad Tx - z = 0 \end{aligned}$$

The updates can be derived,

$$\begin{cases} x^{(k+1)} := (A^H A + 0.5\rho T^H T)[A^H b + 0.5\rho T^H(z^{(k)} - \mu^{(k)})] \\ z^{(k+1)} := \mathcal{T}_{\lambda/\rho}(Tx^{(k+1)} + \mu^{(k)}) \\ u^{(k+1)} := u^{(k)} + Tx^{(k+1)} - z^{(k+1)} \end{cases}$$