# MRI: Speed, Phase, Echo

Zhengguo Tan

Artificial Intelligence in Biomedical Engineering (AIBE) Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU)

June 28, 2023

# Outline

Self Introduction

What I have done in Frahm lab jointly in Frahm & Uecker lab in Knoll lab Inspirations Deep Learning Empowered Image Reconstruction

#### Summary

# Self Introduction

# $\sf Zhengguo \leftrightarrow \sf Jung \; \sf Gwoh$



how to pronounce the chinese name Zheng Guo



The Chinese name "Zheng Guo" is pronounced as "jung gwoh."

The pronunciation of "Zheng" is similar to the English word "jungle," but with a sharper "j" sound at the beginning, like the "s" in "measure." It is followed by a short "uh" sound.

The pronunciation of "Guo" sounds like the English word "go," but with a slight "w" sound at the end. The "o" is pronounced as a short "oh" sound.

Put together, "Zheng Guo" is pronounced as "jung gwoh."

# Academic Background

- 1. Chronologically,
  - 2022 now, senior postdoc in Prof. Florian Knoll's lab in Erlangen
  - 2019 2021, DFG<sup>1</sup> funded temporary principal investigator<sup>2</sup> in Prof. Martin Uecker's lab in University Medical Center Göttingen
  - > 2012 2016, PhD in Prof. Jens Frahm's lab in Max Planck Institute

<sup>&</sup>lt;sup>1</sup>DFG: Deutsche Forschungsgemeinschaft, https://www.dfg.de/

<sup>&</sup>lt;sup>2</sup>project number: 427934942

# Academic Background

- 1. Chronologically,
  - 2022 now, senior postdoc in Prof. Florian Knoll's lab in Erlangen
  - 2019 2021, DFG<sup>1</sup> funded temporary principal investigator<sup>2</sup> in Prof. Martin Uecker's lab in University Medical Center Göttingen
  - > 2012 2016, PhD in Prof. Jens Frahm's lab in Max Planck Institute
- 2. Technically,
  - Pulse sequence programming skill trained by the FLASH inventor
  - Iterative image reconstruction skill trained by the BART inventor
  - Artificial intelligence skill trained by the VarNet inventor

<sup>&</sup>lt;sup>1</sup>DFG: Deutsche Forschungsgemeinschaft, https://www.dfg.de/

<sup>&</sup>lt;sup>2</sup>project number: 427934942

# Collaboration & Teaching

- 1. Collaboration
  - UHF Predevelopment Team at Siemens
  - Prof. Frederik Laun at University Hospital Erlangen
  - Prof. Gene Kim at Cornell University

# Collaboration & Teaching

- 1. Collaboration
  - UHF Predevelopment Team at Siemens
  - Prof. Frederik Laun at University Hospital Erlangen
  - Prof. Gene Kim at Cornell University
- 2. Teaching at FAU
  - Computational Imaging Project for master students
  - Pulseq (together with Prof. Moritz Zaiss) for master students
  - Medical Engineering II (blackboard exercises) for bachelor students

# Collaboration & Teaching

- 1. Collaboration
  - UHF Predevelopment Team at Siemens
  - Prof. Frederik Laun at University Hospital Erlangen
  - Prof. Gene Kim at Cornell University
- 2. Teaching at FAU
  - Computational Imaging Project for master students
  - Pulseq (together with Prof. Moritz Zaiss) for master students
  - Medical Engineering II (blackboard exercises) for bachelor students
- 3. Master thesis at FAU
  - Ms. Soundarya Soundarresan
  - 🕨 Mr. Kai Zhao

# What I have done

# Real-Time Flow MRI based on Asymmetric-Echo Radial Sampling <sup>3</sup>

lnterleaved acquisition: 1x flow-compensated (S = 0) + 1x flow-encoded (S = 1)



<sup>3</sup>Untenberger M #, Tan Z #, et al. Advances in real-time phase-contrast flow MRI using asymmetric radial gradient echoes. *Magn Reson Med* (2016). # equal contribution

What I have done | in Frahm lab

# Real-Time Flow MRI based on Asymmetric-Echo Radial Sampling <sup>3</sup>

- lnterleaved acquisition: 1x flow-compensated (S = 0) + 1x flow-encoded (S = 1)
- Asymmetric-echo readout to reduce TR



<sup>3</sup>Untenberger M #, Tan Z #, et al. Advances in real-time phase-contrast flow MRI using asymmetric radial gradient echoes. Magn Reson Med (2016). # equal contribution

What I have done | in Frahm lab

# Real-Time Flow MRI based on Asymmetric-Echo Radial Sampling <sup>3</sup>

- Interleaved acquisition: 1x flow-compensated (S = 0) + 1x flow-encoded (S = 1)
- Asymmetric-echo readout to reduce TR
- ▶ Temporal resolution: 36 ms per velocity map



<sup>3</sup>Untenberger M #, Tan Z #, et al. Advances in real-time phase-contrast flow MRI using asymmetric radial gradient echoes. *Magn Reson Med* (2016). # equal contribution

What I have done | in Frahm lab

Idea: to jointly estimate phase-difference maps

<sup>5</sup>Wang X, Tan Z, et al. Physics-based reconstruction methods for MRI. Philos Trans Royal Soc A (2021).

<sup>&</sup>lt;sup>4</sup>Tan Z, et al. Model-based reconstruction for real-time phase-contrast flow MRI: Improved spatiotemporal accuracy. Magn Reson Med (2017).

- Idea: to jointly estimate phase-difference maps
- Solution: to solve a nonlinear least square problem

$$\Phi(\mathbf{x}) = \operatorname{argmin}_{\mathbf{x}} \left\| \mathbf{y} - \mathbf{PFC} \{ \rho \cdot e^{i\Delta\phi \cdot S} \} \right\|_{2}^{2} + \lambda \left\| \mathbf{x} \right\|_{2}^{2}$$

$$\mathbf{x} = (\rho, \Delta\phi, c_{1}, \cdots, c_{N})^{T}$$
(1)

<sup>&</sup>lt;sup>4</sup> Tan Z, et al. Model-based reconstruction for real-time phase-contrast flow MRI: Improved spatiotemporal accuracy. Magn Reson Med (2017).

<sup>&</sup>lt;sup>5</sup>Wang X, Tan Z, et al. Physics-based reconstruction methods for MRI. Philos Trans Royal Soc A (2021).

- Idea: to jointly estimate phase-difference maps
- Solution: to solve a nonlinear least square problem

$$\Phi(x) = \operatorname{argmin}_{x} \left\| \mathbf{y} - \mathbf{PFC} \{ \rho \cdot e^{i\Delta\phi \cdot S} \} \right\|_{2}^{2} + \lambda \left\| x \right\|_{2}^{2}$$

$$x = (\rho, \Delta\phi, c_{1}, \cdots, c_{N})^{T}$$
(1)

▶ Pros: enable the regularization of phase-difference maps  $(\Delta \phi)$ 

<sup>&</sup>lt;sup>4</sup>Tan Z, et al. Model-based reconstruction for real-time phase-contrast flow MRI: Improved spatiotemporal accuracy. Magn Reson Med (2017).

<sup>&</sup>lt;sup>5</sup>Wang X, Tan Z, et al. Physics-based reconstruction methods for MRI. Philos Trans Royal Soc A (2021).

- Idea: to jointly estimate phase-difference maps
- Solution: to solve a nonlinear least square problem

$$\Phi(x) = \operatorname{argmin}_{x} \left\| \mathbf{y} - \mathsf{PFC} \{ \rho \cdot e^{i\Delta\phi \cdot S} \} \right\|_{2}^{2} + \lambda \left\| x \right\|_{2}^{2}$$

$$x = (\rho, \Delta\phi, c_{1}, \cdots, c_{N})^{T}$$
(1)

- ▶ Pros: enable the regularization of phase-difference maps  $(\Delta \phi)$
- Cons: require the implementation of the Jacobian matrix and the balance of partial derivatives

<sup>&</sup>lt;sup>4</sup>Tan Z, et al. Model-based reconstruction for real-time phase-contrast flow MRI: Improved spatiotemporal accuracy. Magn Reson Med (2017).

<sup>&</sup>lt;sup>5</sup>Wang X, Tan Z, et al. Physics-based reconstruction methods for MRI. Philos Trans Royal Soc A (2021).

# Balancing Partial Derivatives: Data-Driven Approach <sup>6</sup>

- kind of self-gating, like XD-GRASP or GRASP-Pro
- Solution: to track the scaling value from measured k-space data

$$s = 0.5 \cdot \frac{\|y_1\|_2 + \|y_2\|_2}{\|y_1 - y_2\|_2}$$



<sup>&</sup>lt;sup>6</sup>Tan Z, et al. Model-based reconstruction for real-time phase-contrast flow MRI: Improved spatiotemporal accuracy. *Magn Reson Med* (2017). What I have done | in Frahm lab

# Balancing Partial Derivatives: Eigenvalue Approach 7

- 1. kind of numerical methods, like batch normalization
- 2. to compute the matrix norm of the derivative operator



<sup>7</sup>**Tan Z**, et al. An eigenvalue approach for the automatic scaling of unknowns in model-based reconstructions: Application to real-time phase-contrast flow MRI. *NMR Biomd* (2017). What I have done | in Frahm Tab.

#### Real-Time Aortic Blood Flow MRI at 36 ms

magnitude images

phase-difference maps

# Multi-Echo Radial Sampling<sup>8,9</sup>

- use blip gradients to traverse among echoes
- use spoiler gradients for stack-of-stars volumetric acquisition



<sup>&</sup>lt;sup>8</sup>**Tan Z**, et al. Dynamic water/fat separation and  $B_0$  inhomogeneity mapping – joint estimation using undersampled triple-echo multi-spoke radial FLASH. Magn Reson Med (2019).

<sup>&</sup>lt;sup>9</sup>Tan Z, et al. Free-breathing liver fat,  $R_2^*$  and  $B_0$  field mapping using multi-echo radial FLASH and regularized model-based reconstruction. *IEEE Trans Med Imaging* (2023).

▶ to solve a generalized nonlinear inverse problem

$$\Phi(x) = \operatorname{argmin}_{x} \|\mathbf{y} - \mathbf{PFCB}(x)\|_{2}^{2} + \lambda R(x)$$
  

$$x = (W, F, R_{2}^{*}, f_{B_{0}}, c_{1}, \cdots, c_{N})^{T}$$
(3)

▶ to solve a generalized nonlinear inverse problem

$$\Phi(x) = \operatorname{argmin}_{x} \|\mathbf{y} - \mathbf{PFCB}(x)\|_{2}^{2} + \lambda R(x)$$
  

$$x = (W, F, R_{2}^{*}, f_{B_{0}}, c_{1}, \cdots, c_{N})^{T}$$
(3)

multi-echo gradient echo signal model

$$B(x): \rho_m = (W + F \cdot z_m) \cdot e^{-R_2^* T E_m} \cdot e^{i2\pi f_{B_0} T E_m}$$
(4)

to solve a generalized nonlinear inverse problem

$$\Phi(x) = \operatorname{argmin}_{x} \|\mathbf{y} - \mathbf{PFCB}(x)\|_{2}^{2} + \lambda R(x)$$
  

$$x = (W, F, R_{2}^{*}, f_{B_{0}}, c_{1}, \cdots, c_{N})^{T}$$
(3)

multi-echo gradient echo signal model

$$B(x): \rho_m = (W + F \cdot z_m) \cdot e^{-R_2^* T E_m} \cdot e^{i2\pi f_{B_0} T E_m}$$
(4)

#### ▶ Cons: the field inhomogeneity map $(f_{B_0})$ is sensitive to initial guess





# Appliation #2: Volumetric Brain $T_2^*$ -Weighted Imaging <sup>10</sup>

- spatial resolution 1 mm isotropic
- ▶ 35 echoes per excitation and 7 shots per partition
- use <u>linear</u> subspace modeling and reconstruction instead

<sup>&</sup>lt;sup>10</sup>Tan Z, et al. under review

# Brain Diffusion MRI at 7 T

#### Challenges:

- 1. Specific Absorption Rate (SAR) is linearly proportional to the square of  $B_0$
- 2. Shorter  $T_2$  relaxation at 7 T
- 3. Increased sensitivity to field inhomogeneity, incl.  $B_0$  and  $B_1$

# Brain Diffusion MRI State-of-the-Art: MUSE <sup>11</sup>

- uses 4-shot interleaved EPI (iEPI), resembling a fully-sampled k-space
- self-navigated shot-to-shot phase variation estimation
- limited number of shots has been reported



<sup>11</sup>Chen NK, et al. A robust multi-shot scan strategy for high-resolution diffusion weighted MRI enabled by multiplexed sensitivity-encoding (MUSE). *NeuroImage* (2013).

What I have done | in Knoll lab

# Undersampled iEPI with $k_{\nu}$ Shift Encoding <sup>12</sup>

Acceleration factor per shot:

 $R_{
m shot} = R_{
m in-plane} imes N_{
m shot}$ 



<sup>12</sup>Tan Z, et al. *under review*.

What I have done | in Knoll lab

(5)

### NAViEPI: where iEPI meets rsEPI

- Navigator-based iEPI with consistent effective ESP between echoes
- enables:
  - 1. minimal distortion mismatch between echoes
  - 2. flexible number of shots
  - 3. reliable shot-to-shot phase estimation





#### What I have done | in Knoll lab

# Efficiency of NAViEPI

#### 3-scan trace acquisition with voxel size 0.5 X 0.5 X 2.0 $\rm mm^3$



# $B_1^+$ Field Inhomogeneity Challenge

#### 3-scan trace acquisition with voxel size 0.5 X 0.5 X 2.0 mm<sup>3</sup>



## JETS-NAViEPI: Reproducibility



Is NAViEPI a Reasonable Approach?

 $\blacktriangleright$  In the sub-mm case, the base resolution is 440  $\times$  440

	Required phase-encoding lines (ETL)		
	1-Shot EPI	4-Shot MUSE	5-Shot NAViEPI
partial Fourier ( $\times(6/8)$ )	330		
Acceleration $(/R_{in-plane})$	110	330	110
Shots $(/N_{shot})$	110	pprox 82	22

 $\rightarrow\,$  Much reduced spatial distortion with NAViEPI

# Inspirations: Speed, Phase, Echo



# Inspirations: Speed, Phase, Echo





# Inspirations: Speed, Phase, Echo







#### Connecting MR in a changing world: Look outwards & inwards



acquisition of spatial harmonics (SMASH) method.

would are not see the second of the second s students not to spenses. For example, Mark Grisvold, who was work- Dare The fact that we have grown so much laws

fray, and parameters and the second races, annual meetings, here

Dass I think that two categories of early responses were large was the meeting in Vancouvert

the ISMRM annual meeting?

listen to me too in me frie few months at Beth Israel Descoress Medical used to feel manageable. Time was, one could not carefully, but, we saved working together. Bob himself was an enthu- scope of changes in the field. Now there are so more rather, to take brad, and he want becare a third muskater and erea- some of the early sense of intimacy has been bed to be their ignorance. very gostifying, though the lead-in as the meeting was er's brilliantly-conceived and highly successful Sort

increasingly, look outwards as well as inwards. Given the ISMRM initiative on High-Value MR7





What I have done

THE MAGNETIC RESONANCE IN MEDICINE HIGHLIGHTS I APRIL 2018 I MOLUME THREE Inspirations

Deep Learning: Any Novelty or Significance?

Trustworthy

#### ► Explainable

- Robust
- Data-Efficiency

Deep Learning: Any Novelty or Significance?

Trustworthy

#### Explainable

- Robust
- Data-Efficiency

- ▶ nonlinear  $\rightarrow$  linear  $\rightarrow$  nonlinear
- ✓ Deep learning frameworks offer powerful optimizers!

# Preliminary Work on Deep Learning: AutoEncoder



# Preliminary Work on Deep Learning: 1.2 mm Isotropic Resolution <sup>13</sup>



<sup>13</sup>Soundarresan S, Tan Z, et al. *submitted to ESMRMB* 

What I have done | Deep Learning Empowered Image Reconstruction

# Preliminary Work on Deep Learning: Latent Signal



# Summary

## Thank You for Your Attention!

1. This talk won't be possible without these great people:

- Dr. Jens Frahm and his team
- Dr. Martin Uecker and his team
- Dr. Florian Knoll and his team
- Dr. Robin Heidemann
- Dr. Patrick Liebig
- Dr. Frederik Laun
- Ms. Soundarya Soundarresan

## Thank You for Your Attention!

1. This talk won't be possible without these great people:

- Dr. Jens Frahm and his team
- Dr. Martin Uecker and his team
- Dr. Florian Knoll and his team
- Dr. Robin Heidemann
- Dr. Patrick Liebig
- Dr. Frederik Laun
- Ms. Soundarya Soundarresan
- 2. Thank you for your attention again.