Motion-resolved Quantitative MRI

Anthony G. Christodoulou, PhD

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Cedars Sinai
Biomedical Imaging Research Institute

UCLA Samueli School of Engineering

David Mack @davidmackau

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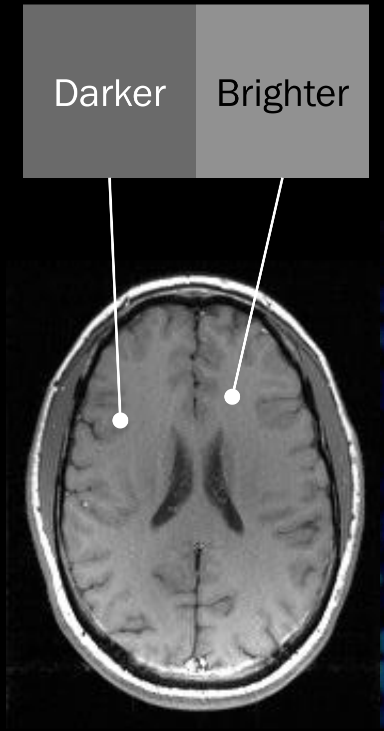
question: is jodie foster really short or is jennifer lawrence really tall?

8:31 PM - 4 Mar 2018

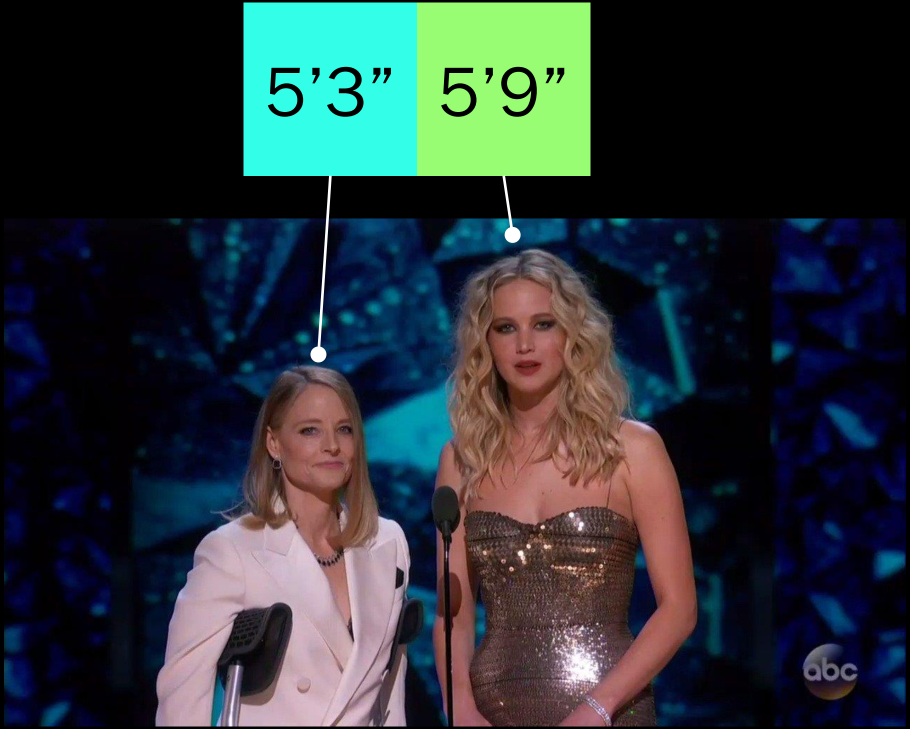
Qualitative imaging

Pixel brightness has no absolute units. We can only make relative measurements.



Qua**n**titative imaging

Pixel value has a physical unit. We can make absolute measurements.

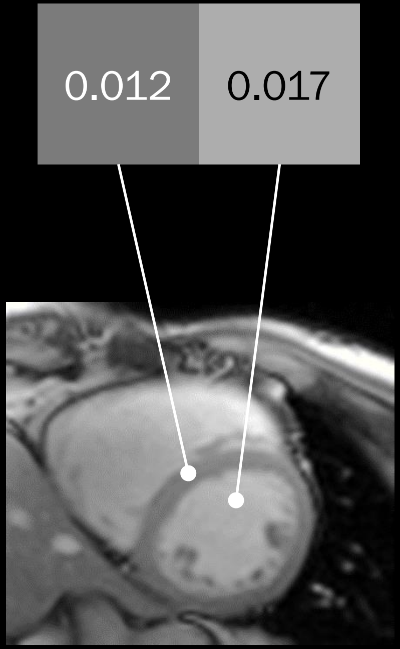


Quantitative imaging

Quantitative vs Qualitative imaging

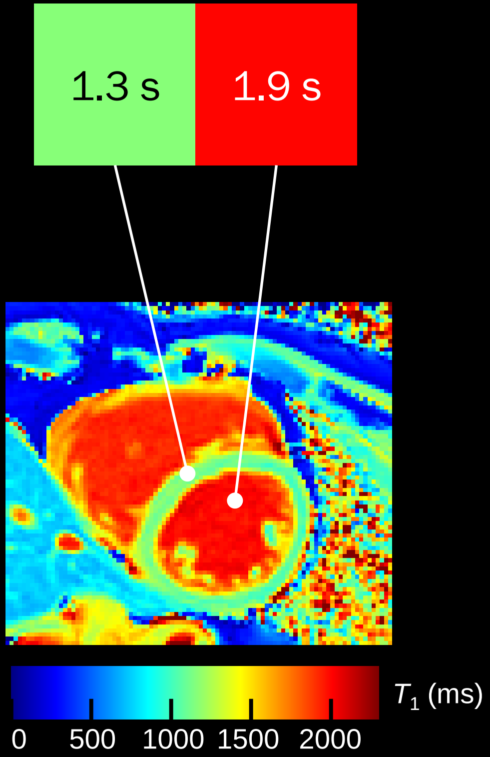
Qualitative

Unitless pixel values



Quantitative

Pixel values have units



More objective

- Measures absolute parameters associated with various (patho)-physiological tissue properties and disease states

More reproducible[1]

- Direct comparison across subjects, sites, and times

More sensitive[2,3]

- Detect mild or diffuse alteration of tissue properties

[1]Metere R et al., PLoS One 2017
[2]Singh P et al., *Biomed Res Int* 2013
[3]h-Ici DO et al., *Eur Heart J CVI* 2014

What can MRI quantify?

Various tissue processes and tissue parameters, e.g.:

- Relaxation (T1, T2, T2*)
- Diffusion (ADC, helix angle, diffusion angle)
- Mechanical properties (stress, strain, stiffness)
- Flow (tissue perfusion or flow in larger vessels)
- Kinetics (K^{trans}/permeability)
- Tissue composition (water-fat, ECV, plasma volume)

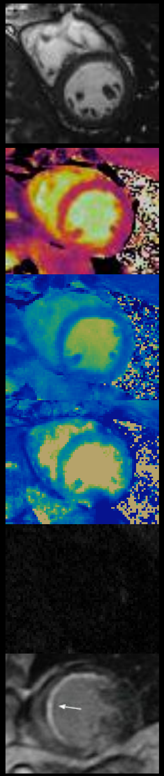
Multi-parametric imaging:

- Combines parameters for comprehensive assessment of tissue state and accurate diagnosis
  - e.g. chronic liver disease[1], prostate cancer[2], cardiovascular disease

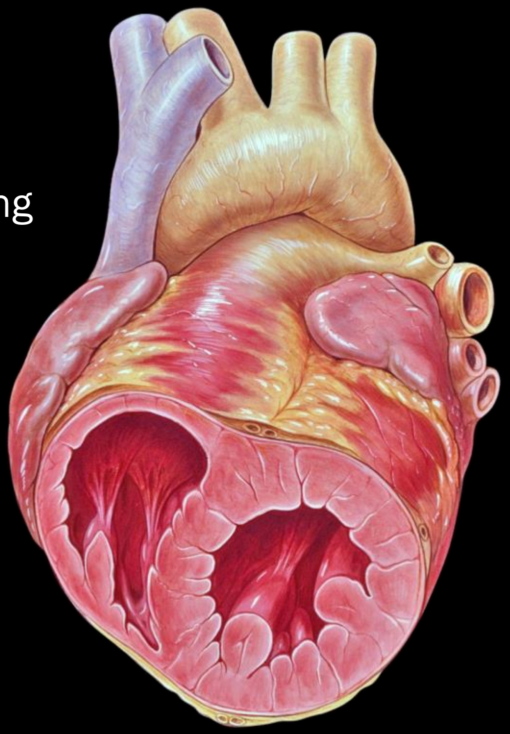
	Diseases	T1	T2	T2*	ADC	SWI/ QSM	FF
Neuro	Stroke	+	+		+	+	
	Traumatic brain injury	+	+		+	+	
	Epilepticus	+	+		+	+	
	Multiple Sclerosis	+	+			+	
	Glioblastoma	+	+	+	+	+	
Cardiovascular	Iron overload cardiomyopathy	+	+	+			
	Myocarditis	+	+				
	Sarcoidosis		+				
	Intramyocardial Hemorrhage		+	+		+	
	Acute/chronic myocardial infarction	+	+		+		
	Dilated Cardiomyopathy	+	+				
	Hypertrophic Cardiomyopathy	+	+		+		
	Amyloidosis	+					
	Systemic lupus erythematosus	+			+		
	Diabetic cardiomyopathy /obesity/cardiac steatosis						+
	Cardiotoxicity	+					
Body	Liver iron overload	+	+	+		+	
	Cancer						
	Breast	+	+		+		
	Prostate	+	+		+	+	
	Liver	+	+	+	+	+	
	Liver fibrosis	+	+		+	+	
	Hepatic Carcinoma	+	+	+	+	+	
	Hepatic/pancreatic steatosis						+

[1]Hussain SM et al., Radiographics 2009
[2]Yu AC et al., Radiology 2017

What can MRI tell us about the heart?



- Structure and function (cine)
- T1 mapping and extracellular volume fraction (ECV) mapping
- T2 mapping
- T2* mapping
- Perfusion
- Late gadolinium enhancement (LGE)



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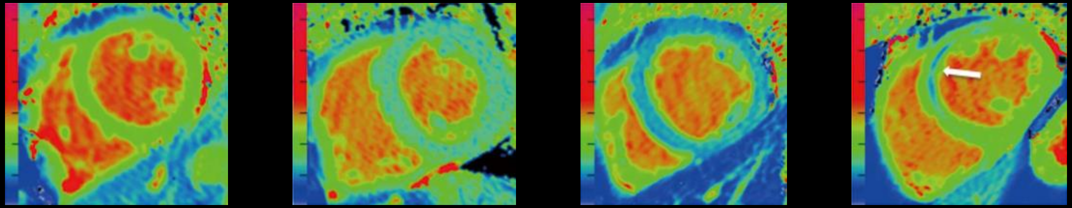
LGE image adapted from De Maria et al., *WJC* 2017

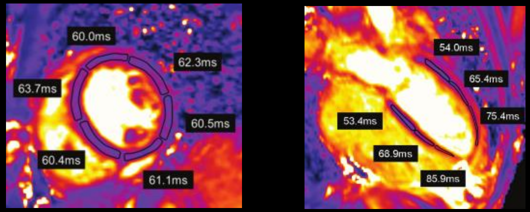
Quantitative cardiovascular MR (CMR)

T_1



Normal | Fabry disease | Iron overload | Fatty metaplasia

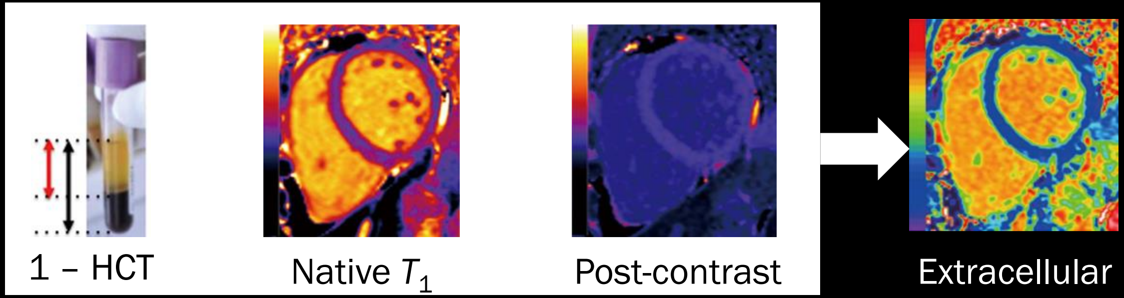
T_2



Diffuse Myocarditis | Takotsubo

T_1 w/Gd

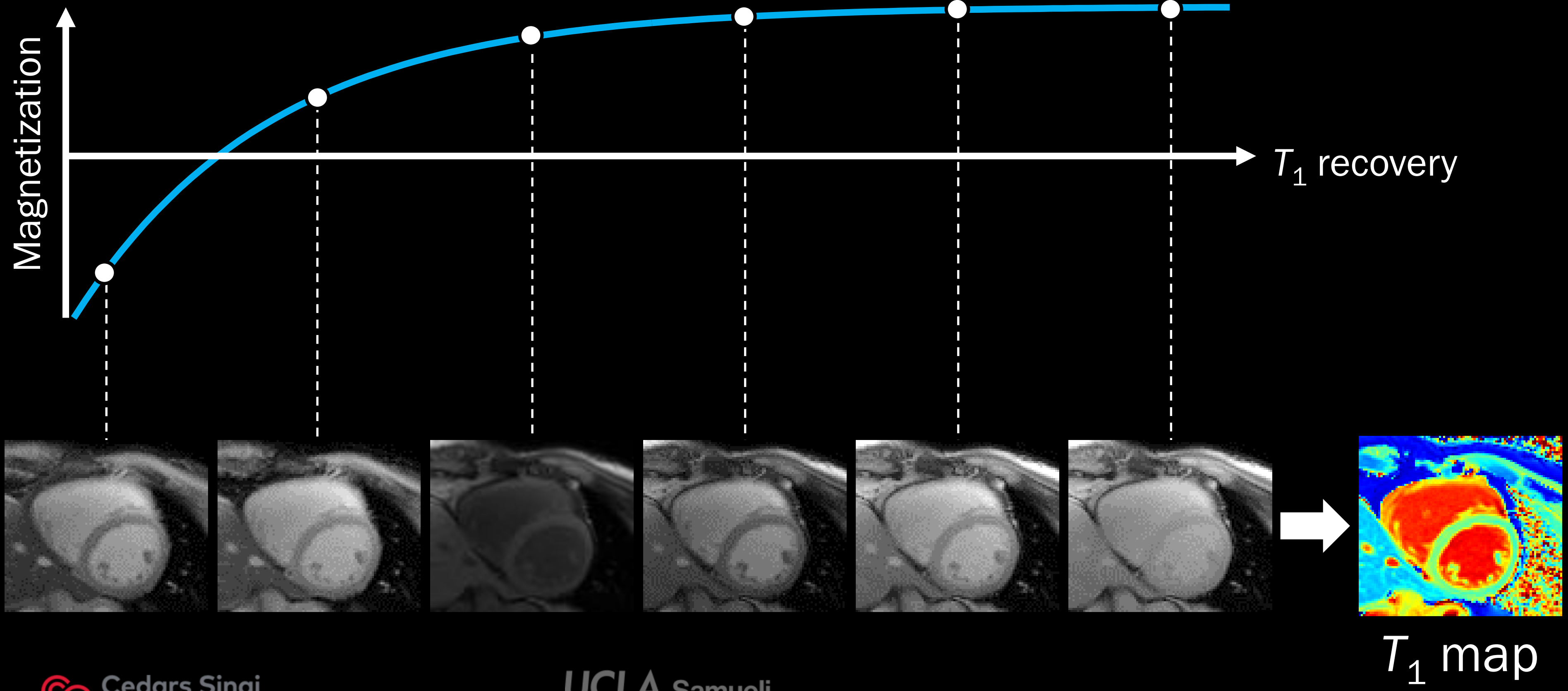
Perfusion



Extracellular volume (ECV)

Bulluck H et al., *Circ J* 2015; Thavendiranathan P et al., *Circ Cardiovasc Imaging* 2012

Quantitative MRI = dynamic MRI



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The challenge in the heart

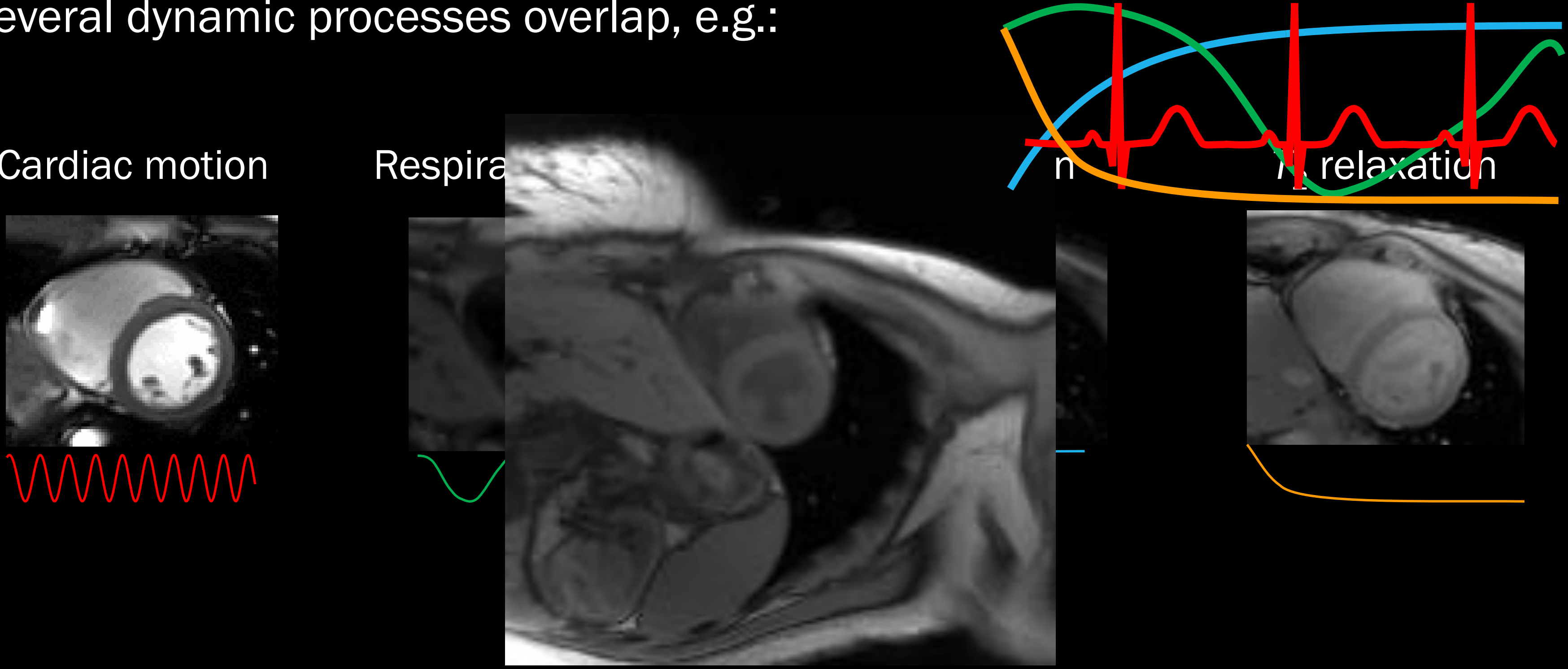
Several dynamic processes overlap, e.g.:

Cardiac motion

Respira

n

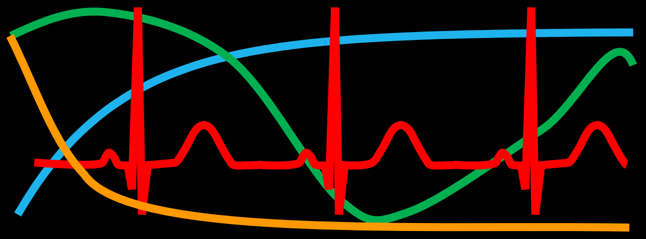
T_1 relaxation



Solutions

Standard approach: "freeze" the motion

- Synchronize imaging with ECG
- Ask the patient to hold their breath
- Often: capture as few processes as possible



Incomplete list of options:

MOLLI[1]	**shMOLLI**[2]	**SASHA**[3]	**SAPPHIRE**[4]
T_2prep-SSFP[5]	**QALAS**[6]	**IR-T_2prep**[7]	**SR-T_2prep**[8]
Fingerprinting[9]			

[1]Messroghli DL et al., *MRM* 2004 [2]Piechnik SK et al., *JCMR* 2010 [3]Chow K, et al., *MRM* 2014 [4]Weingärtner S et al., *SCMR* 2013
[5]Giri S et al., *JCMR* 2009 [6]Kvernby S et al., *JCMR* 2014 [7]Blume U et al., *JMRI* 2010 [8]Akçakaya M et al., *MRM* 2015
[9]Hamilton JI et al., *MRM* 2016

Standard motion approach

Typically limits imaging to **<u>one</u>** dynamic at a time

	Cine	T_1 mapping	T_2 mapping
Cardiac motion	○	✗	✗
T_1 relaxation	✗	○	✗
T_2 relaxation	✗	✗	○
Respiration	✗	✗	✗

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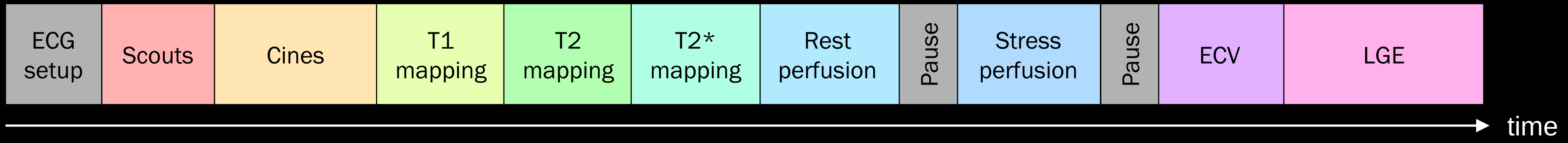
Example current workflow: Serial

Long exams made from a disjointed sequence of scans, e.g.:



Each scan requires special setup by the technologist

Each scan uses ECG triggering or gating

Each scan uses a different breath hold (often one breath-hold per slice)

- Scans from different breath holds are not co-registered

Extended scan times and complex workflow limit the availability of cardiac MRI

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Ideal workflow: All-in-one, free-running

Brief 20–30 min exam in one push-button scan:

Scan
(Cine, T1, T2, T2*, Rest/Stress Perfusion, LGE, ECV)

→ time

No setup by the technologist

No ECG triggering or gating

No breath holds

- All maps and images are co-registered

All with 3D spatial coverage

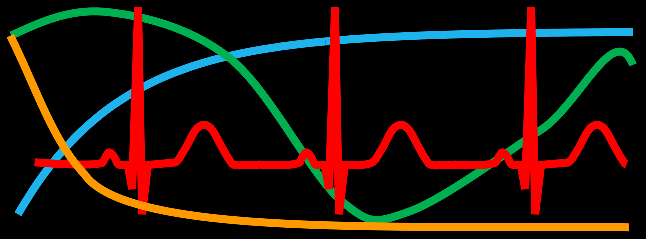
- **How can we get there?**
- **Where are we now?**

Simple workflow and short scan time could make cardiac MRI far more accessible

Solutions

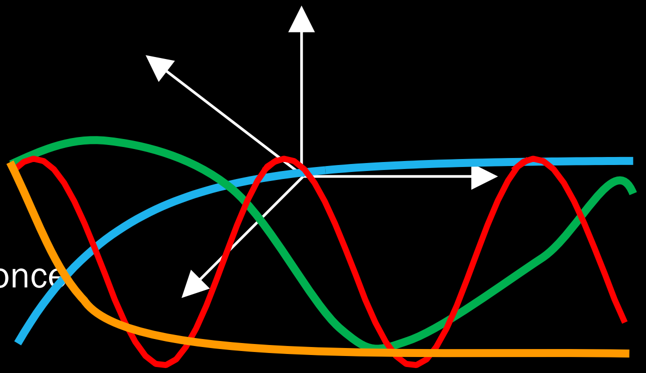
Standard approach: "freeze" the motion

- Synchronize imaging with ECG
- Ask the patient to hold their breath
- Often: capture as few processes as possible



Alternative paradigm: embrace the motion

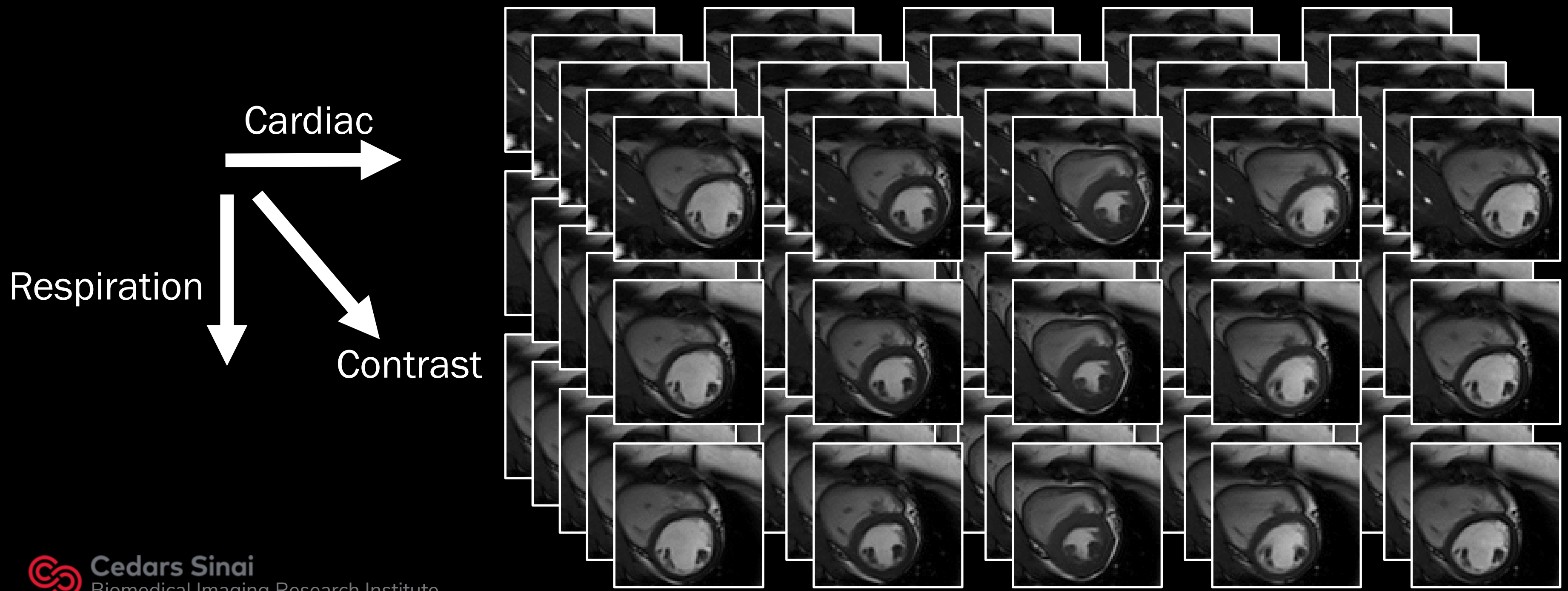
- Assign each dynamic its own time dimension
- No need for ECG
- Patient can breathe freely
- Resolve multiple overlapping processes, performing multiple tasks at once



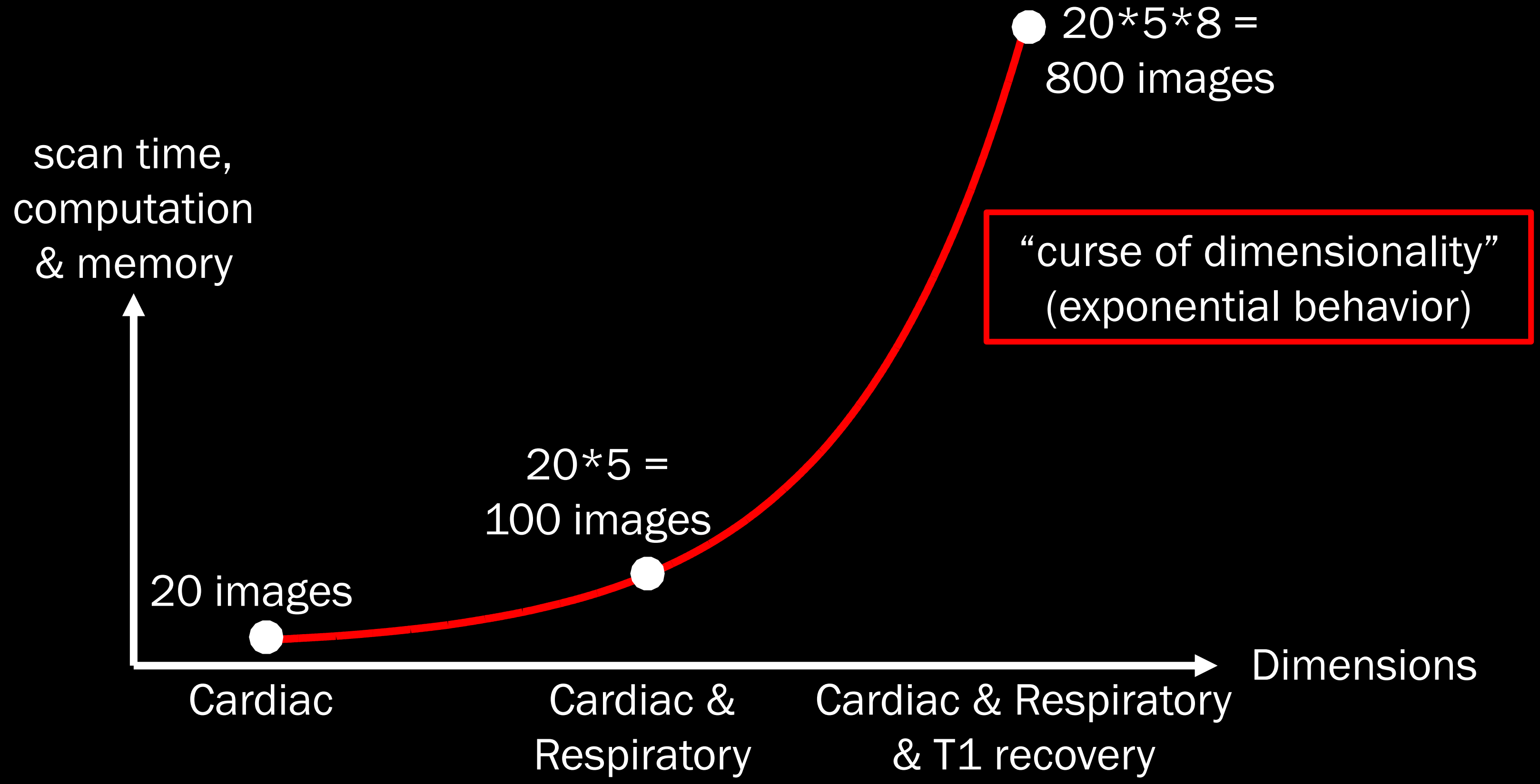
Alternative paradigm: Multidimensional imaging

Scan continuously, *capturing* (rather than freezing) overlapping dynamics

Organize data/images into array with multiple time dimensions



Multidimensional imaging: Challenge



Multidimensional imaging: Opportunity

Despite the "curse of dimensionality", there is also an opportunity!

The "blessing of dimensionality":

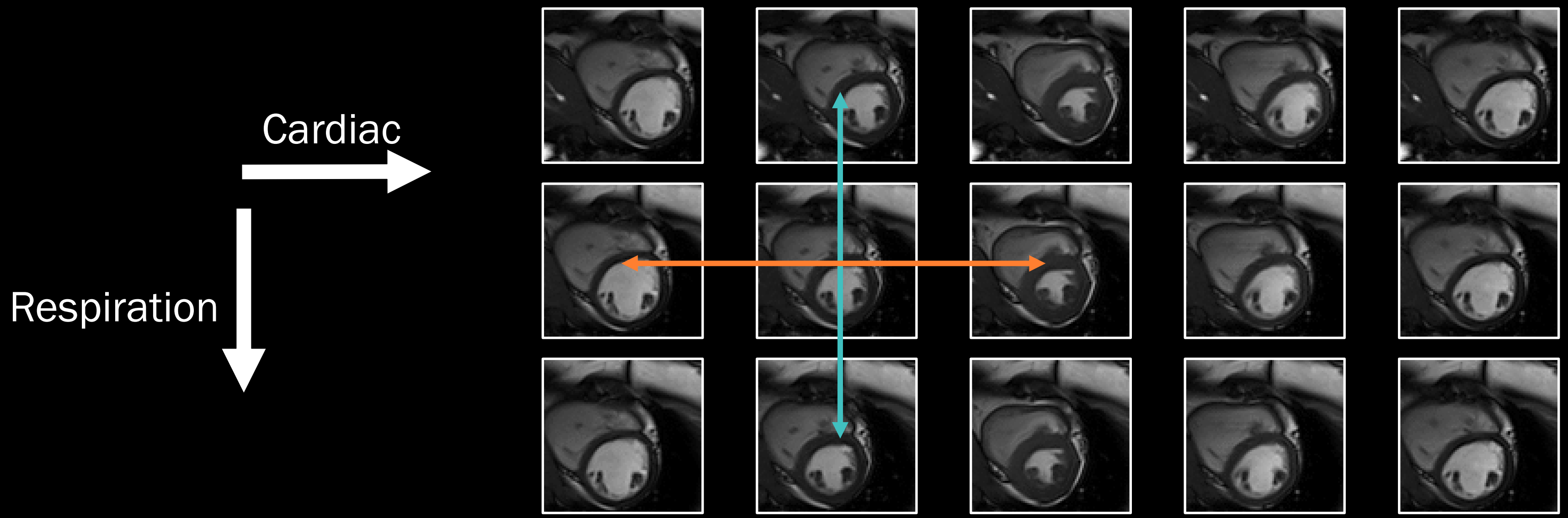
- High-dimensional spaces → sparse representations
- Organized structure → sparse representation along each individual dimension

Multidimensional image reconstruction approaches offer a way around the "curse"

• XD-GRASP:	Compressed sensing	Feng L et al., *Magn Reson Med* 2016
• XD flow:	Compressed sensing	Cheng JY et al., *Sci Rep* 2017
• Multitasking:	Low-rank tensors	Christodoulou AG et al., *Nature Biomed Eng* 2018
• HD-PROST:	Low-rank tensors	Bustin A et al., *Magn Reson Med* 2019
• LRTA:	Low-rank tensors	Yaman B et al., *IEEE Trans Comput Imaging* 2020

XD-GRASP: Multidimensional Compressed Sensing

Treats cardiac motion/respiration as separate time dimensions, then applies multidimensional compressed sensing.



Neighboring images in both directions are very similar

Feng L et al., *MRM* 2016

XD-GRASP: Multidimensional Compressed Sensing

Treats cardiac motion/respiration as separate time dimensions,

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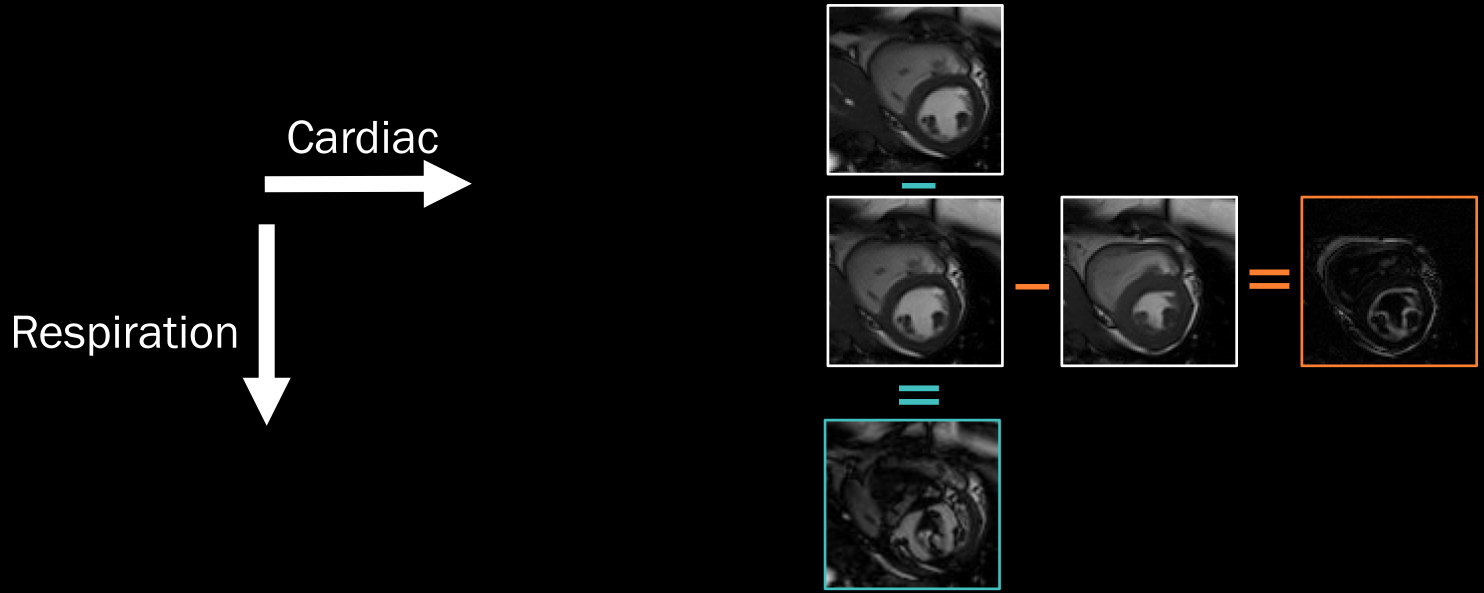
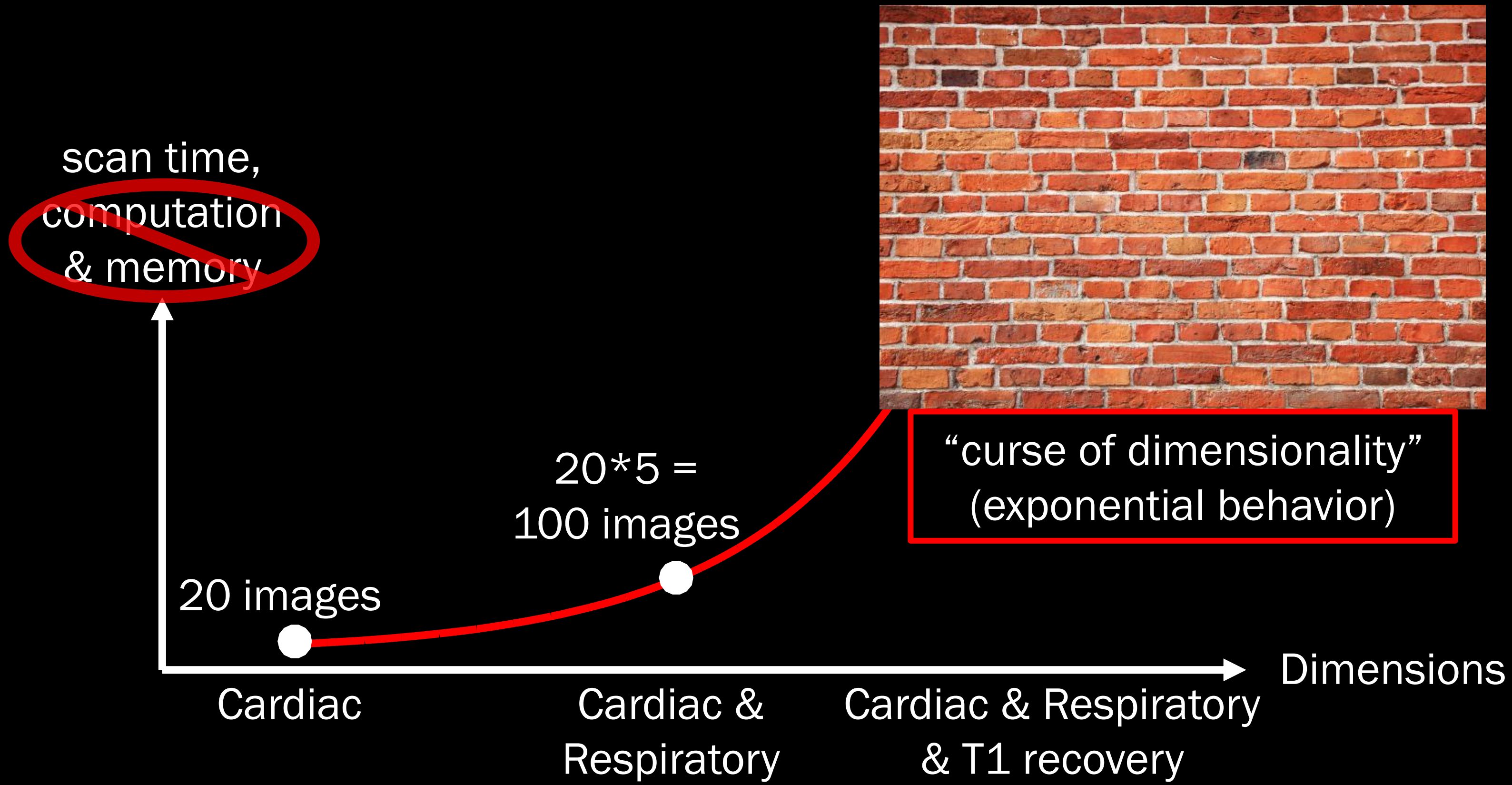


Neighboring images in both directions
have sparse differences

Feng L et al., *MRM* 2016

Multidimensional imaging: Challenge



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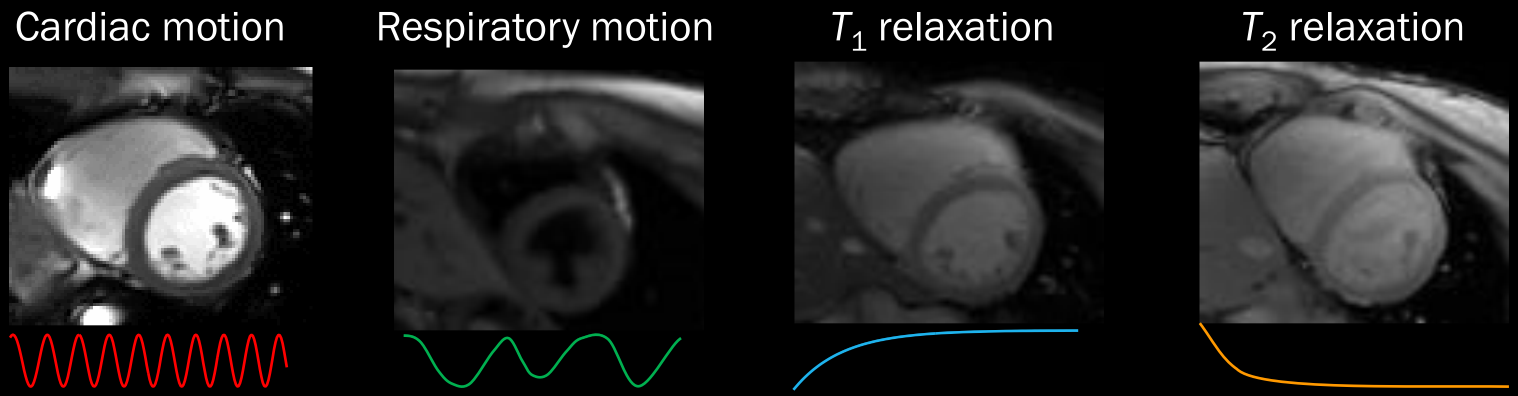
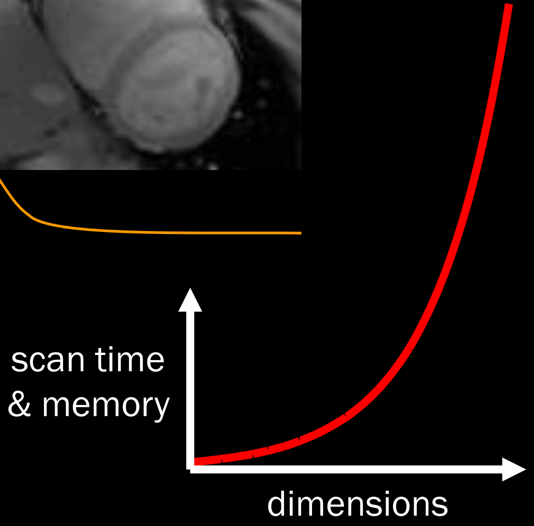
Multidimensional motion-resolved quantitative imaging: Challenge #1

Physiological motion dimensions AND physical process dimensions



Curse of dimensionality is especially relevant

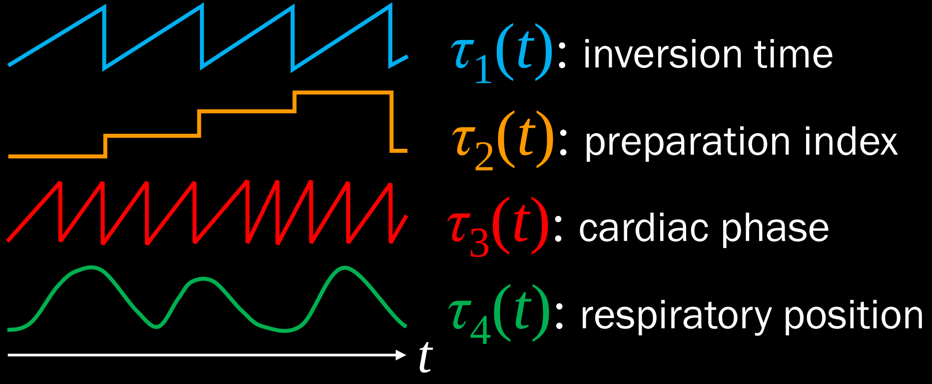
- Scan time and memory increase exponentially with # of dimensions

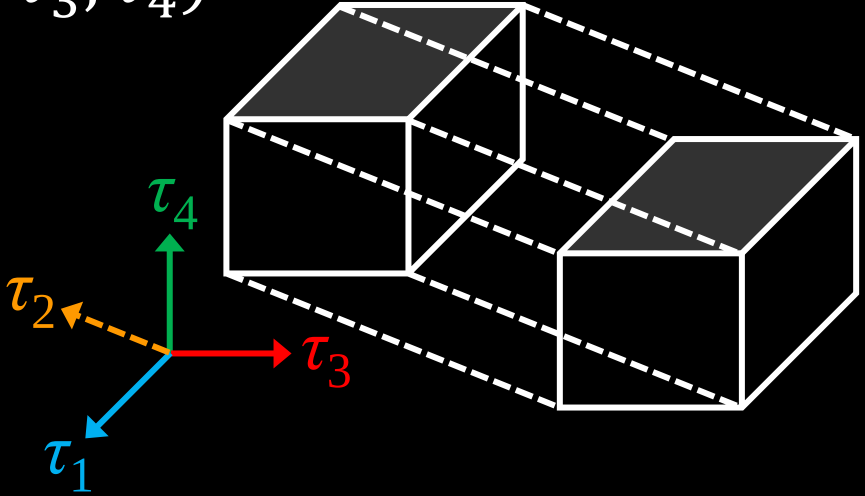


Multidimensional motion-resolved quantitative imaging: Challenge #2

Physiological motion dimensions are controlled by patient physiology

$$t \leftrightarrow (\tau_1, \tau_2, \tau_3, \tau_4)$$





Need to be robust to unpredictable $(\mathbf{k}, \tau_1, \tau_2, \tau_3, \tau_4)$-space sampling

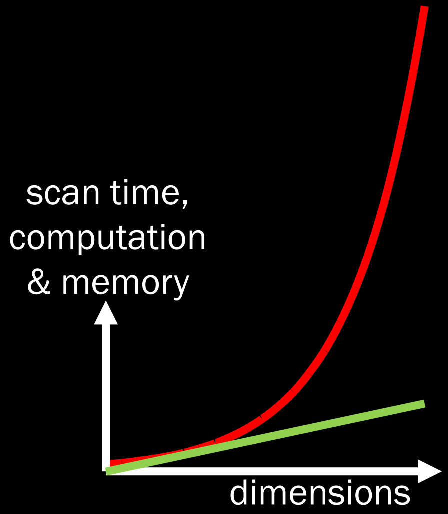
Magnetic resonance multitasking

Multidimensional imaging framework for quantitative imaging

- Particularly focused on motion-resolved quantitative imaging

Challenge #1: Curse of dimensionality

- Solution: Low-rank tensor[1] (LRT) imaging to reduce scan time and memory
  - Directly addresses the curse of dimensionality
  - Scales well (~linearly), even ≥5 dimensions



Challenge #2: Unpredictable motion dimensions

- Solution: Hybrid implicit-explicit LRT reconstruction[2,3] with flexible sampling requirements

[4]Liang Z-P, *IEEE-ISBI* 2007
[2]Christodoulou AG et al., *ISMRM* 2016
[3]Christodoulou AG et al., *Nature Biomed Eng* 2018

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Low-rank image model

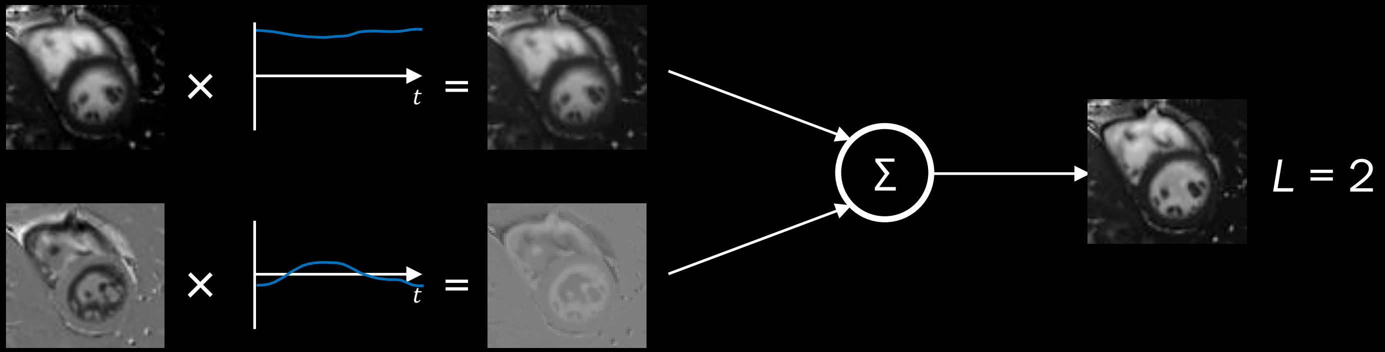
For one time dimension

Example: cardiac motion (cine imaging)

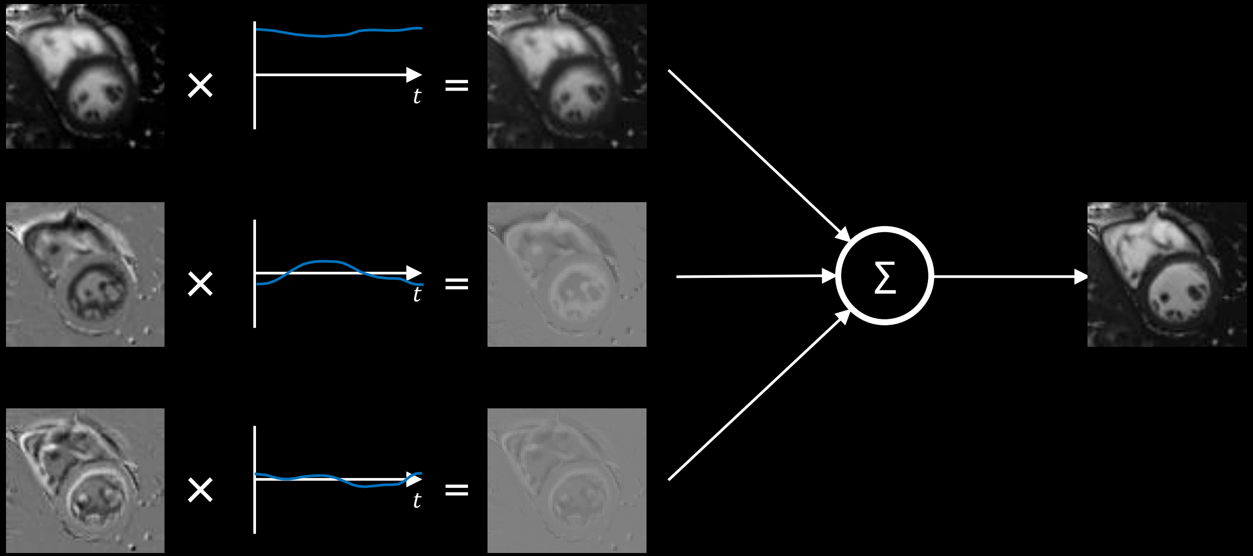
- 30 images (cardiac phases) in this sequence
- Images are so correlated as to be linearly dependent
    - Any image is a combination of L underlying basis images, $L < 30$
    - Any voxel time function is a combination of L temporal basis functions
- Image sequence is "low-rank" because rank $L < 30$

Liang Z-P, *IEEE-ISBI* 2007
Pedersen H et al., *MRM* 2009

Low-rank image model

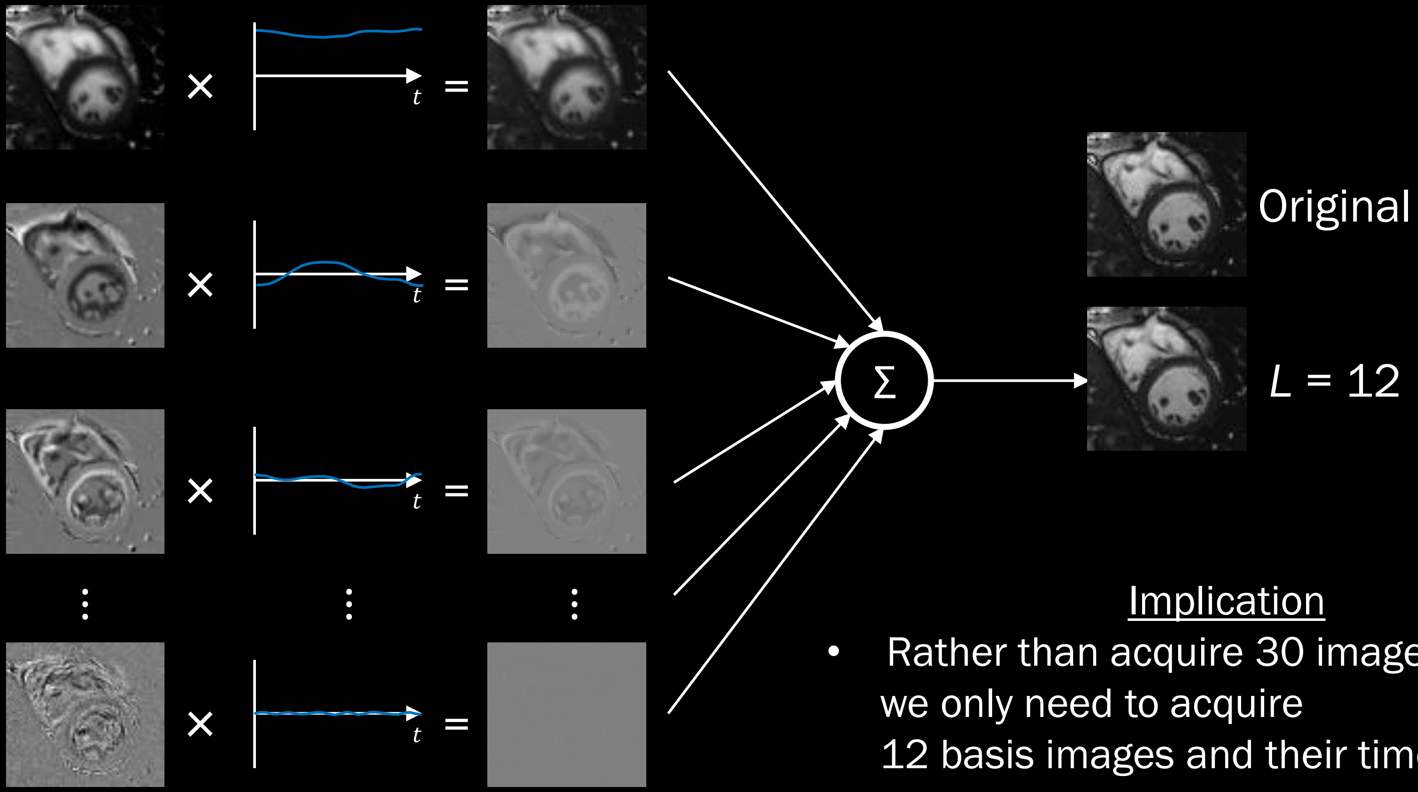


Low-rank image model



$L = 3$

Low-rank image model



<u>Implication</u>

- Rather than acquire 30 images, we only need to acquire 12 basis images and their time functions

Low-rank image model

For one time dimension

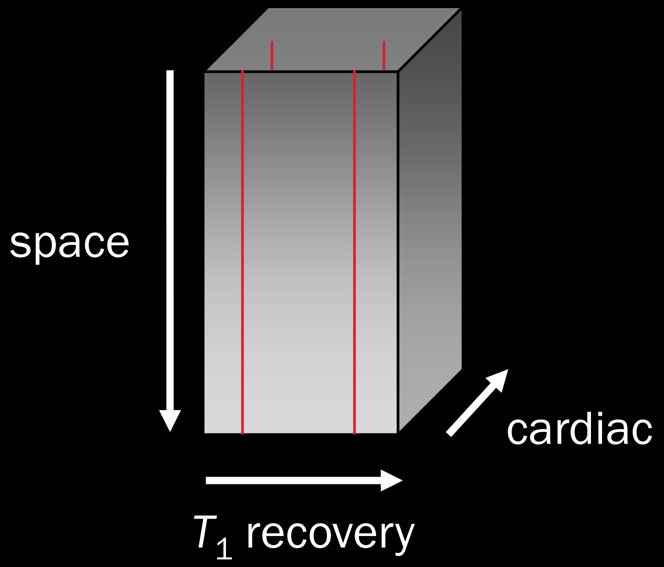
Example: cardiac motion (cine imaging)

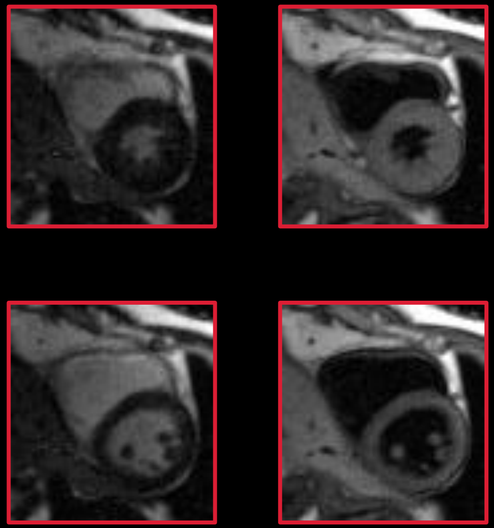
- Low-rank property established for many types of dynamics:
  - Dynamic contrast enhancement[1]
  - Cardiac motion (cine)[2]
  - Free-breathing cine[2]
  - NMR relaxation[3] (T1, T2)

[1]Liang Z-P, *IEEE-ISBI* 2007 [2]Pedersen H et al., *MRM* 2009 [3]Petzchner FH et al., *MRM* 2011

Multitasking: Low-rank tensor imaging

Represent images as tensor/array

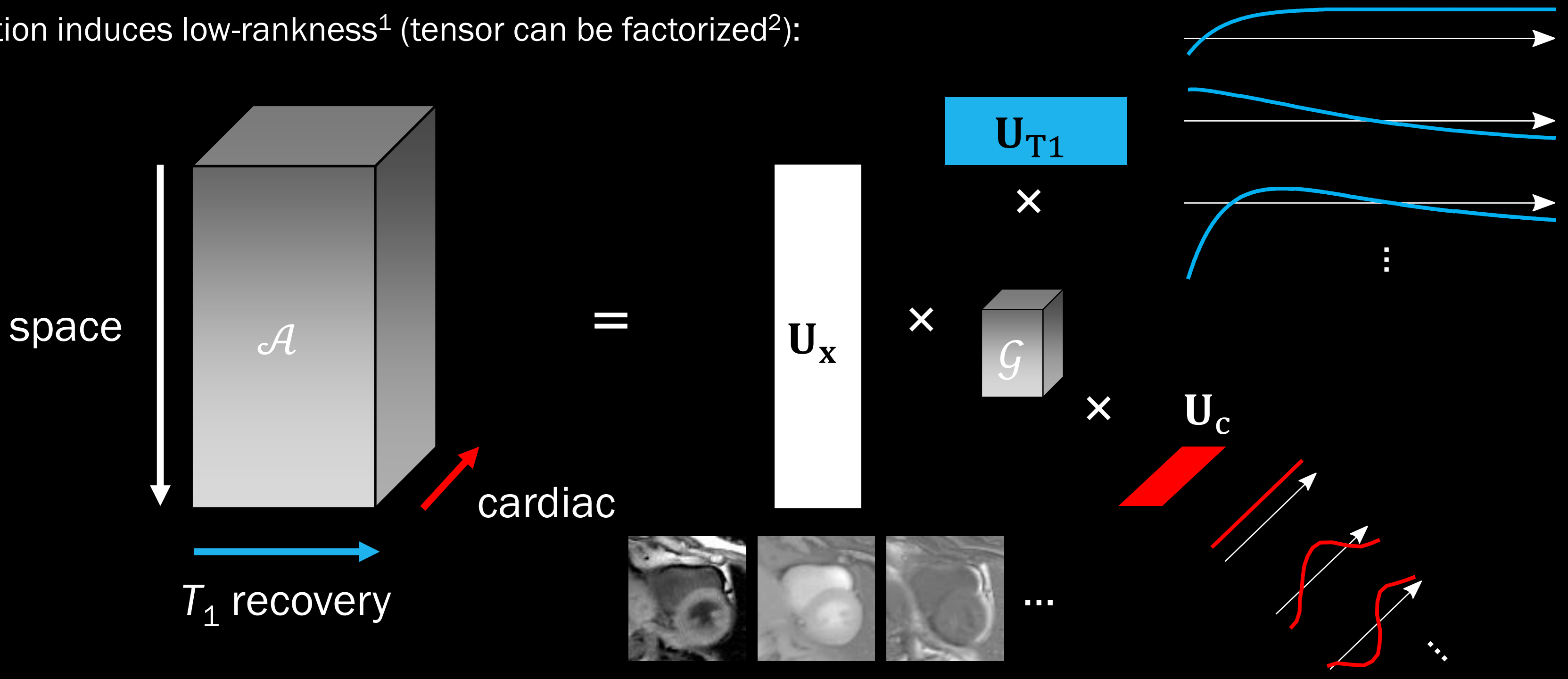




Low-rank tensor model

Represent images as tensor/array

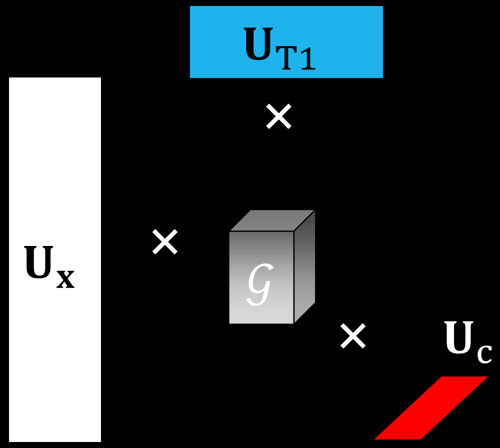
Correlation induces low-rankness[1] (tensor can be factorized[2]):



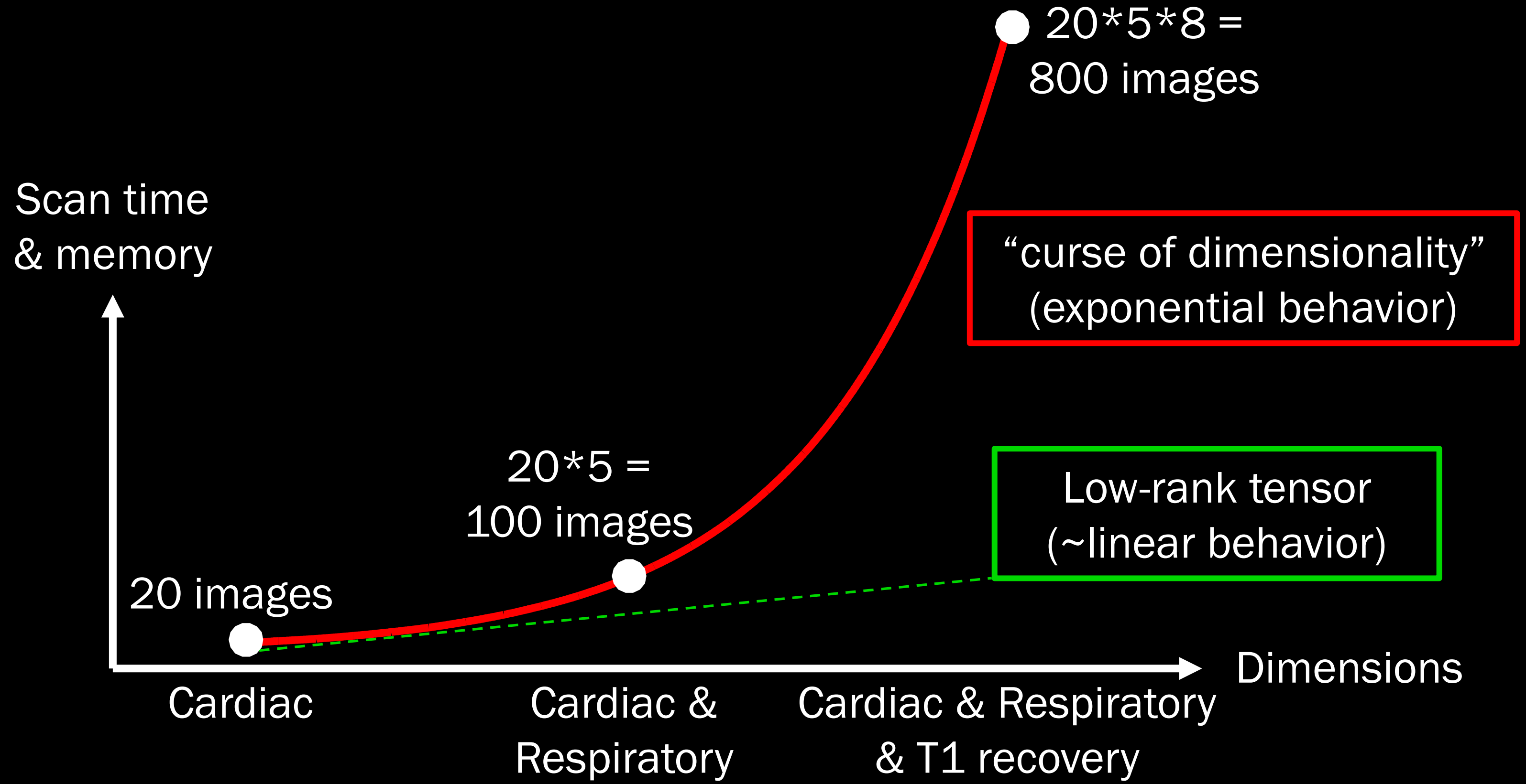
[1]Liang Z-P, *IEEE-ISBI* 2007
[2]Tucker LR, *Psychometrika* 1966

Low-rank tensor model: Implications

1. Factors are smaller than whole tensor
   - Short scan time, low memory
2. Exploits global correlation
   - Goes beyond image neighborhoods
3. Separates space from time
   - Will inform sampling/reconstruction
4. Each dimension has one factor matrix
   - # of dimensions = # of factor matrices



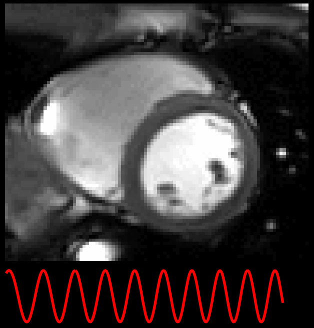
Multidimensional imaging: Challenge



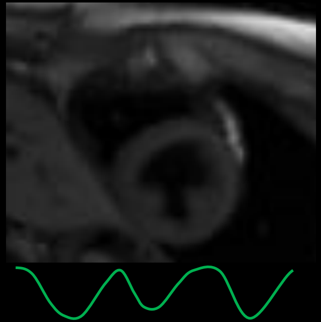
Multidimensional motion-resolved quantitative imaging: Challenge #1

Physiological motion dimensions AND physical process dimensions

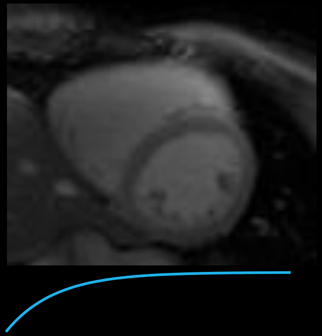
Cardiac motion



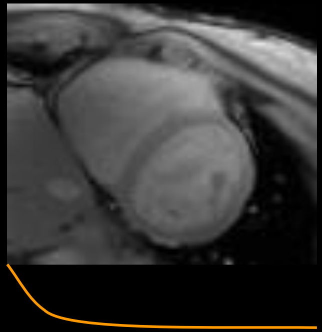
Respiratory motion



T_1 relaxation

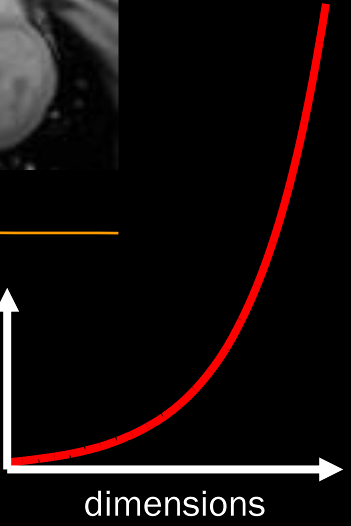


T_2 relaxation



Curse of dimensionality is especially relevant

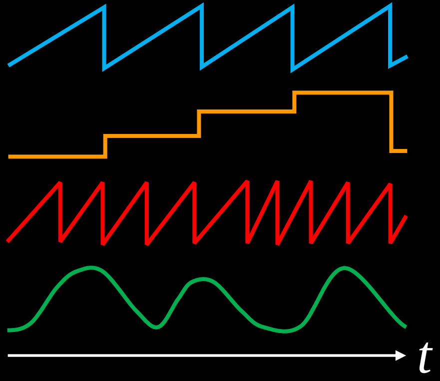
- Scan time and memory increase exponentially with # of dimensions



Multidimensional motion-resolved quantitative imaging: Challenge #2

Physiological motion dimensions are controlled by patient physiology

$$t \leftrightarrow (\tau_1, \tau_2, \tau_3, \tau_4)$$

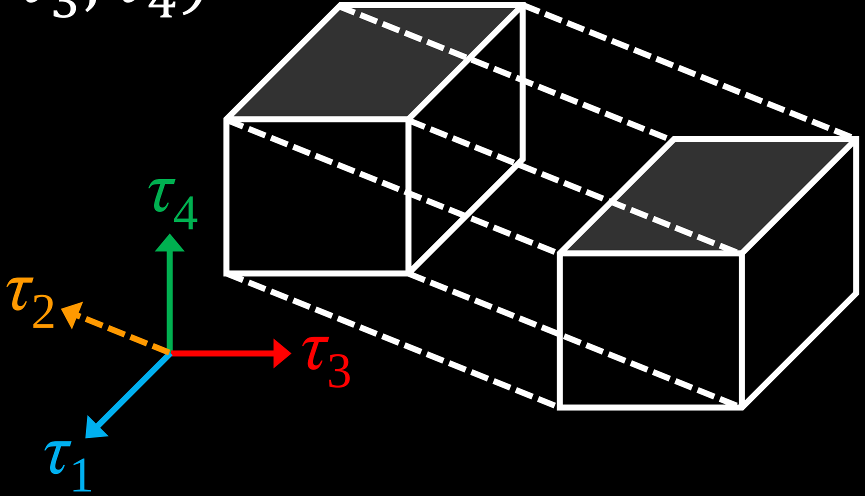


$\tau_1(t)$: inversion time

$\tau_2(t)$: preparation index

$\tau_3(t)$: cardiac phase

$\tau_4(t)$: respiratory position



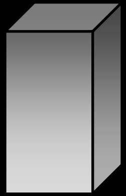
Need to be robust to unpredictable $(\mathbf{k}, \tau_1, \tau_2, \tau_3, \tau_4)$-space sampling

LRT imaging strategies

Implicit strategy[1,2]

$$\arg\min_{\mathcal{A}} \|\mathbf{d} - E(\mathcal{A})\|_2^2 + \lambda \sum_i \left\|\mathbf{A}_{(i)}\right\|_*$$

- Leaves tensor unfactored
- Tensor size still grows exponentially
  - E.g., 2 spatial + 4 time:
    - **210 GB per tensor**



- Flexible sampling patterns

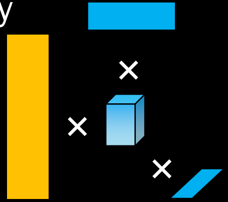
[1]Trzasko JD et al., *ISMRM* 2013

[2]Yu Y et al., *PLoS One* 2014

Explicit strategy[3,4]

1. Extract $\mathcal{G}$ & temporal $\mathbf{U}$'s from SVDs of training data
2. $\arg\min_{\mathbf{U}_\mathbf{x}} \|\mathbf{d} - E(\mathcal{G} \times_1 \mathbf{U}_\mathbf{x} \times_2 \mathbf{U}_\mathrm{c} \times_3 \cdots \times_5 \mathbf{U}_{\mathrm{T1}})\|_2^2$

- Directly recovers tensor factors
- Storage of tensor factors grows ~linearly
  - E.g., 2 spatial + 4 time:
    - **67 MB per tensor**



- Uses specific training data sampling pattern

[1]Christodoulou AG and Liang Z-P, *ISMRM* 2015

[2]He J et al., *IEEE-TMI* 2016

Multitasking strategy

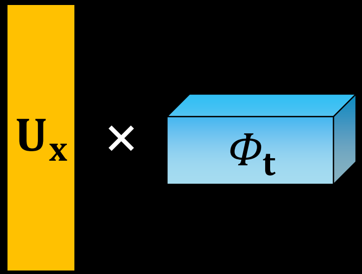
Hybrid strategy

1. Implicit LRT recovery of missing training data

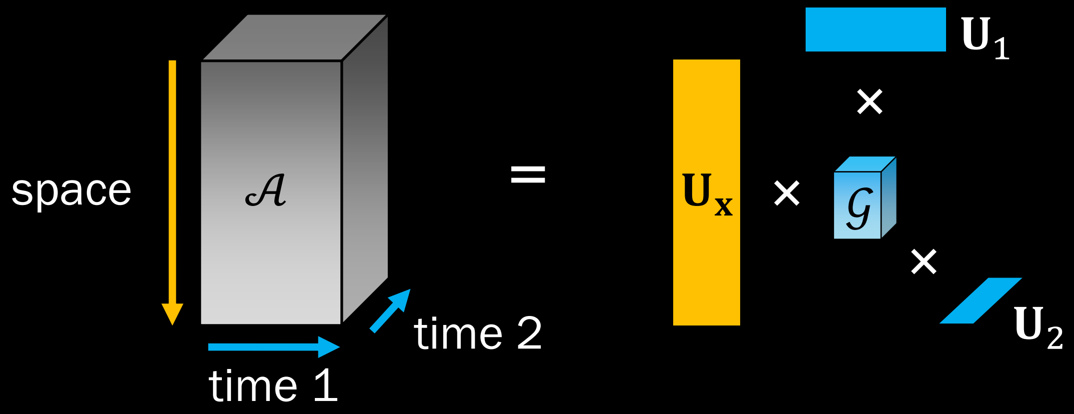
2. Extract $\Phi_{\mathbf{t}}$ from HOSVD of completed training data

3. $\underset{\mathbf{U_x}}{\arg\min} \|\mathbf{d} - E(\Phi_{\mathbf{t}} \times_1 \mathbf{U_x})\|_2^2$

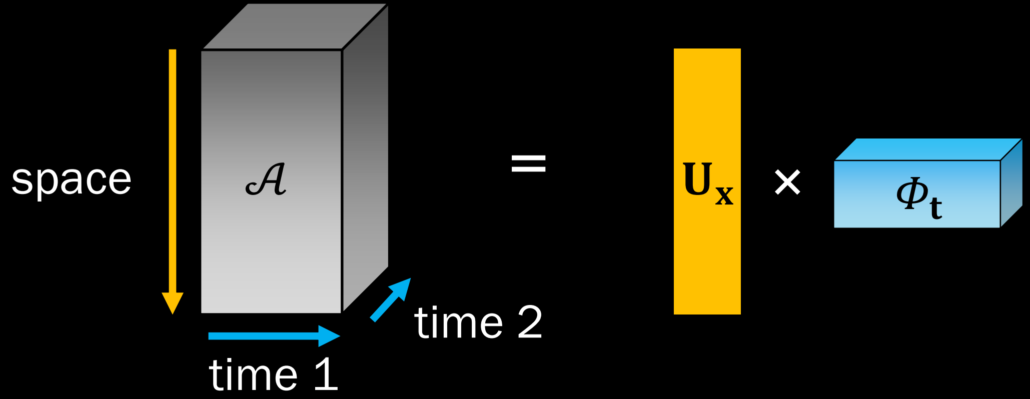
- Implicit recovery step only done for training subset of k-space
  - still only MBs/coil
- Training data used, but no specific pattern required
- Retains computational benefits of explicit strategy



Space is separated from time(s)



Space is separated from time(s)



Collect two interleaved sets of data:

Imaging data

Targets spatial factor $\mathbf{U_x}$

High spatial resolution

Extensive **k**-space coverage

Training data

Targets temporal factor $\Phi_\mathbf{t}$

High speed

One (or a few) **k**-space trajectories repeated

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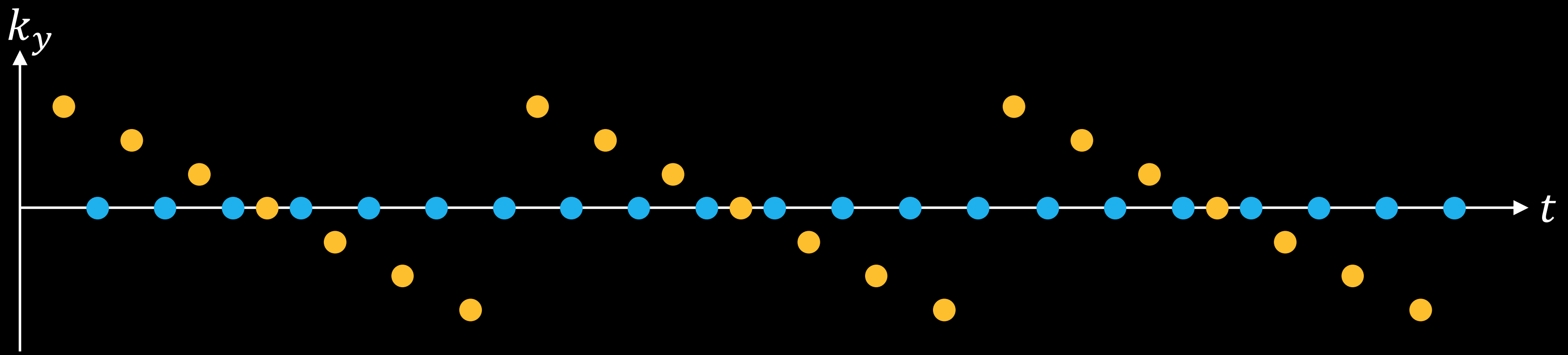
Space is separated from time(s)



Collect two interleaved sets of data:

Imaging data

Targets spatial factor $\mathbf{U_x}$

High spatial resolution

Extensive **k**-space coverage

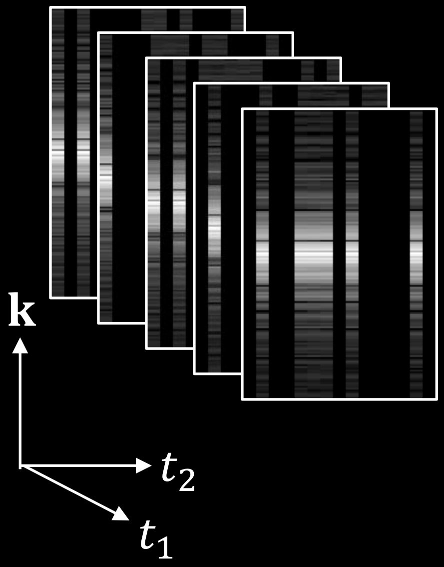
Training data

Targets temporal factor $\Phi_{\mathbf{t}}$

High speed

One (or a few) **k**-space trajectories repeated

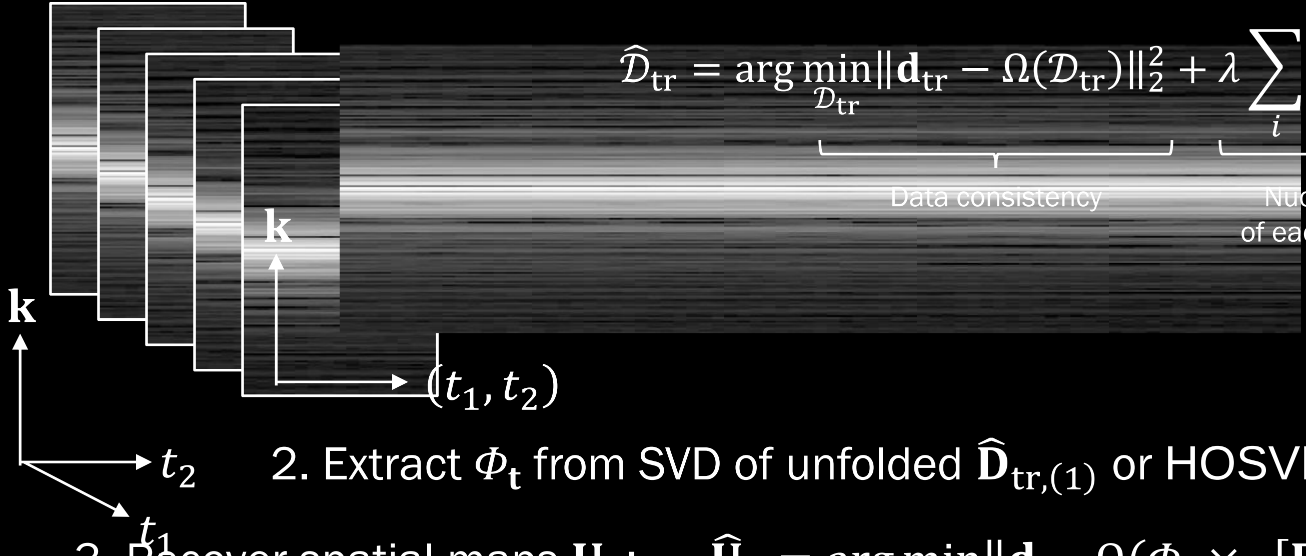
Image reconstruction



- For training data $\mathcal{D}_{\mathrm{tr}}$, one (or a few) **k**-space trajectories are sampled very frequently
- This will cover many—but not necessarily all—time point combinations
- ”Missing” training data is recovered by <u>unfactored</u> low-rank tensor completion
  - Only one **k**-space trajectory → still only MBs/coil

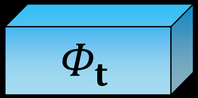
Image reconstruction

1. Complete low-rank training data tensor $\mathcal{D}_{\text{tr}}$



$$\hat{\mathcal{D}}_{\text{tr}} = \arg\min_{\mathcal{D}_{\text{tr}}} \underbrace{\|\mathbf{d}_{\text{tr}} - \Omega(\mathcal{D}_{\text{tr}})\|_2^2}_{\text{Data consistency}} + \lambda \underbrace{\sum_i \left\|\mathbf{D}_{\text{tr},(i)}\right\|_*}_{\text{Nuclear norm of each unfolding}} + \underbrace{R(\mathcal{D}_{\text{tr}})}_{\text{Optional additional penalty}}$$

2. Extract $\Phi_{\mathbf{t}}$ from SVD of unfolded $\hat{\mathbf{D}}_{\text{tr},(1)}$ or HOSVD of $\hat{\mathcal{D}}_{\text{tr}}$



3. Recover spatial maps $\mathbf{U_x}$:

$$\hat{\mathbf{U}}_{\mathbf{x}} = \arg\min_{\mathbf{U_x}} \underbrace{\|\mathbf{d} - \Omega(\Phi_{\mathbf{t}} \times_1 [\mathbf{FSU_x}])\|_2^2}_{\text{Data consistency}} + \underbrace{R(\mathbf{U_x})}_{\text{Optional additional penalty}}$$

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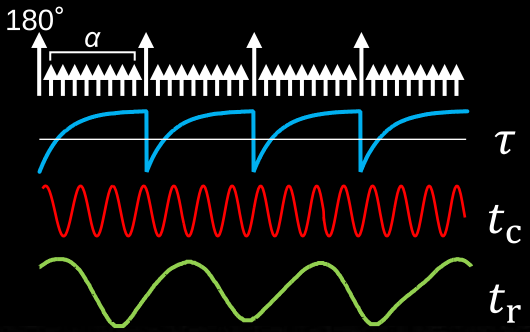
T_1 multitasking: Free-breathing, non-ECG T_1 mapping

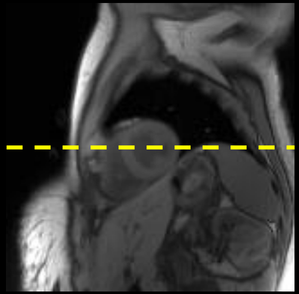
Continually acquire IR-FLASH

688 inversion times ($\Delta\tau$ =3.56 ms) up to 2.5 sec

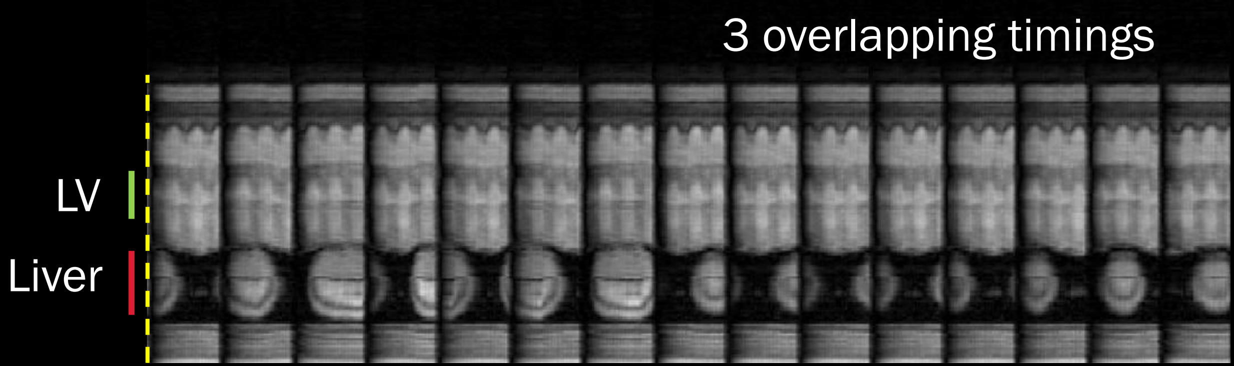
- With LRT model, has similar scan time as
  far fewer inversion times (e.g., 8)
- Avoids binning radial spokes



3 overlapping timings



Real-time evolution



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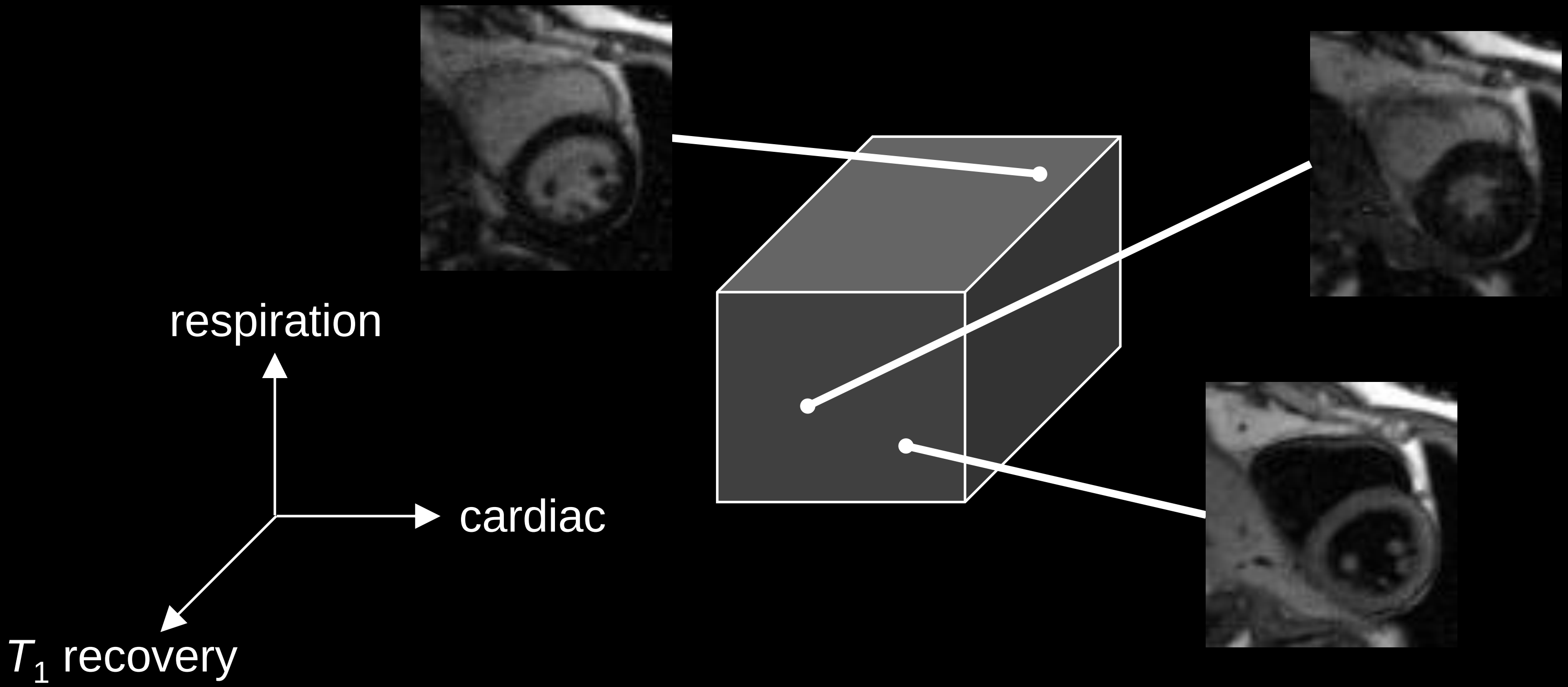
Shaw JL et al., *ISMRM* 2016
Shaw JL et al., *MRM* 2019

T_1 multitasking: Free-breathing, non-ECG T_1 mapping

3 time dimensions gives us a “cube” with an image at each point



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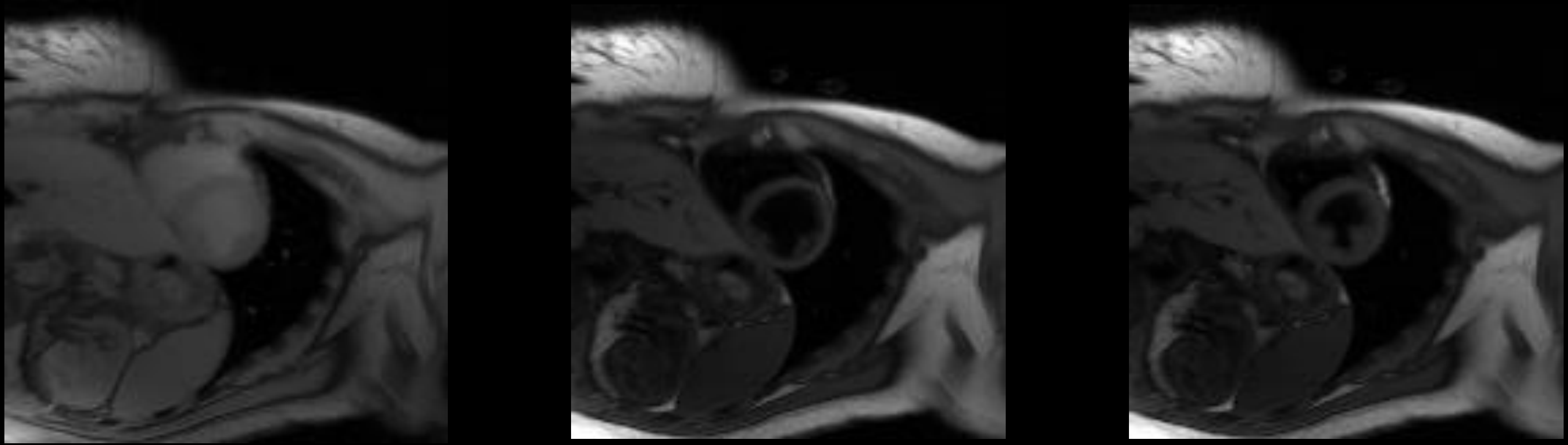
T_1 multitasking: Free-breathing, non-ECG T_1 mapping

Can retrospectively isolate any of 3 time dimensions



T_1 recovery

Cardiac motion

Respiratory motion

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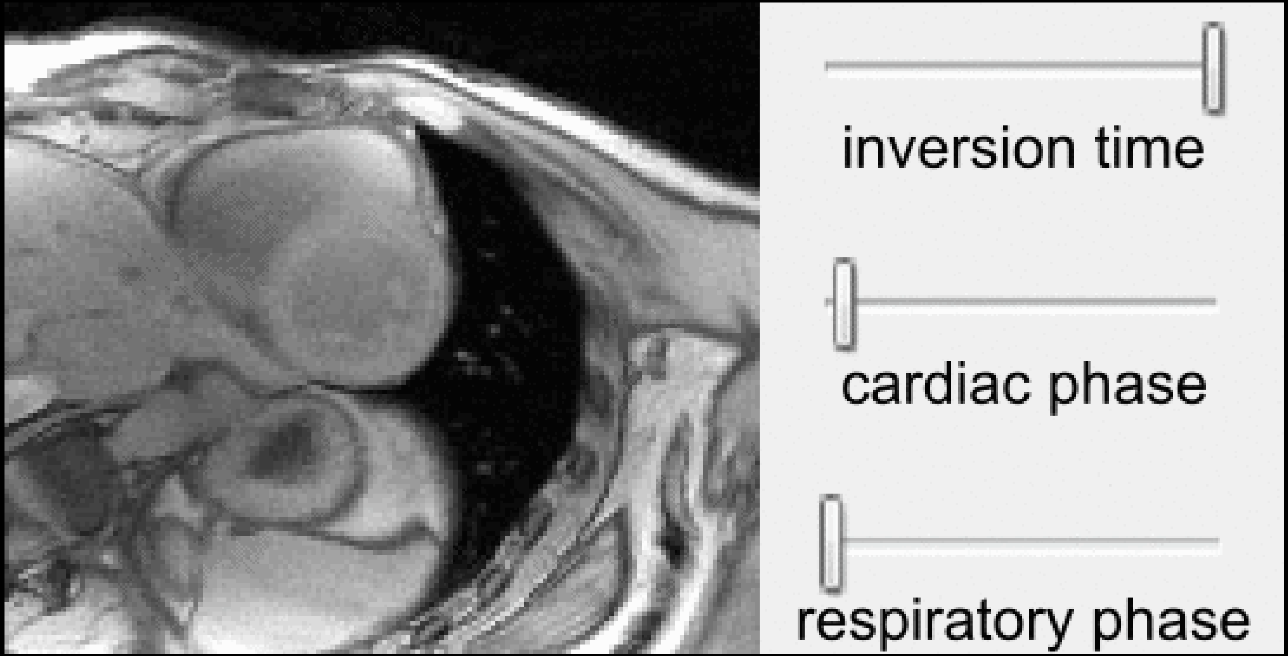
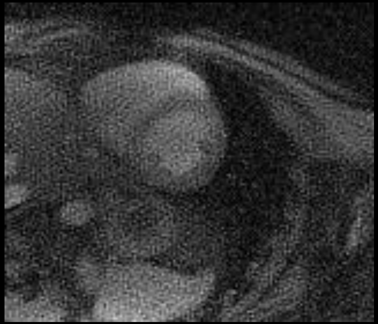
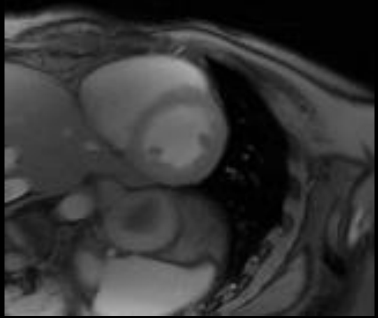
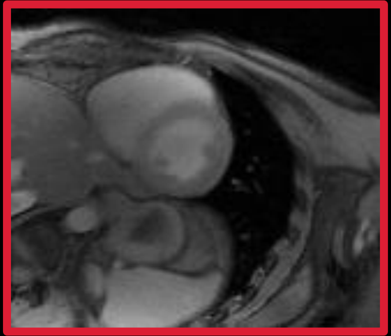
T_1 multitasking: Free-breathing, non-ECG T_1 mapping

Provides multiple contrasts at every cardiac and respiratory phase



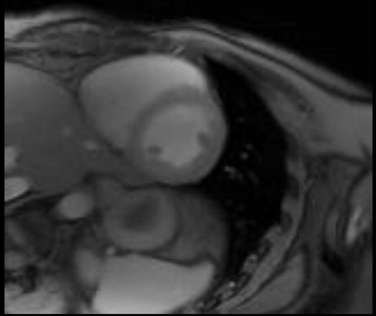
T_1 multitasking: Acceleration demonstration

	SENSE (8 τ bins, $\Delta\tau$=306 ms)	Low-rank tensor (344 τ bins, $\Delta\tau$=7 ms)
12 min scan		
1 min scan		

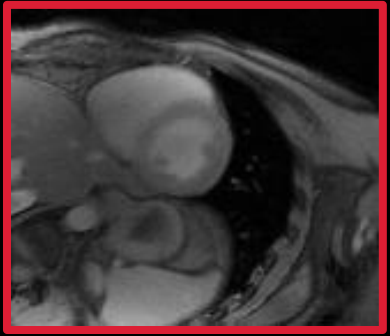
T_1 multitasking: Acceleration demonstration

Low-rank tensor

12 min scan

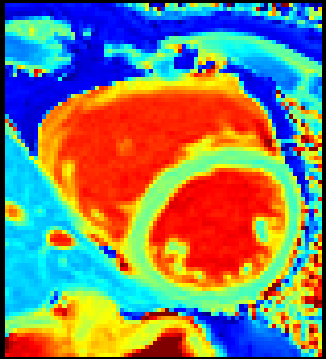


1 min scan



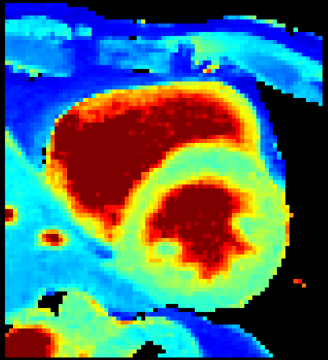
T_1 multitasking: Free-breathing, non-ECG T_1 mapping

MOLLI

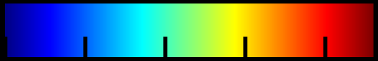


ECG-triggered
Breath-held

Multitasking

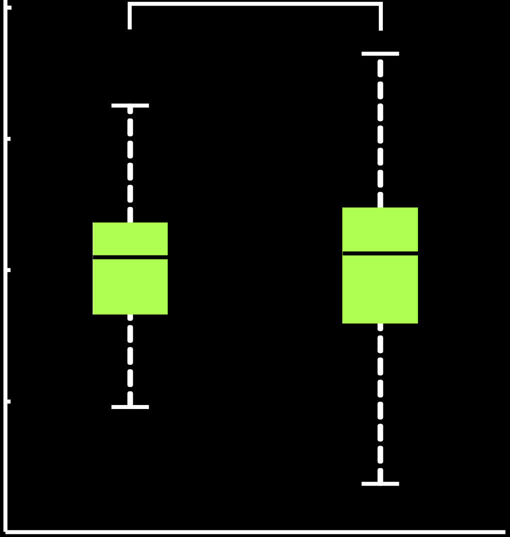


No ECG
Free-breathing



ROI: myocardium

End-diastolic myocardial T_1



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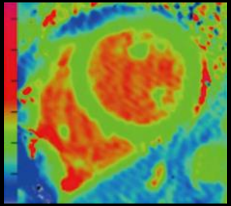
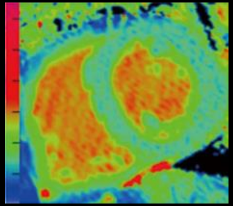
Shaw JL et al., *ISMRM* 2016
Shaw JL et al., *MRM* 2019

Quantitative cardiovascular MR (CMR)

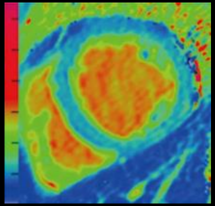
T_1



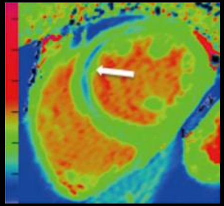
Normal



Fabry disease

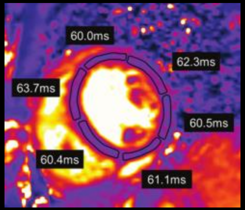


Iron overload

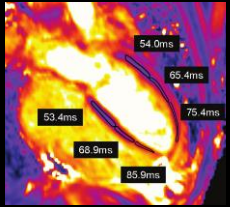


Fatty metaplasia

T_2



Diffuse Myocarditis

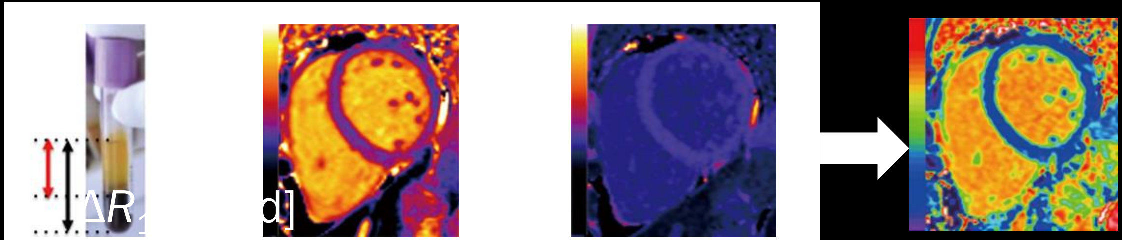


Takotsubo

T_1 w/Gd

Perfusion

ECV



1 -- HCT

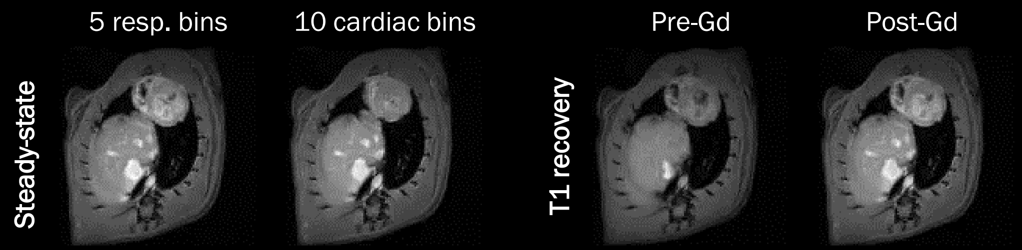
Native T_1

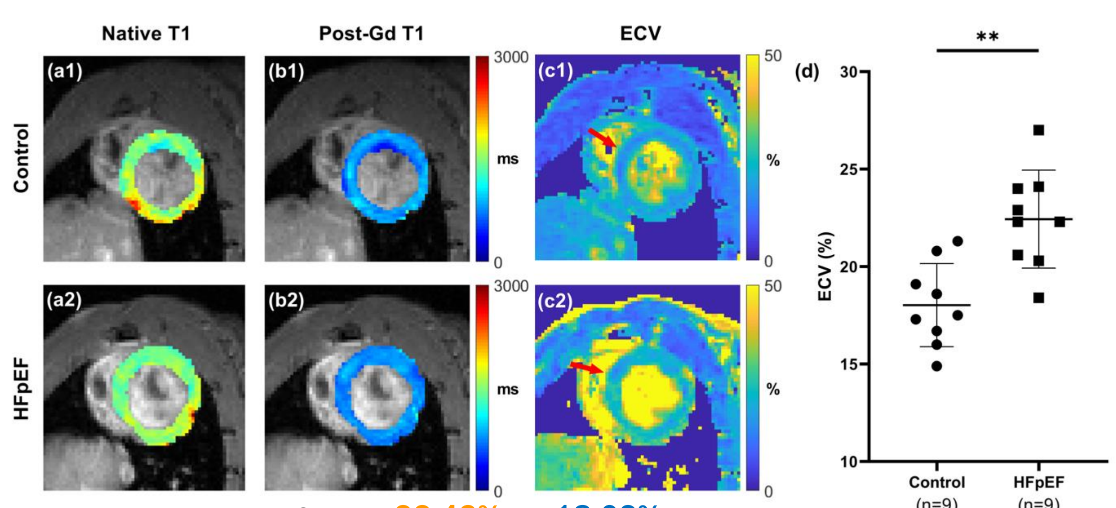
Post-contrast

Extracellular volume (ECV)

Bulluck H et al., *Circ J* 2015; Thavendiranathan P et al., *Circ Cardiovasc Imaging* 2012

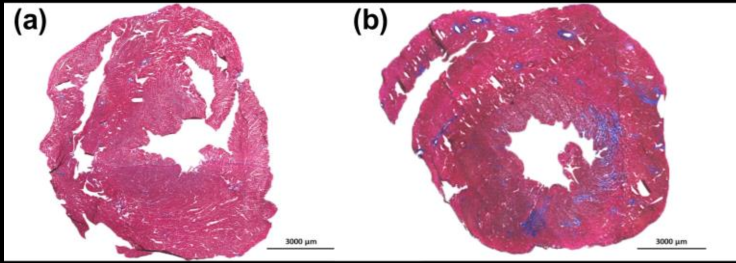
ECV Multitasking in small animals

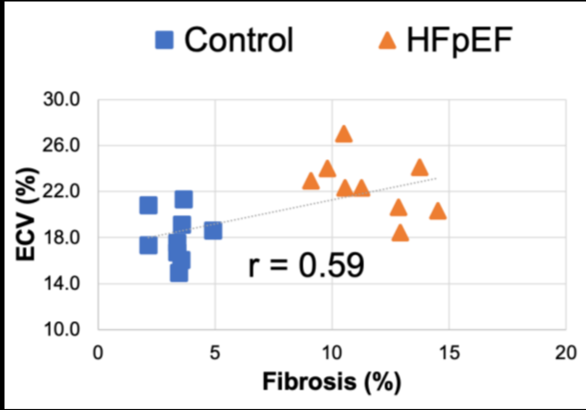




HFpEF v.s. Control: 22.43% v.s. 18.02%

HFpEF animal model:
Dahl salt-sensitive (DSS) rats





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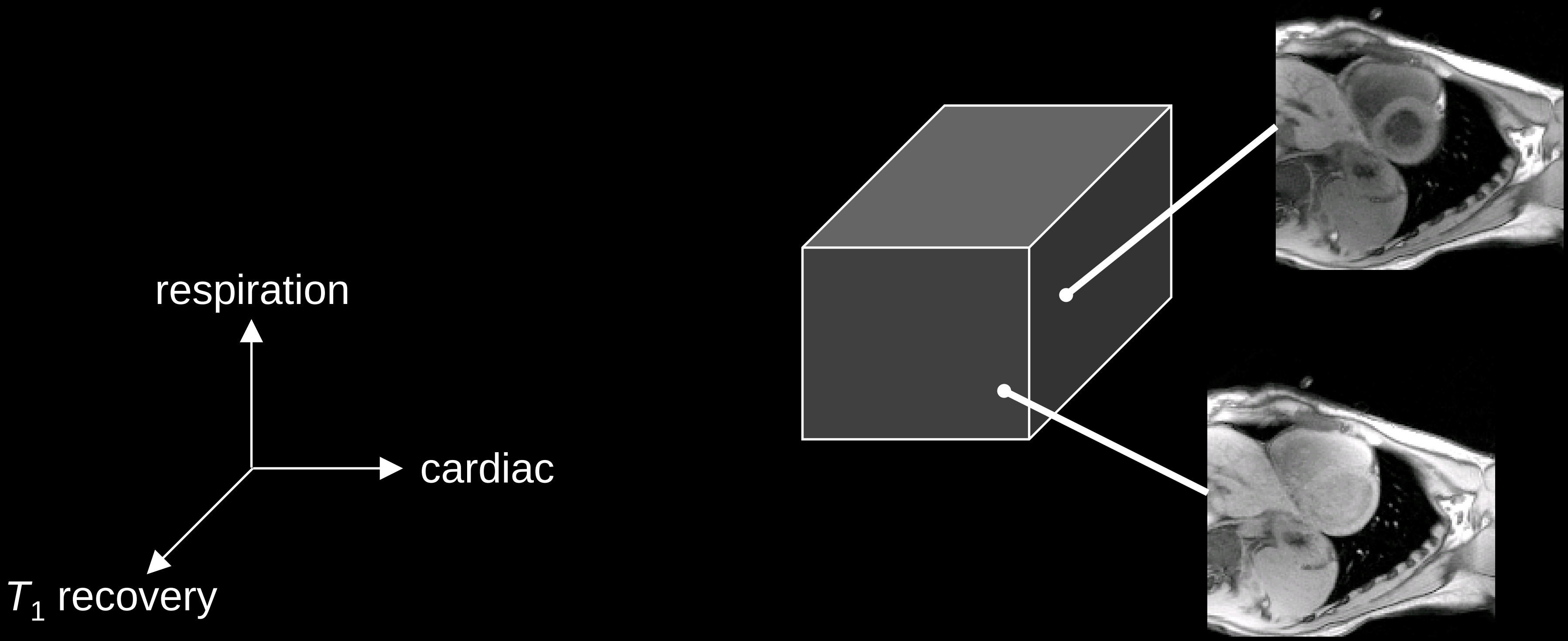
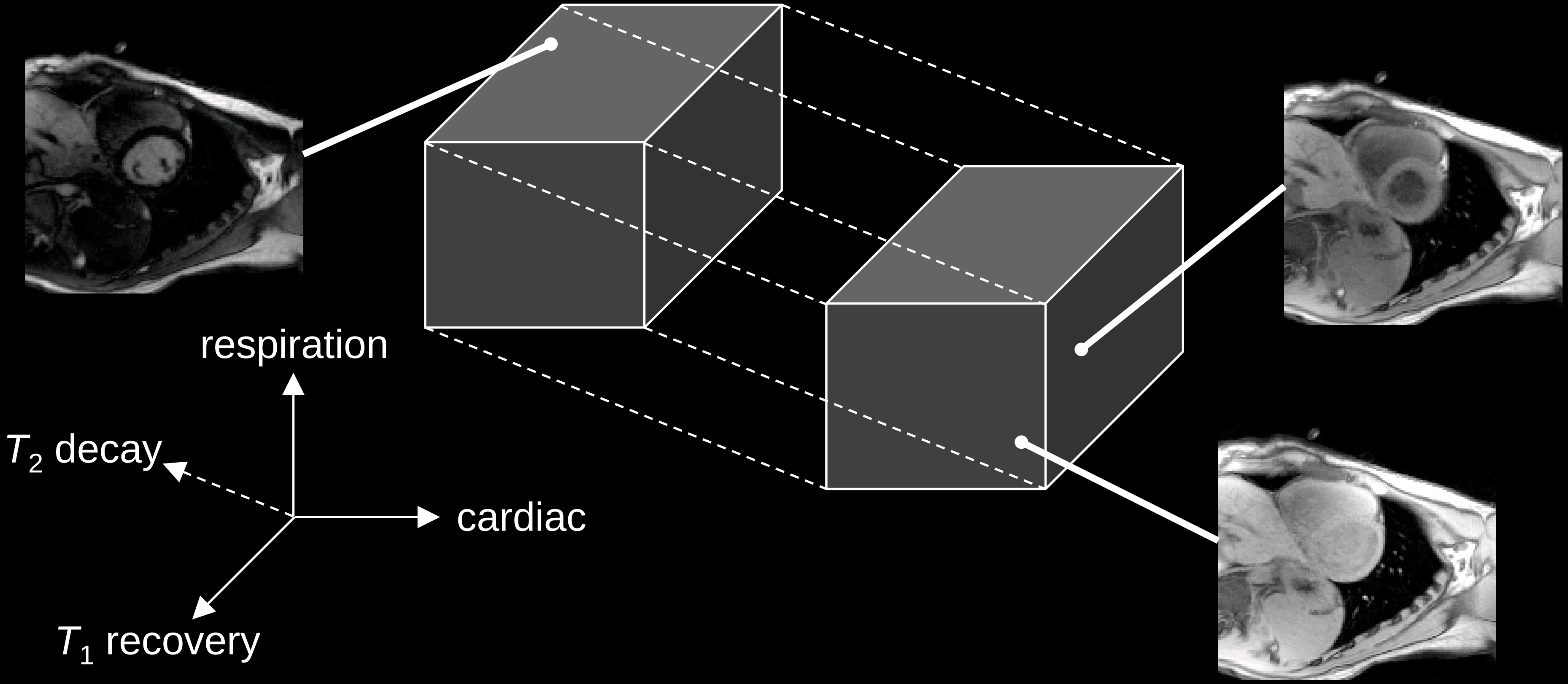
Han P et al., *JCMR* 2021

Adding more time dimensions



Adding more time dimensions



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T_1-T_2 multitasking: Free-breathing, non-ECG T_1-T_2 mapping

Adiabatic T2prep[1]/inversion recovery[2] (T2IR)–prepared FLASH

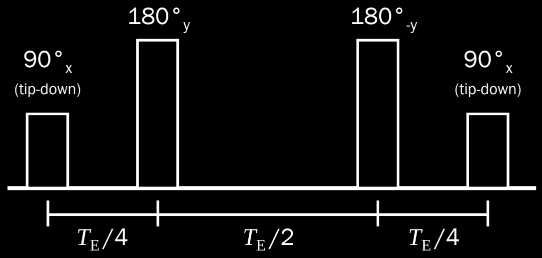
[1]Nezafat R et al., *MRM* 2006
[2]Brown R et al., *MRM* 2010

First 90° rotation tips magnetization into transverse plane

Refocusing pulses ensure T2 decay instead of T2*

Second 90° rotation interrupts T2 decay and stores T2-weighted magnetization along –*z*

T2-weighted "inversion"
(starting point of T1 recovery depends on T2)



Christodoulou AG et al., *SCMR* 2017

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Adiabatic T2prep[1]/inversion recovery[2] (T2IR)–prepared FLASH

[1]Nezafat R et al., *MRM* 2006
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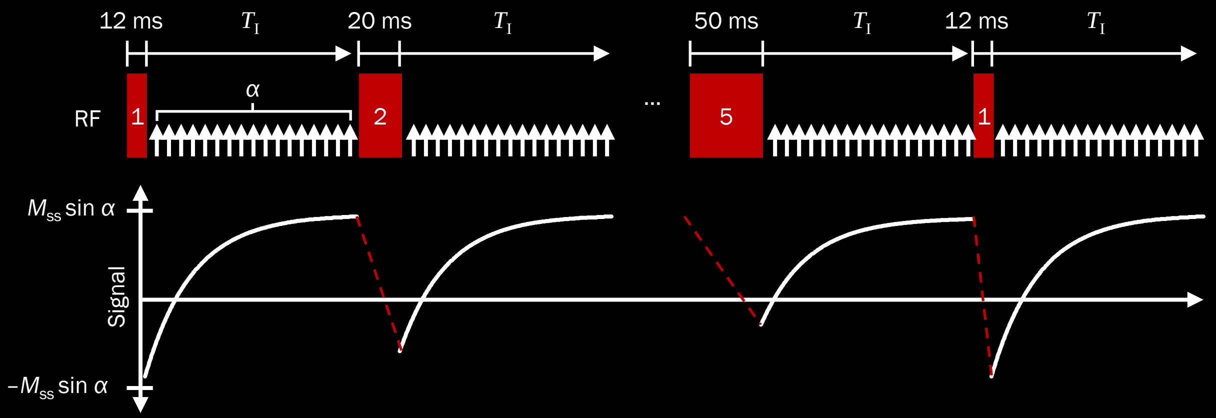
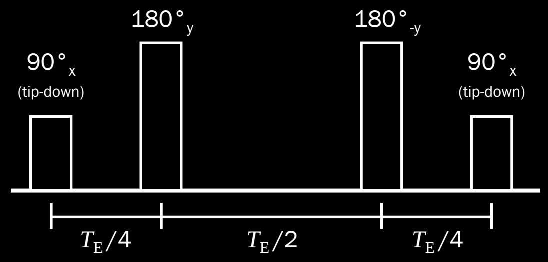
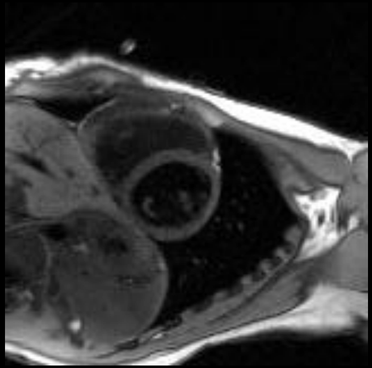


T2IR :

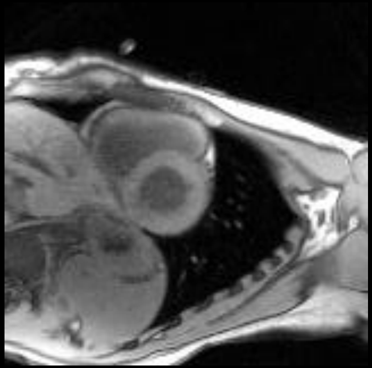


Christodoulou AG et al., *SCMR* 2017

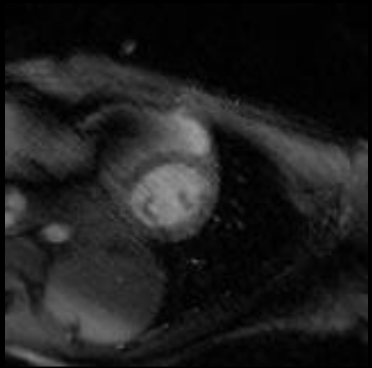
T_1-T_2 multitasking: Free-breathing, non-ECG T_1-T_2 mapping



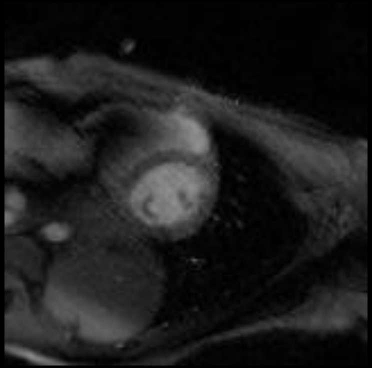
Cardiac motion



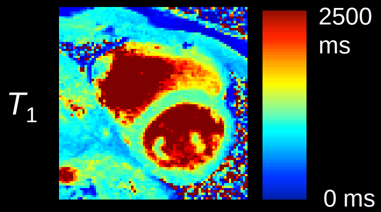
Respiration

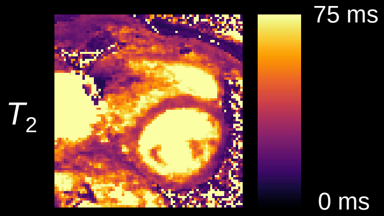


T_1 recovery



T2prep duration





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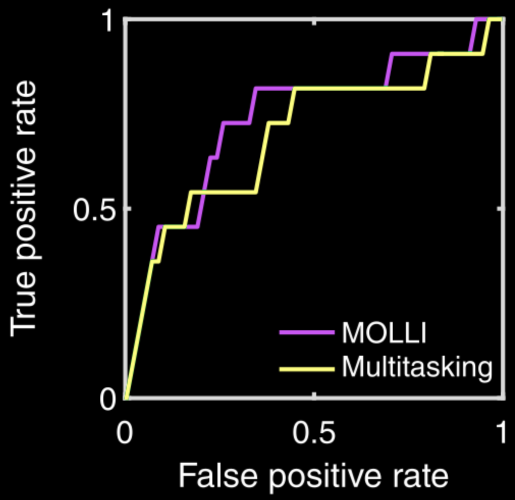
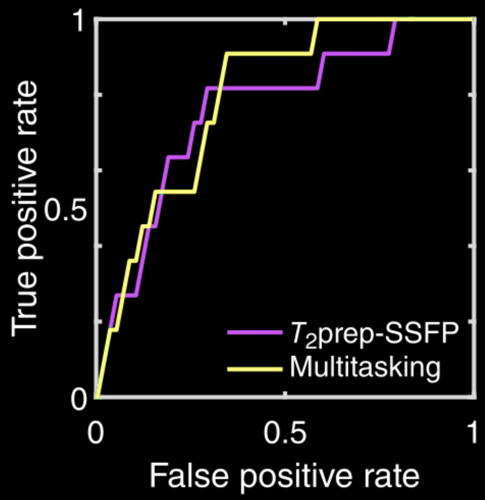
Christodoulou AG et al., *Nature BME* 2018

T_1-T_2 multitasking: Can native T_1-T_2 predict LGE in acute MI?

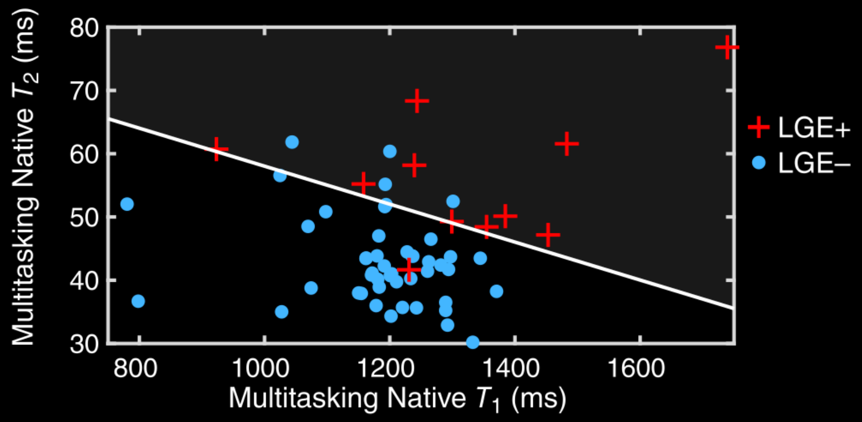
Pilot study in n = 10 acute MI patients



Method	AUC
MOLLI	0.74
Multitasking	0.70



Method	AUC
T_2prep-SSFP	0.77
Multitasking	0.80



91% sensitivity, 91% specificity

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Christodoulou AG et al., *Nature BME* 2018

Simultaneous Multi Slice (SMS) Multitasking

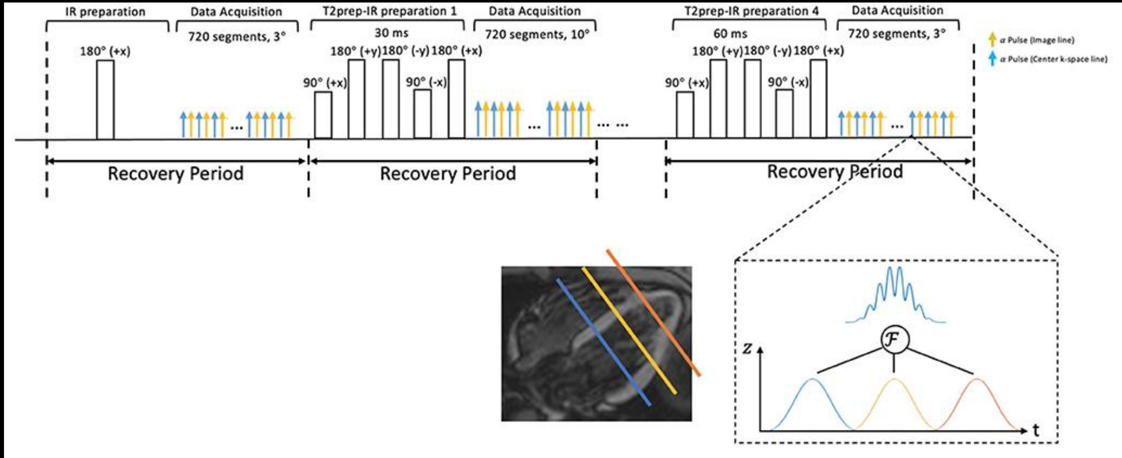
Radial SMS implementation of T1-T2 multitasking

3 slices with SMS Multitasking

- No ECG
- No breath-holds
- 3 min acquisition

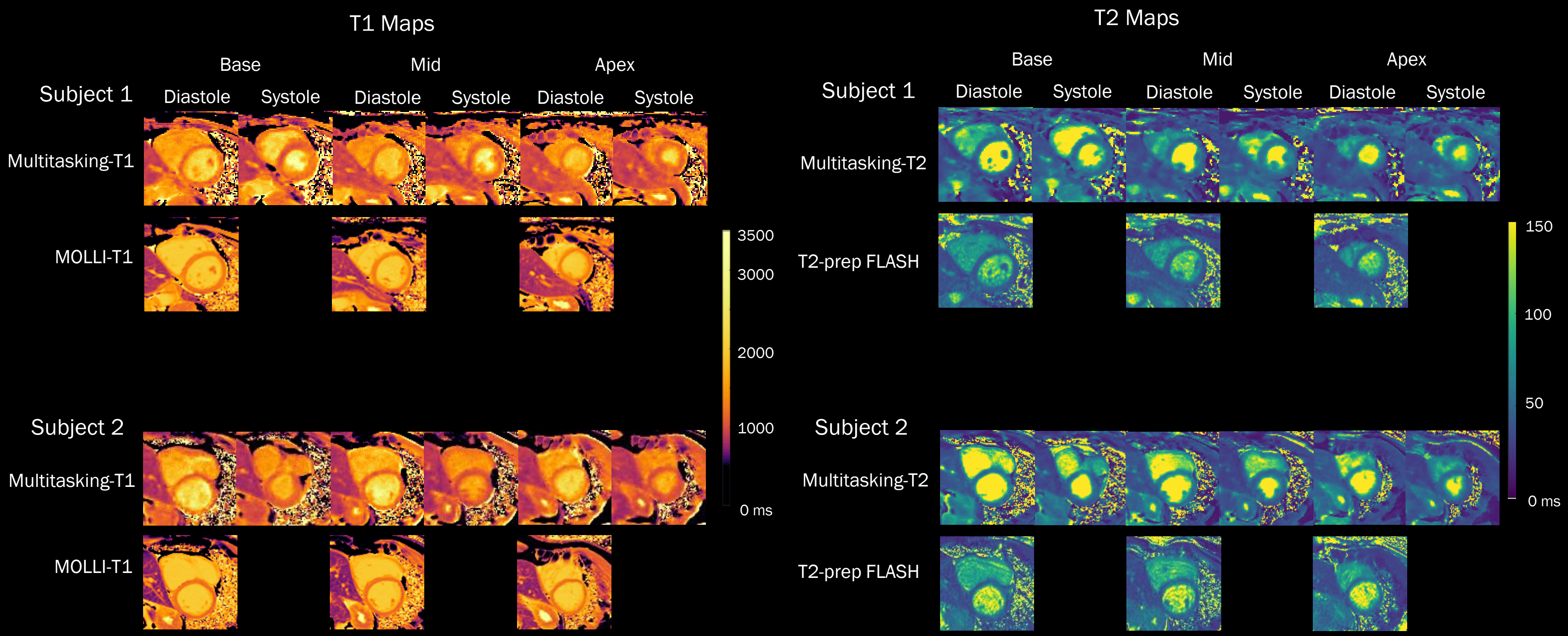
3 slices with conventional mapping techniques

- ECG triggered
- 6 breath holds
- 4–7 min acquisition (with breath-hold recovery)



Mao X et al., *Front Cardiovasc Med* 2022

T1-T2 Simultaneous Multislice (SMS)



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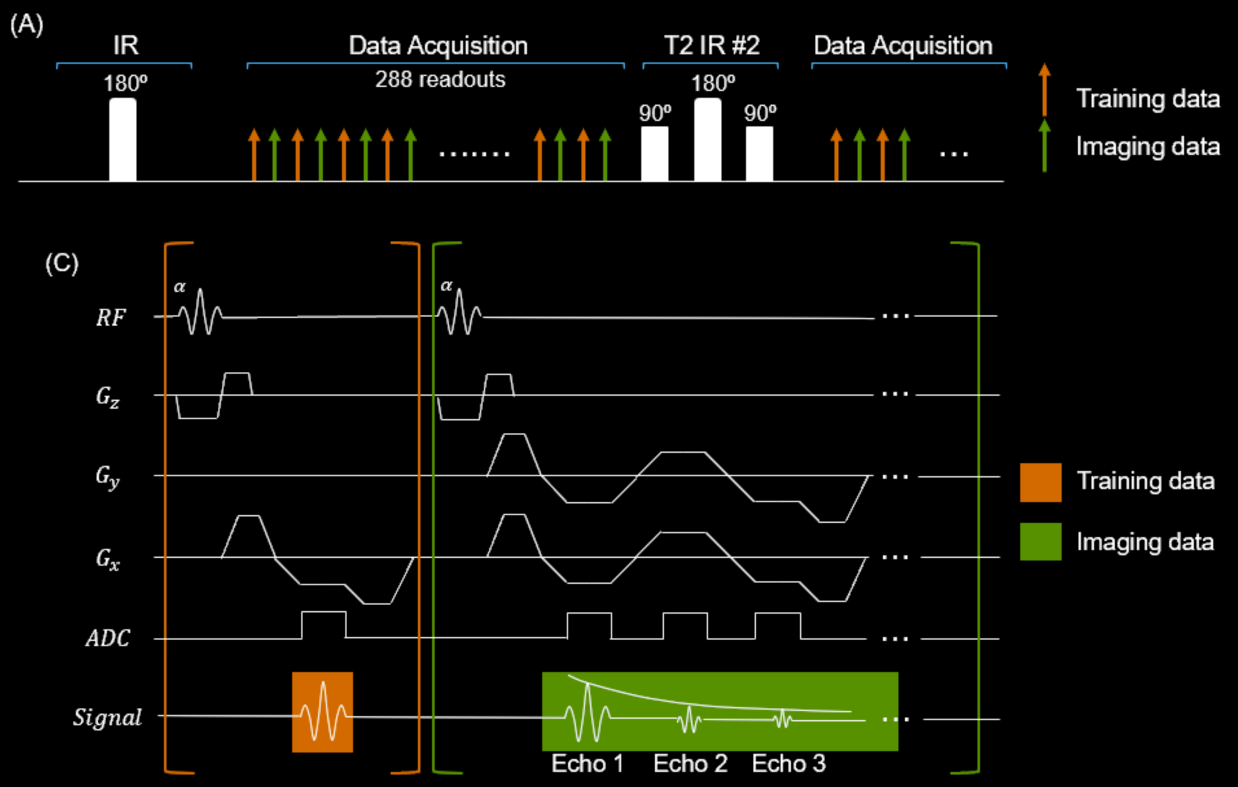
Mao X et al., *Front Cardiovasc Med* 2022

Multiecho multitasking for T1-T2-T2*-fat fraction (FF)



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Cao T et al., *MRM* 2022

MR Multitasking 2D T1-T2-T2*-fat fraction mapping

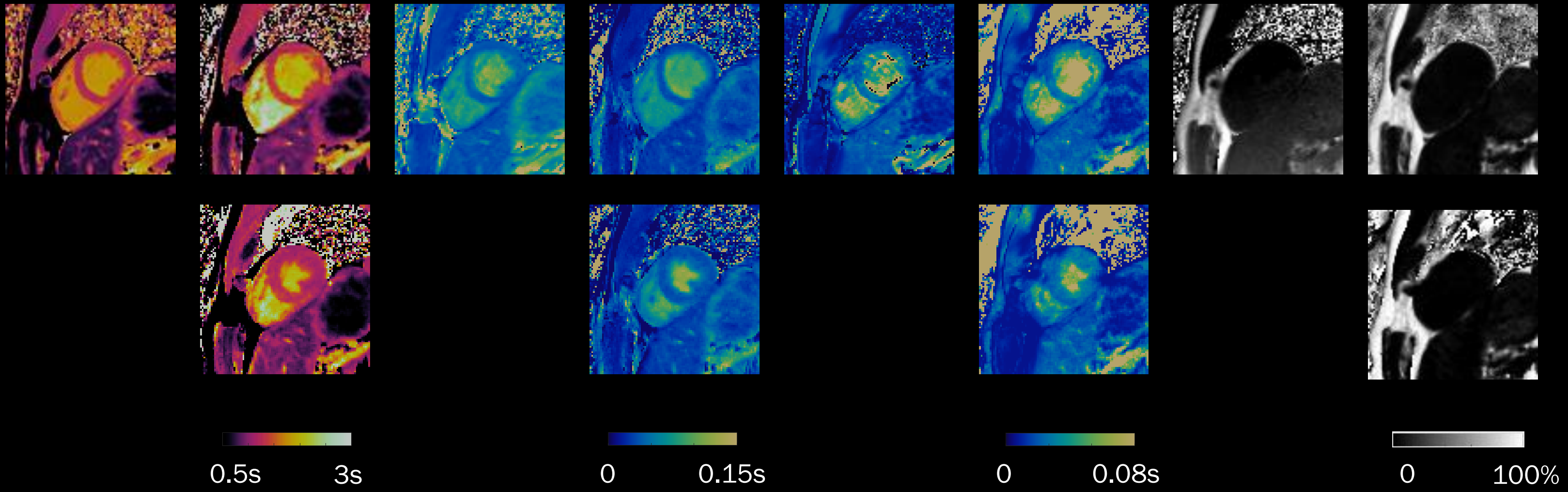
Healthy volunteer example

3-T scanner | 1.7 x 1.7 x 8 mm resolution | Non-ECG, Free-breathing | 2.5 min scan

T1 — Reference, Multitasking
T2 — Reference, Multitasking
T2* — Reference, Multitasking
Fat fraction — Reference, Multitasking

Diastolic

Cardiac-resolved



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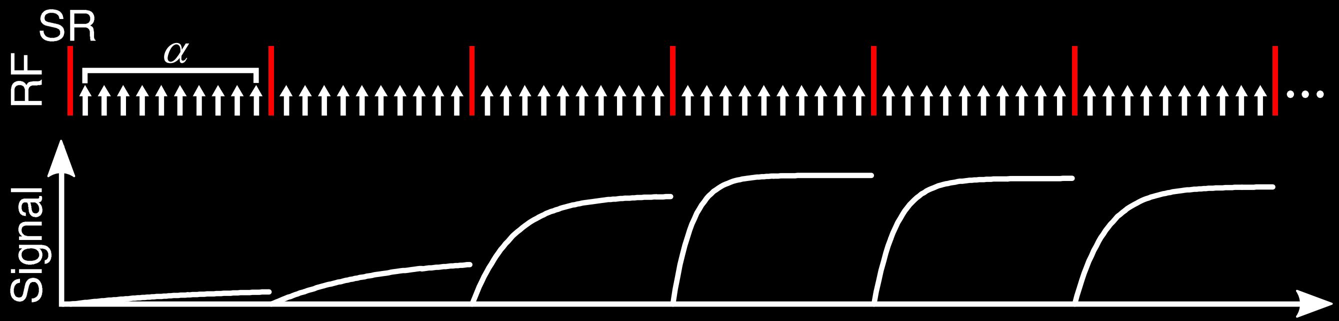
Cao T et al., *MRM* 2022

Myocardial perfusion multitasking

Continuous-acquisition saturation recovery (SR)–prepared FLASH



Real-time evolution

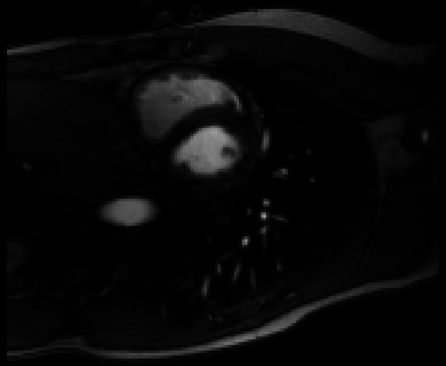
3 time dimensions representing:

1) Cardiac motion 2) Saturation recovery 3) Gd dynamics

Christodoulou AG et al., *SCMR* 2017

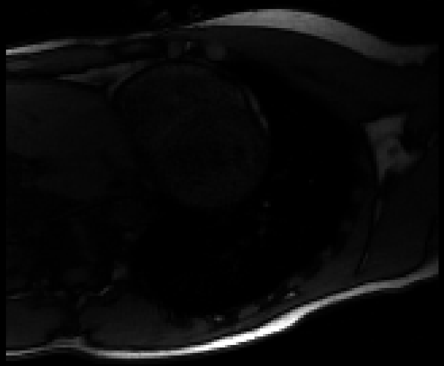
Myocardial perfusion multitasking

Retrospective time dimension/“task” selection



Task: Cine

τ = 160 ms
18th cardiac cycle



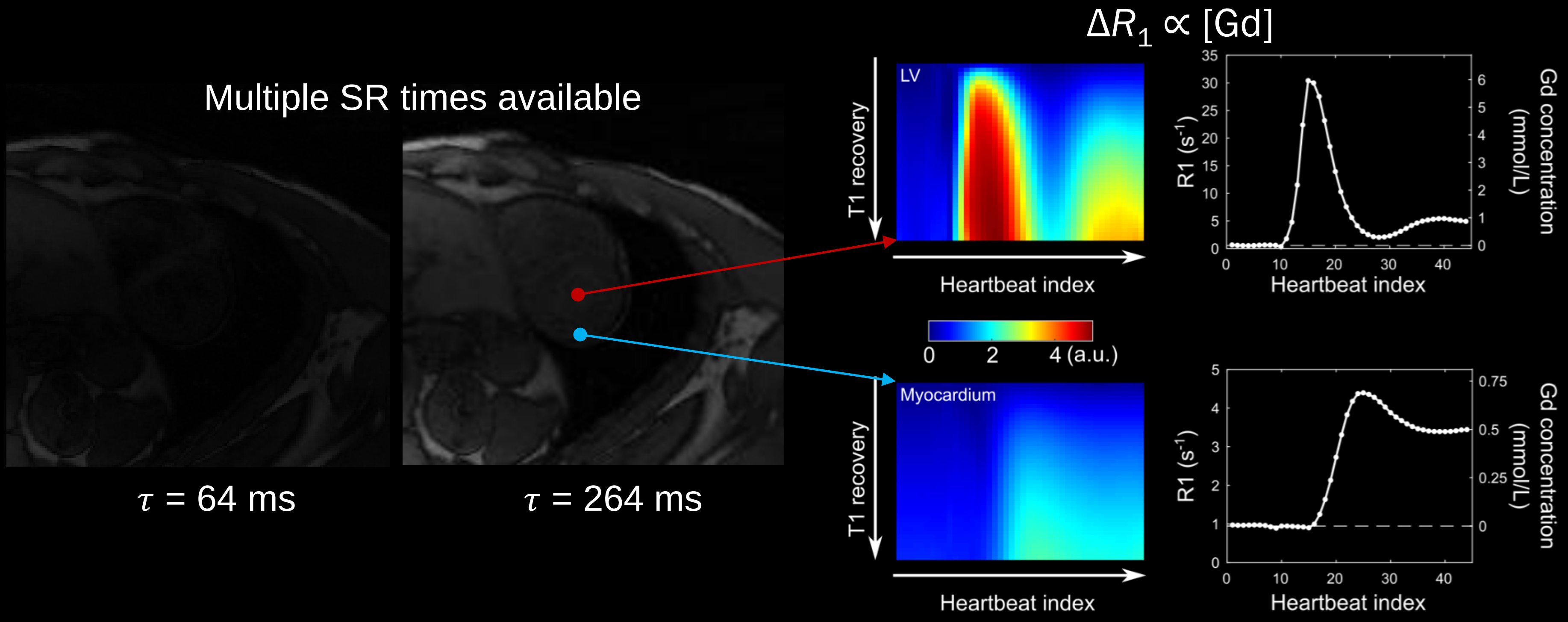
Task: Perfusion

τ = 280 ms
End-diastole

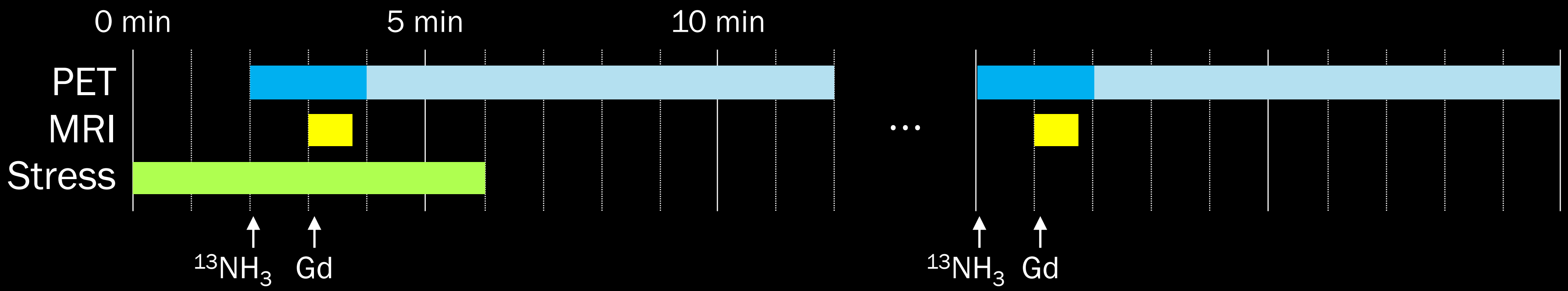
Christodoulou AG et al., *SCMR* 2017

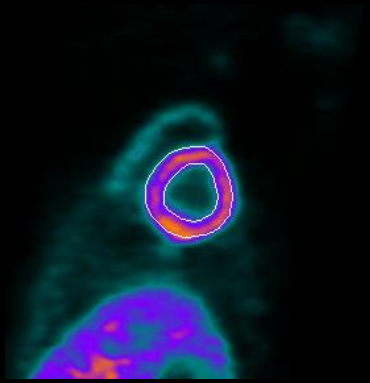
Myocardial perfusion multitasking

Single-bolus perfusion quantification from time-resolved T_1 maps

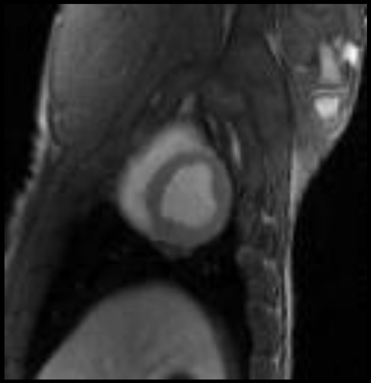


Myocardial perfusion multitasking: Simultaneous PET-MR

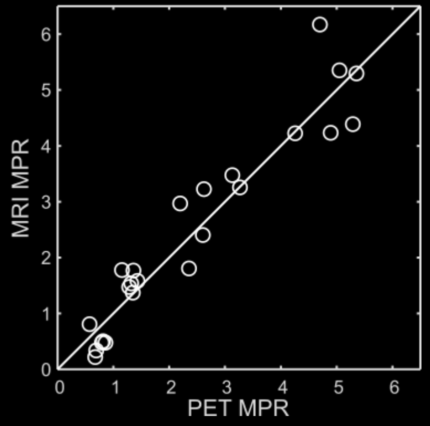




^{13}N-ammonia PET



MR Multitasking



ICC = 0.95

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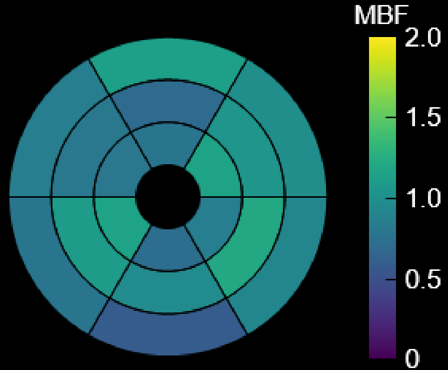
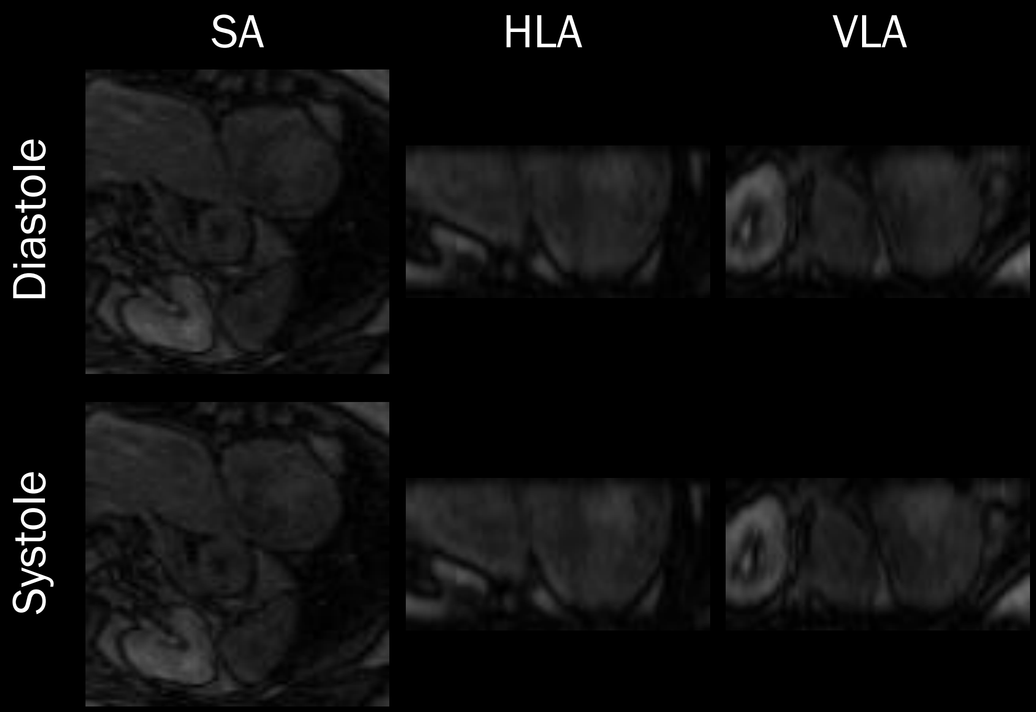
Christodoulou AG et al., *ISMRM* 2018

New developments: 3D perfusion

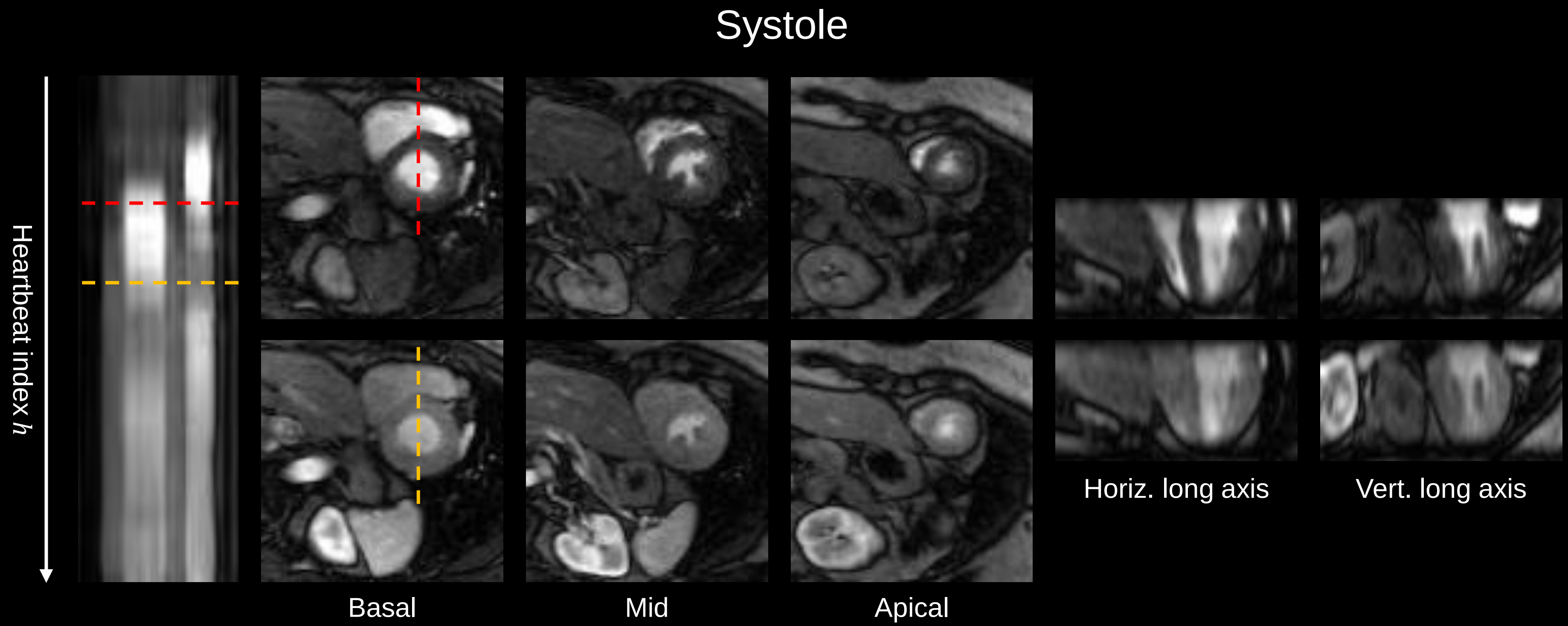
- 3D spatial coverage
  - 2 x 2 x 8 mm
  - 12 slices
- Free-breathing, non-ECG
- 20 cardiac phases
- Single-bolus quantification





Christodoulou AG et al., *SMRA* 2019

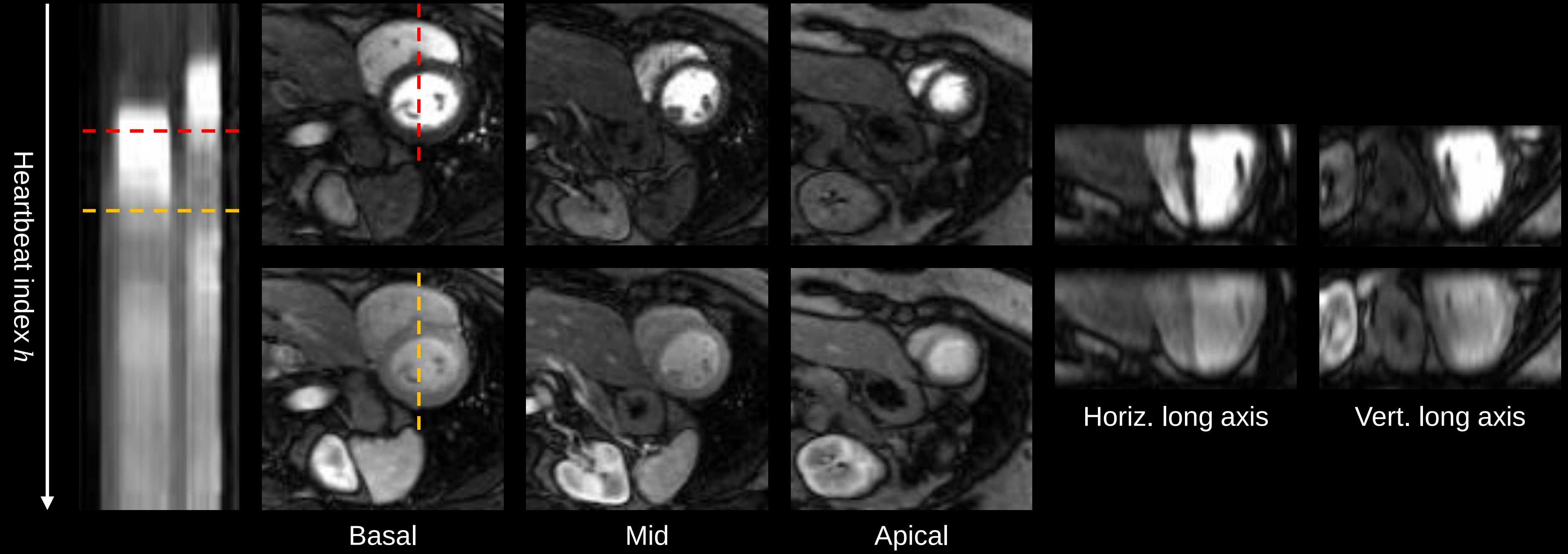
Myocardial perfusion multitasking: 3D free-breathing



Christodoulou AG et al., *ISMRM* 2019

Myocardial perfusion multitasking: 3D free-breathing

Diastole



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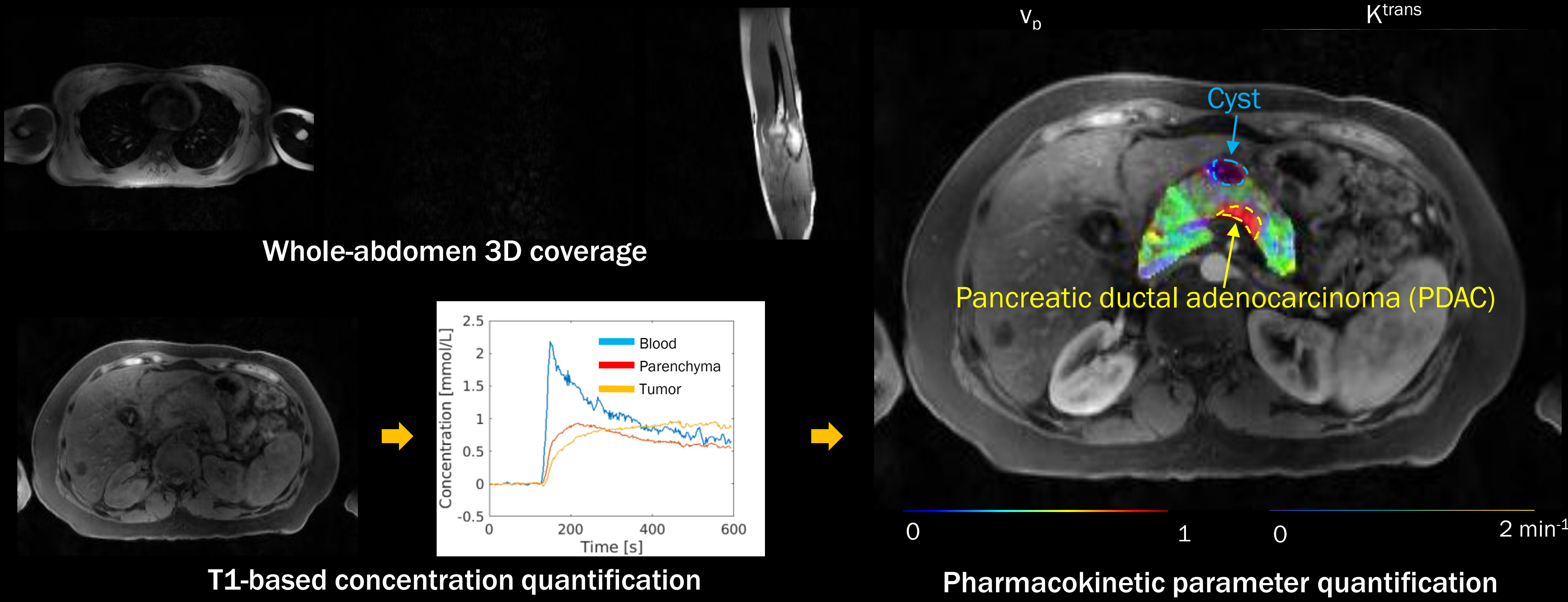
Christodoulou AG et al., *ISMRM* 2019

MR Multitasking for free-breathing quantitative DCE

6-D imaging: 3 spatial dimensions × respiration × T_1 recovery × DCE



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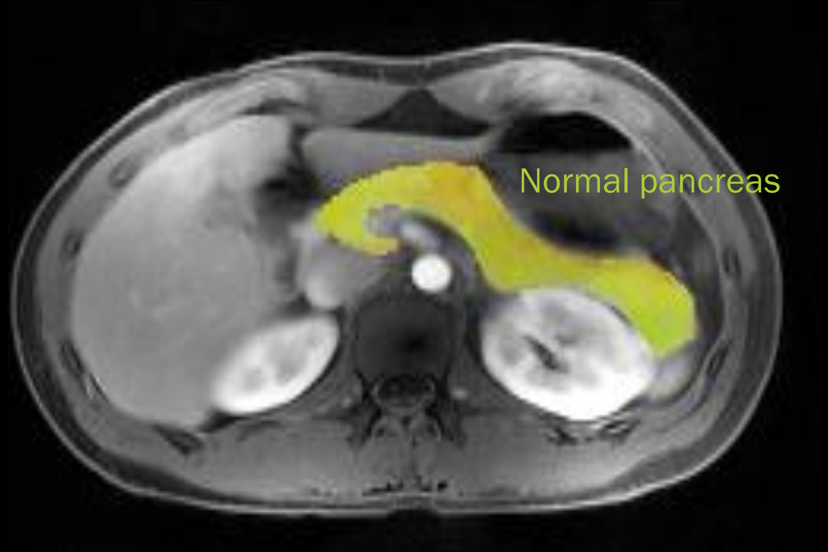
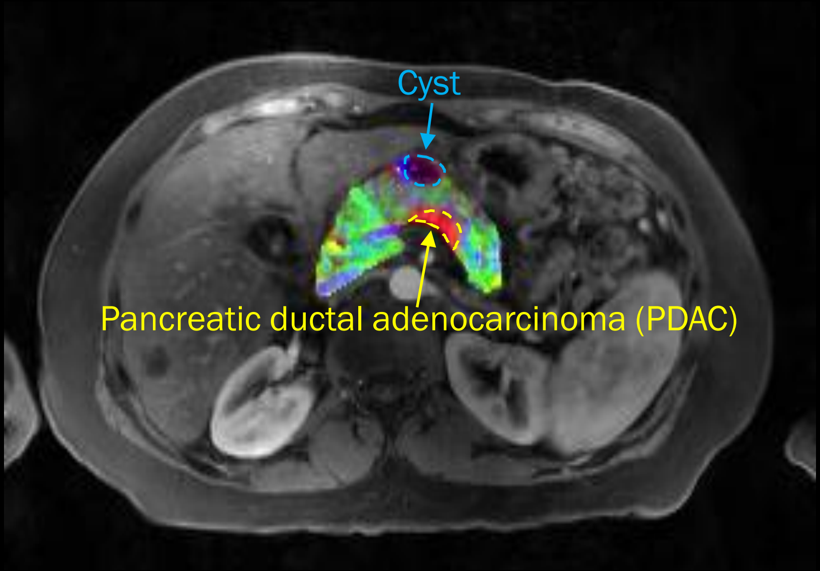
Wang N et al. *Magn Reson Med* 2020

MR Multitasking for free-breathing quantitative DCE

6-D imaging: 3 spatial dimensions × respiration × T_1 recovery × DCE



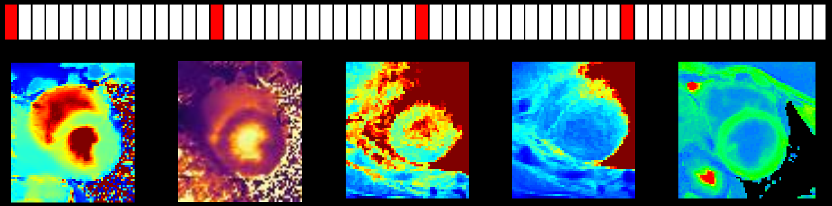


Wang N et al. *Magn Reson Med* 2020

MR Multitasking: Outlook

Potential implications

- No need for ECG or breath holds
- Shorter and simpler exams
- Retrospective imaging decisions
- Reduced financial and training demands
- Replacement of serial clinical protocols with a single, quantitative "push-button" scan



Future directions

<u>Translate</u>

- Validate extensively
- Integrate into PACS
- Develop high-dimensional display tools

<u>Improve</u>

- Explore new, more powerful image models
- Incorporate additional biomarkers and dimensions
- Investigate time-resolved parameter maps

<u>Analyze</u>

- Develop multiparameter analysis for diagnosis, risk prediction, therapy monitoring, and more

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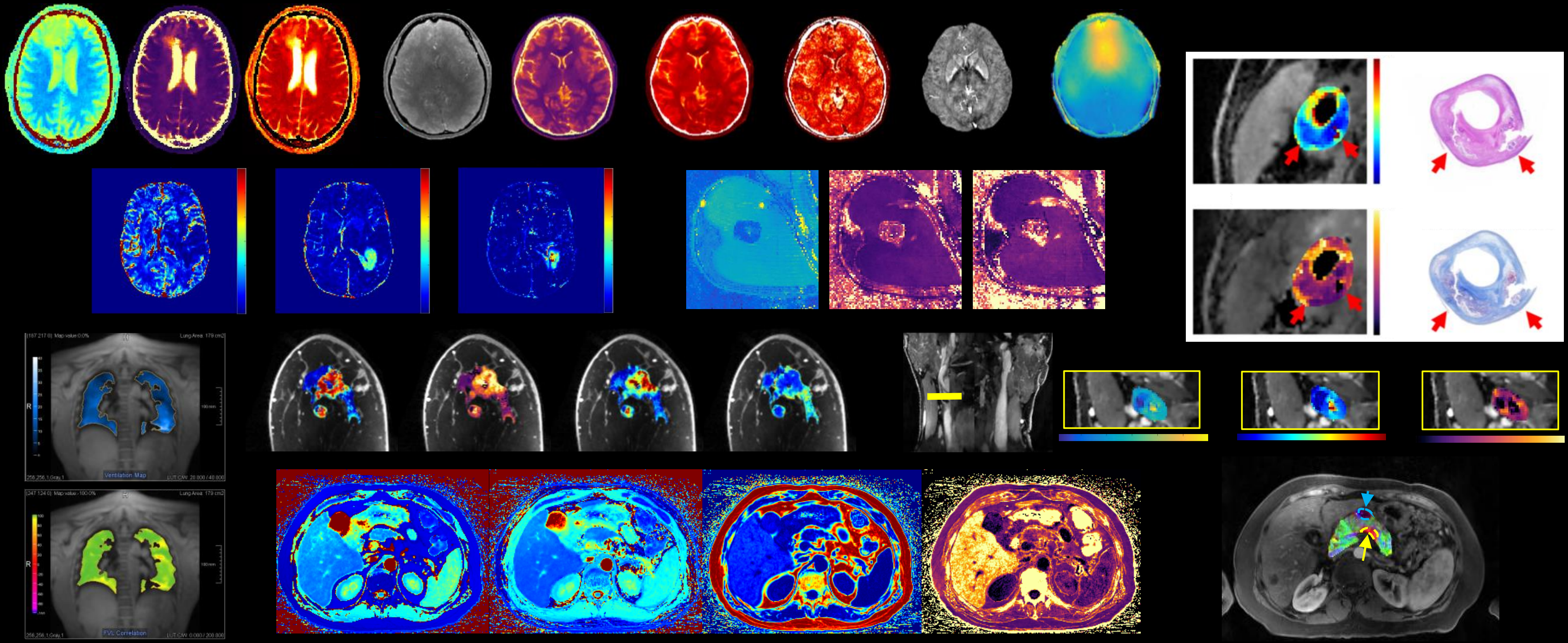
MR Multitasking throughout the body



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