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Van De Ville D[3,4]
Braunersreuther V[2]
Pellieux C[2]
Hyacinthe J-N[1]
Lerch R[2]
Mach F[2]
Vallée J-P[1]

High time-resolved cardiac functional imaging with temporal regularization in mouse on a clinical 3T scanner

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BASP Workshop - Villars 09.08.2011

Context

Cardiac imaging on rodents on clinical scanners

- Importance of research on rodents
- Dedicated scanners not always available
- Importance of translational research for drug or medicine studies
- Problem of hardware limitations (gradient amplitude and slew-rate)

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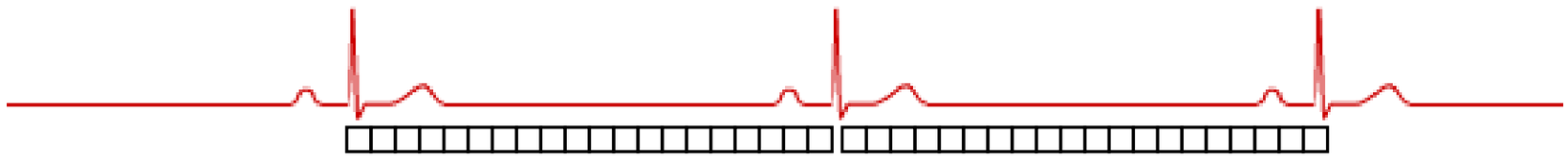
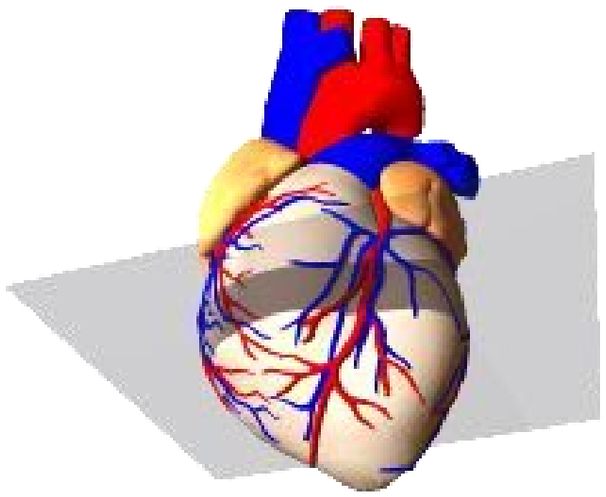
New cine sequence

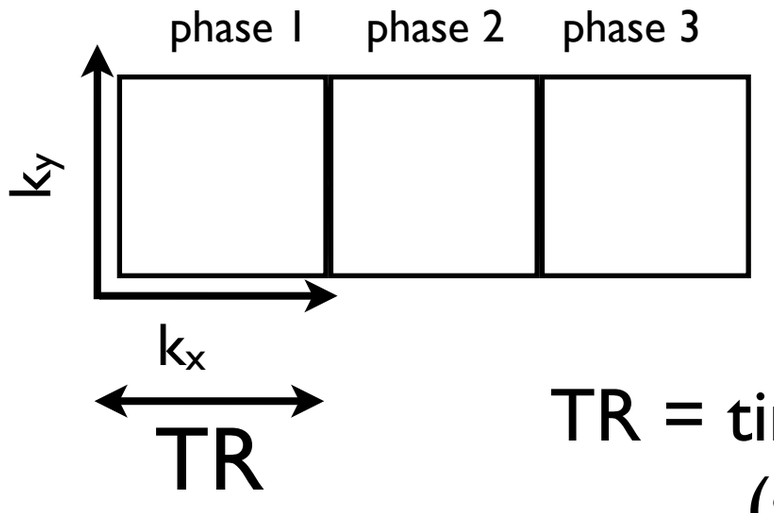
Compatible with resolutions needed in stress studies in mice (TR=8.6ms)[1]

1- Wiesmann et al. Circ. Res. 88 :563-569 (2001)

Cine acquisition



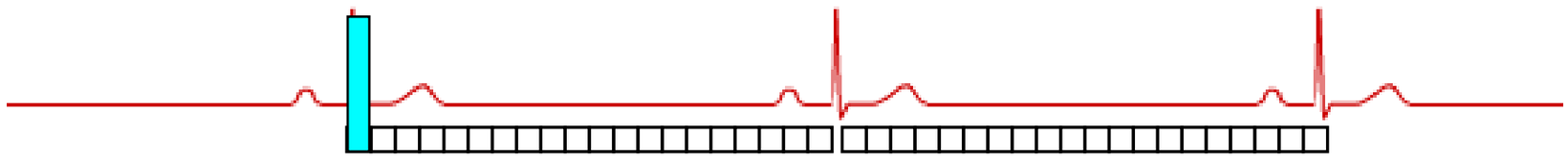


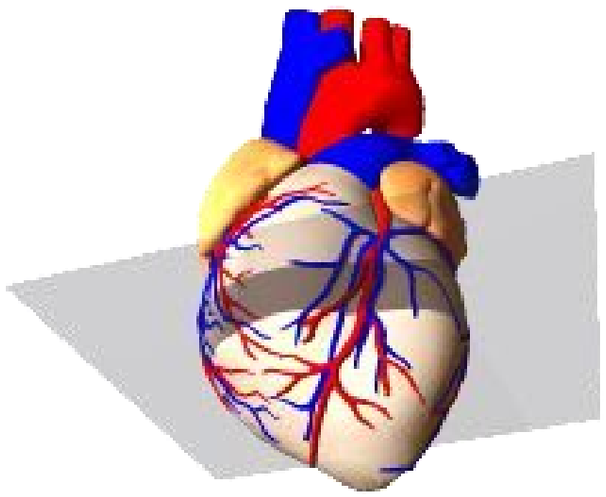


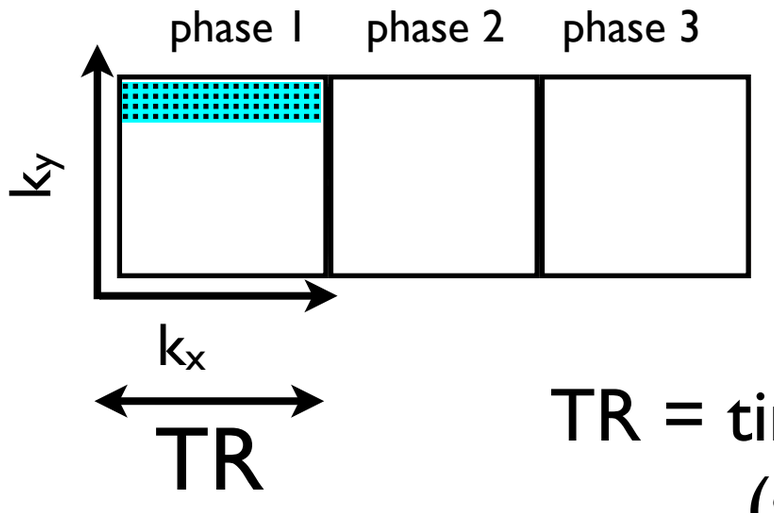
...

TR = time to acquire one segment
(several *k*-space lines)

Cine acquisition



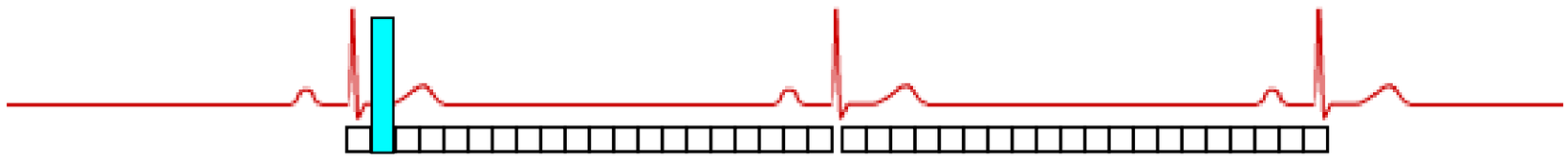


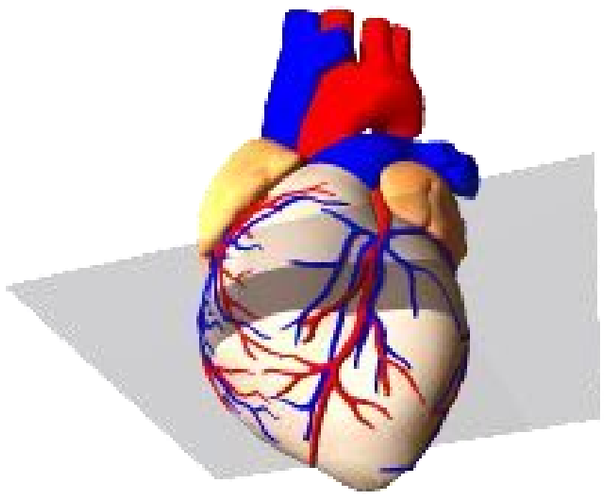


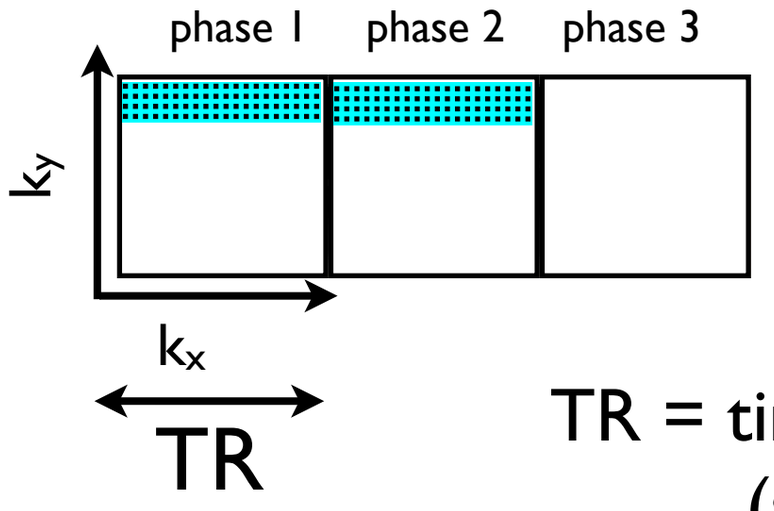
...

TR = time to acquire one segment
(several *k*-space lines)

Cine acquisition



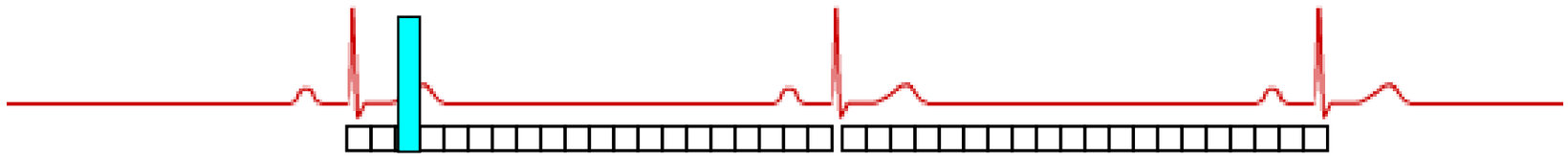


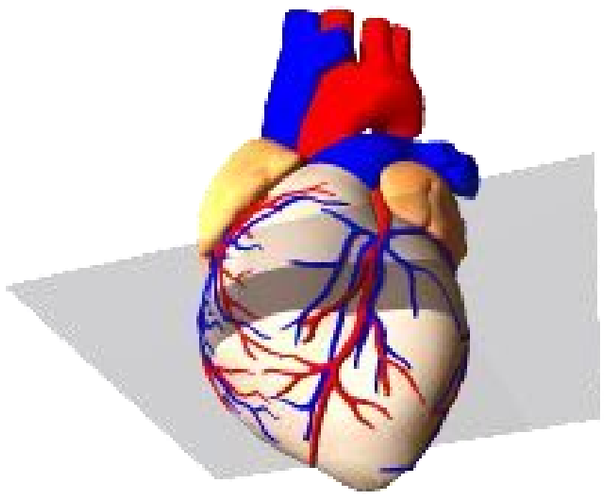


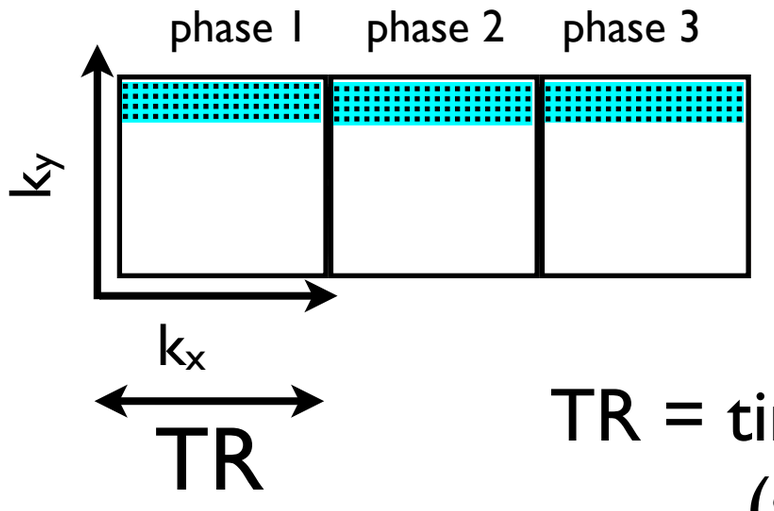
...

TR = time to acquire one segment
(several *k*-space lines)

Cine acquisition



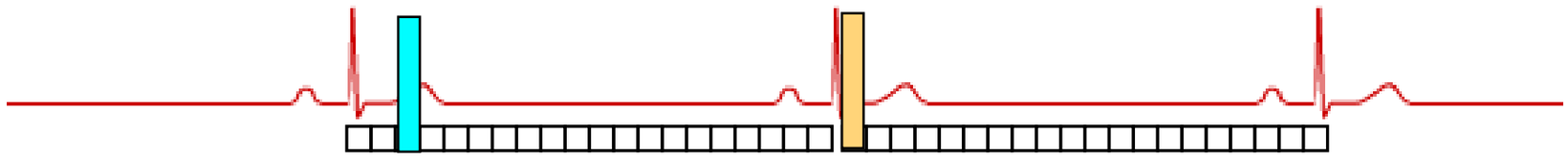


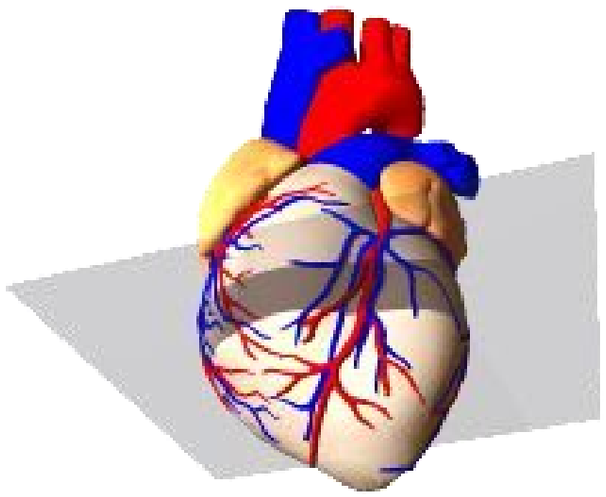


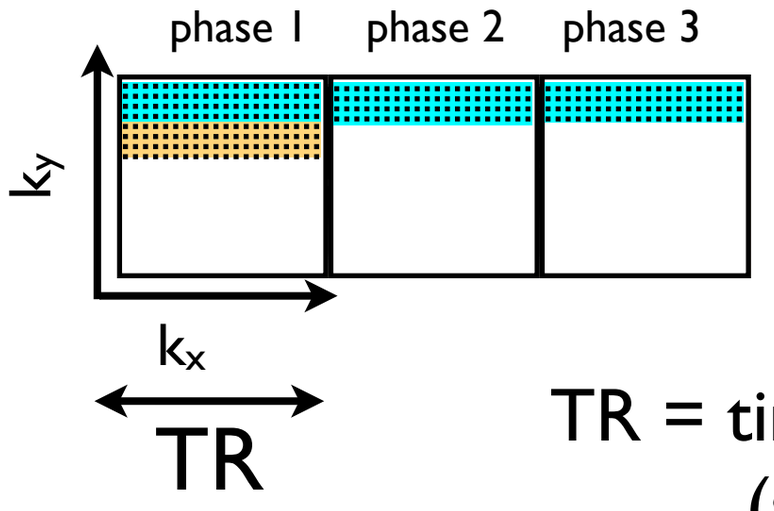
...

TR = time to acquire one segment
(several *k*-space lines)

Cine acquisition







...

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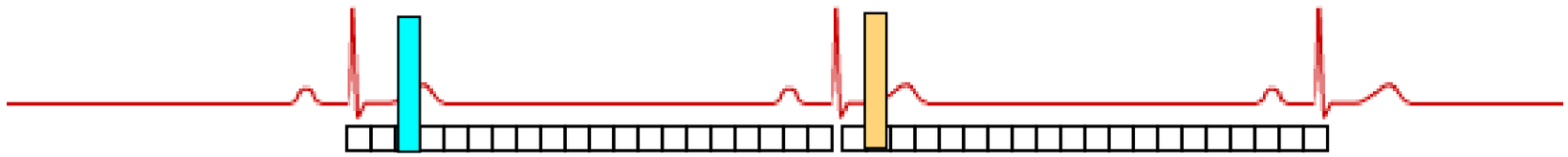
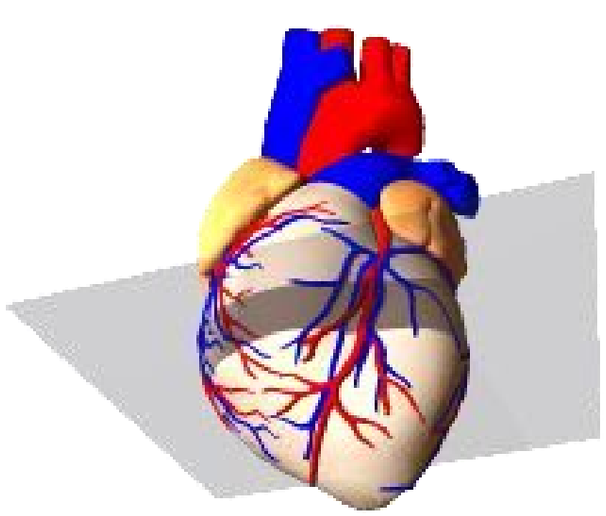
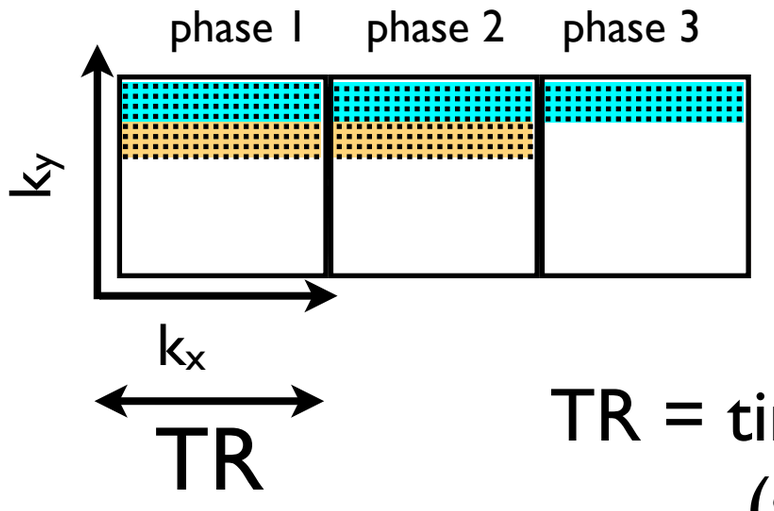
Cine acquisition







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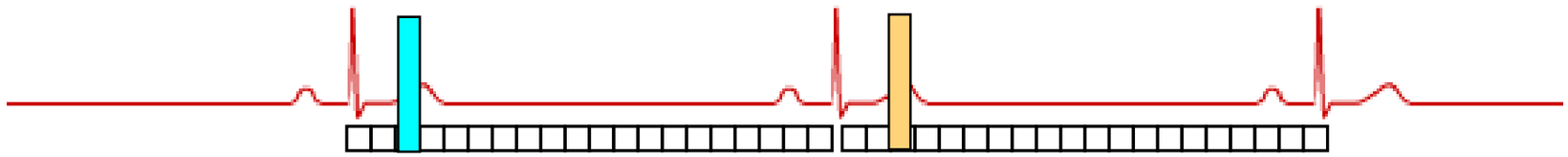
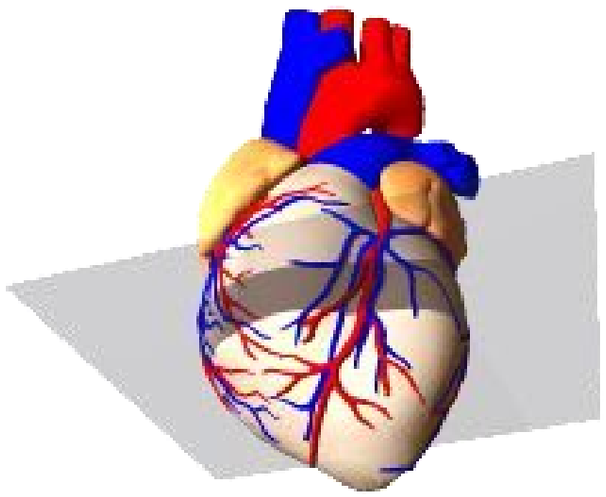
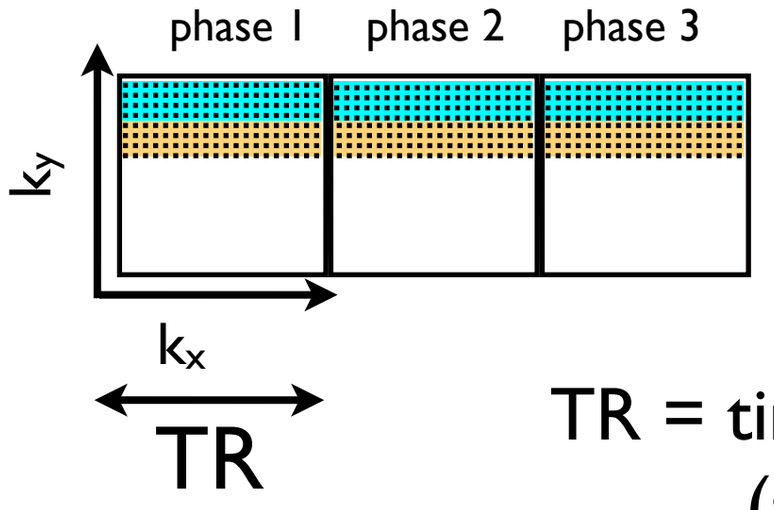
Cine acquisition







...

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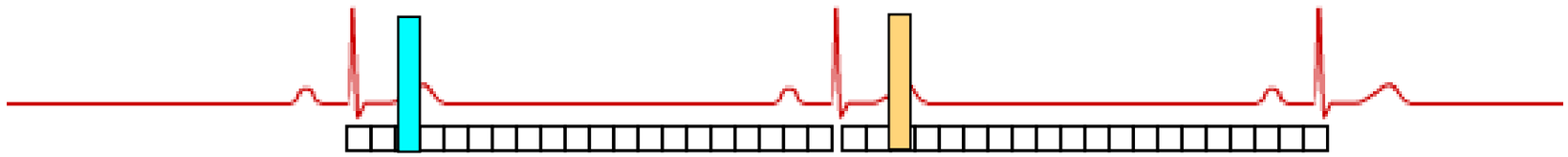
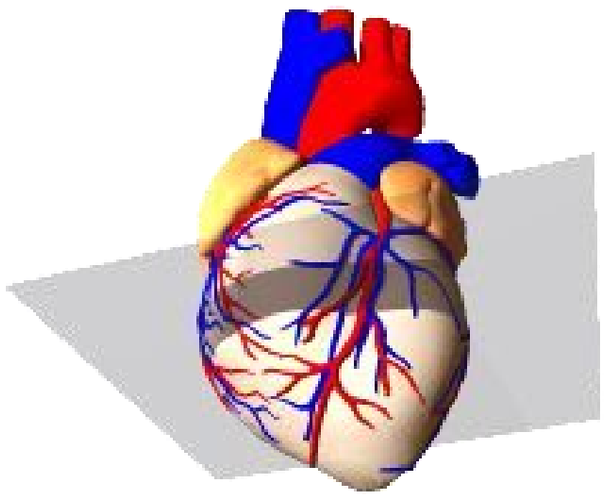
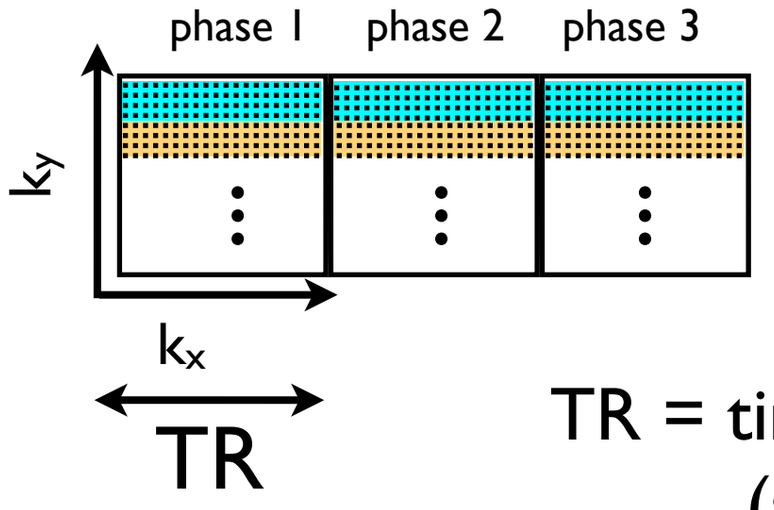
Cine acquisition







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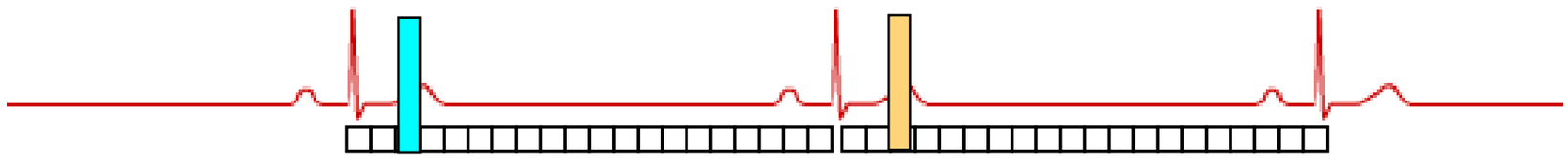
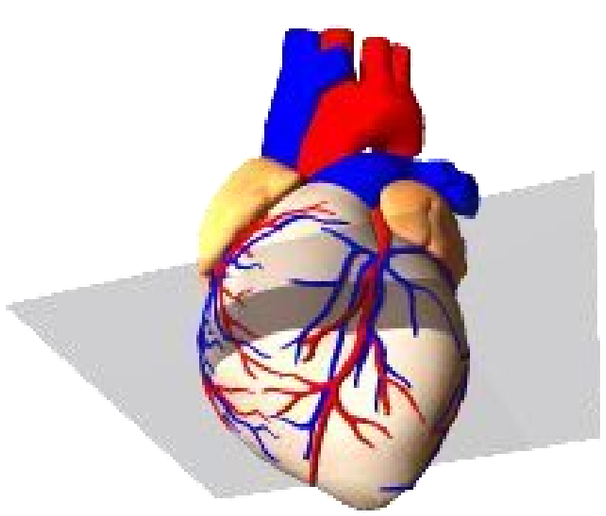
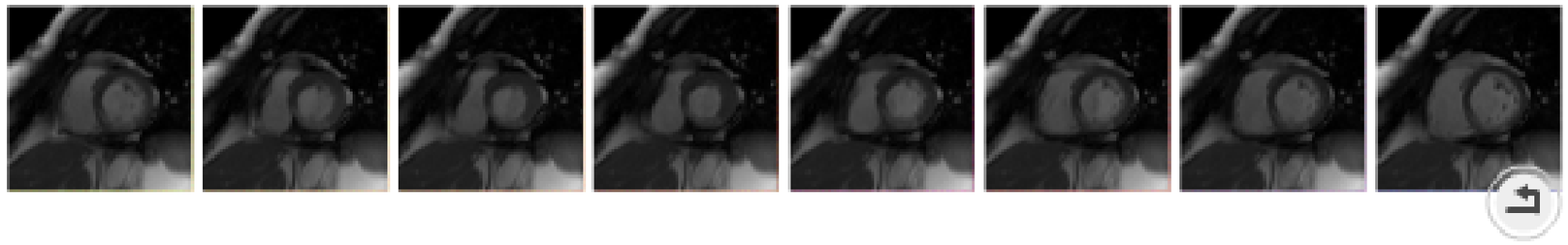
Cine acquisition





phase 1 phase 2 phase 3



TR

TR = time to acquire one segment
(several *k*-space lines)

Robust function evaluation: 11 phases per cycle (Roussakis et al., JCMR 2004)

Cine acquisition

Human
15 cm
60 bpm

Cine acquisition

Human
15 cm
60 bpm

11 phases

Cine acquisition

Human
15 cm
60 bpm

11 phases

TR should be around 9 ms

Mouse
1 cm
600 bpm

Cine acquisition

Human
15 cm
60 bpm

11 phases

TR should be around 9 ms

Mouse
1 cm
600 bpm

On dedicated scanner: in-plane resolution 117 μm^2, TR **8.4** ms[1]

The best we can do: in-plane resolution 257 μm^2, TR 13.5 ms

[1]Wiesmann et al., Circ Res, 88(6):563-9, 2001

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Best is not enough...

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11 phases

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1 cm
600 bpm

On dedicated scanner: in-plane resolution 117 μm^2, TR **8.4** ms[1]

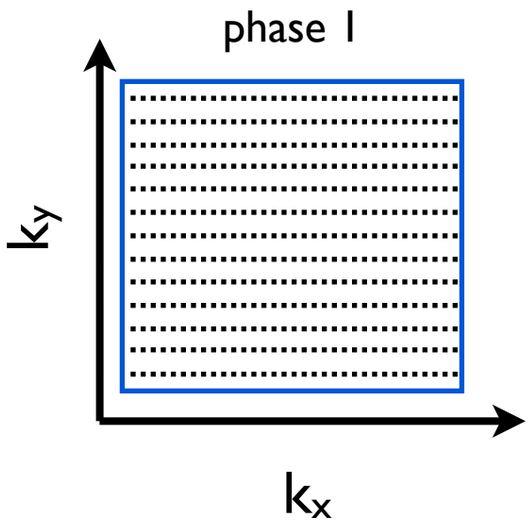
The best we can do: in-plane resolution 257 μm^2, TR 13.5 ms

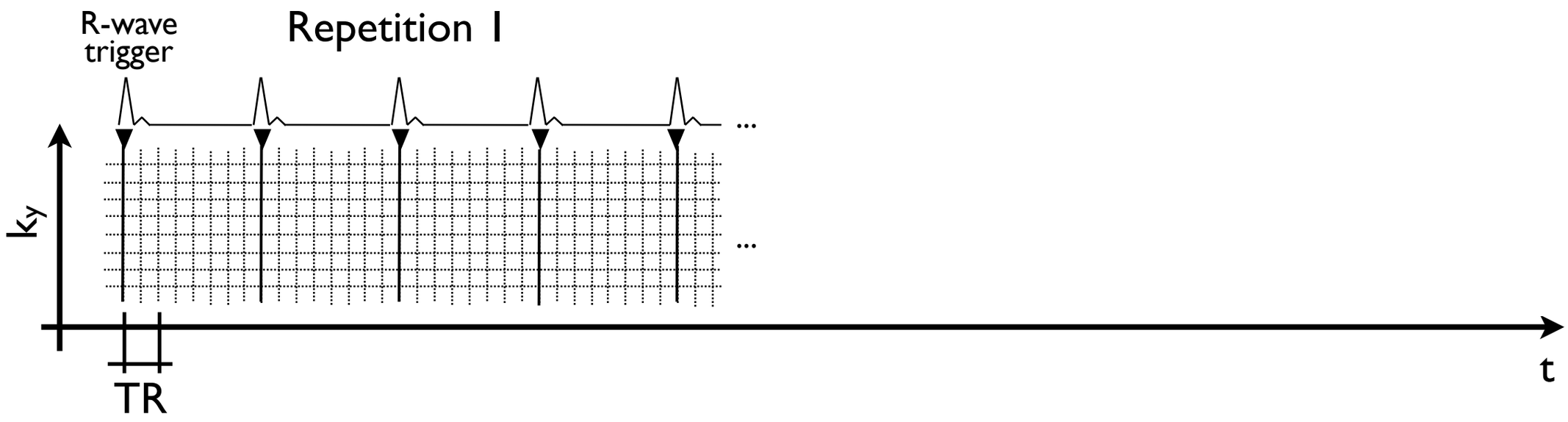
Best is not enough...

- 10 times higher gradient strength
- Modify sequence scheme

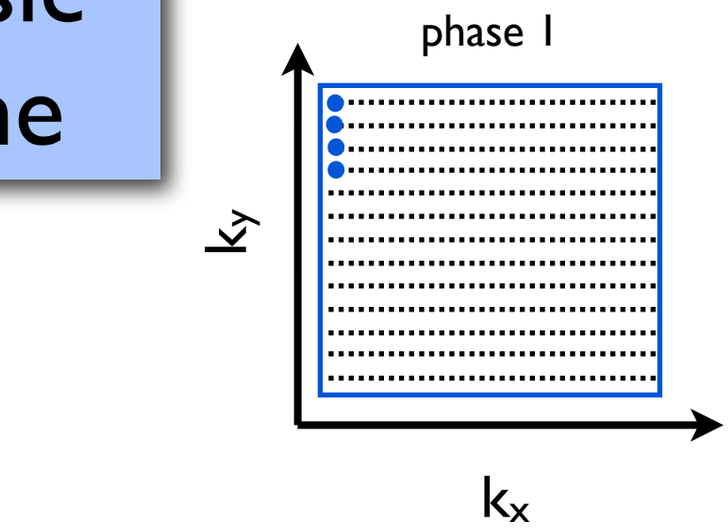
[1]Wiesmann et al., Circ Res, 88(6):563-9, 2001

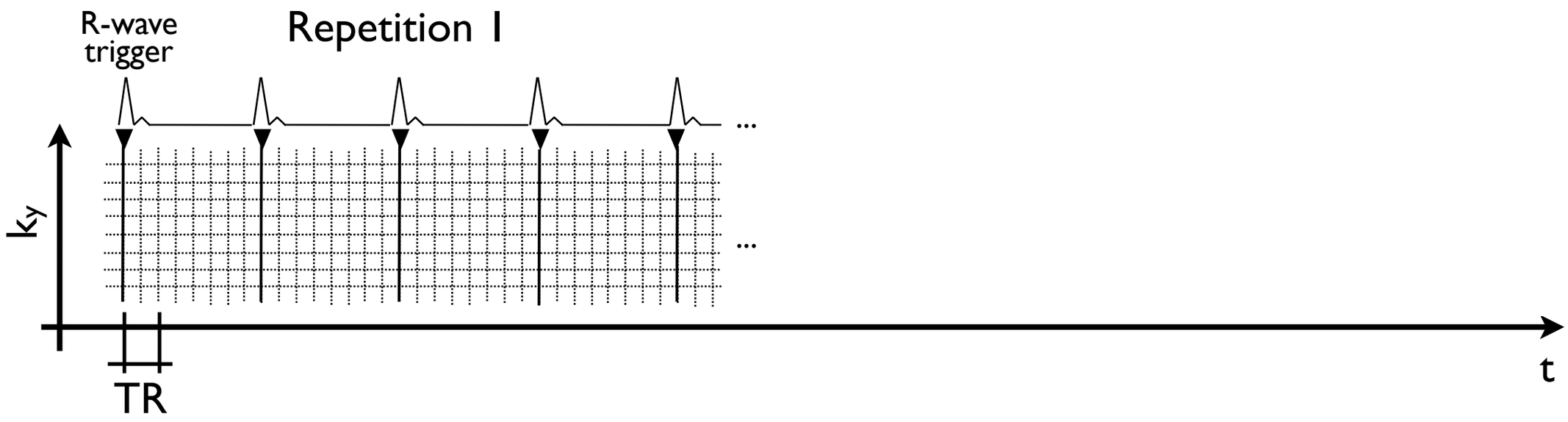
Basic cine



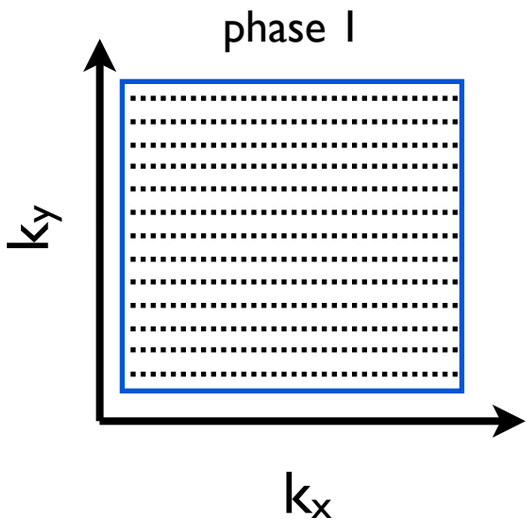


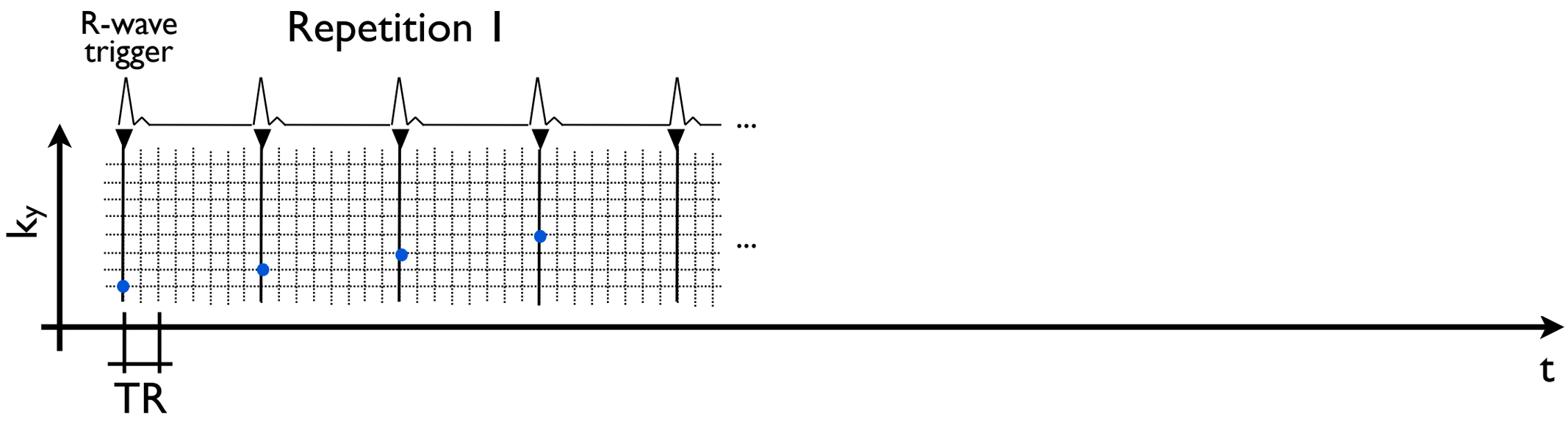
Basic cine



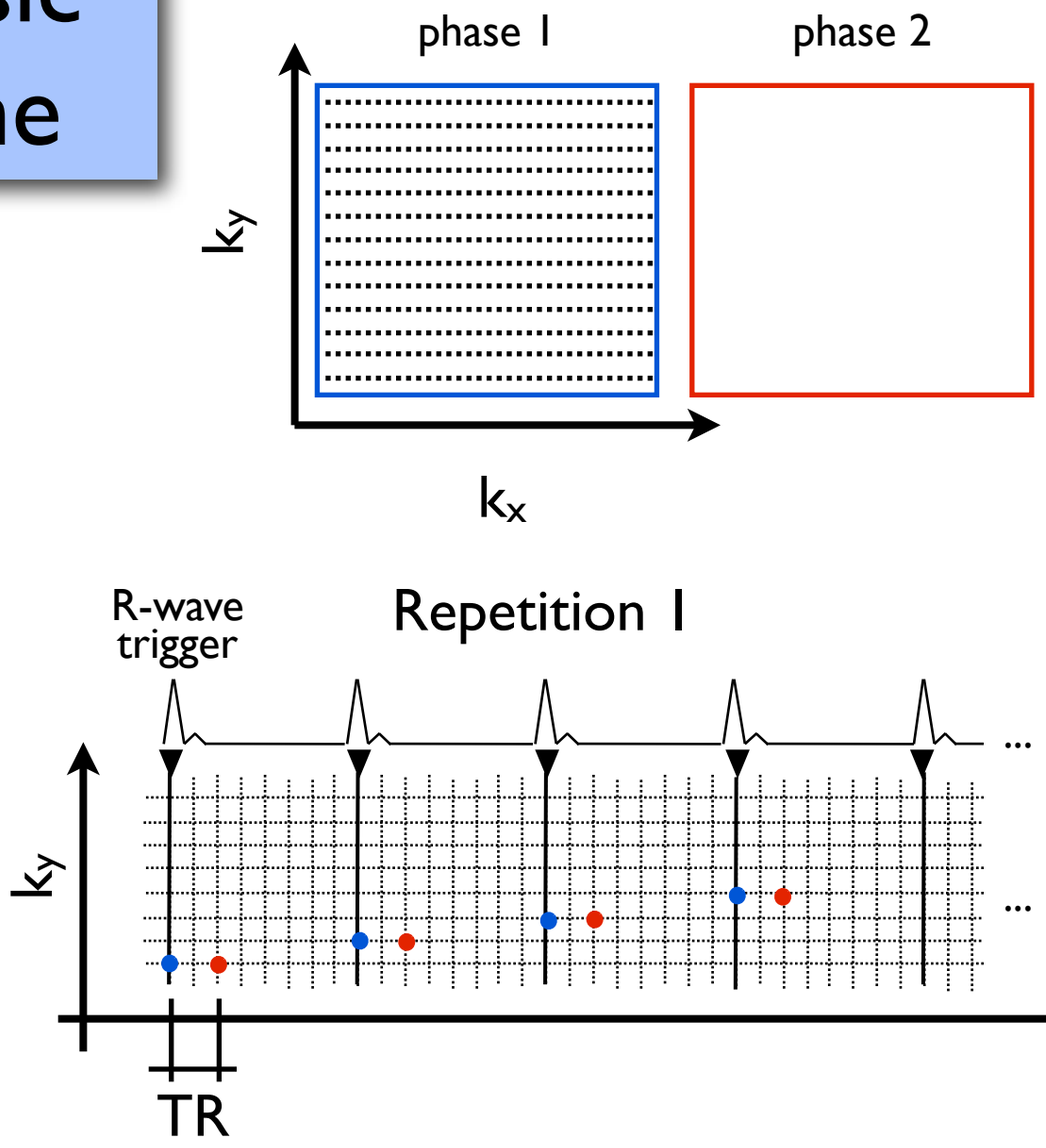


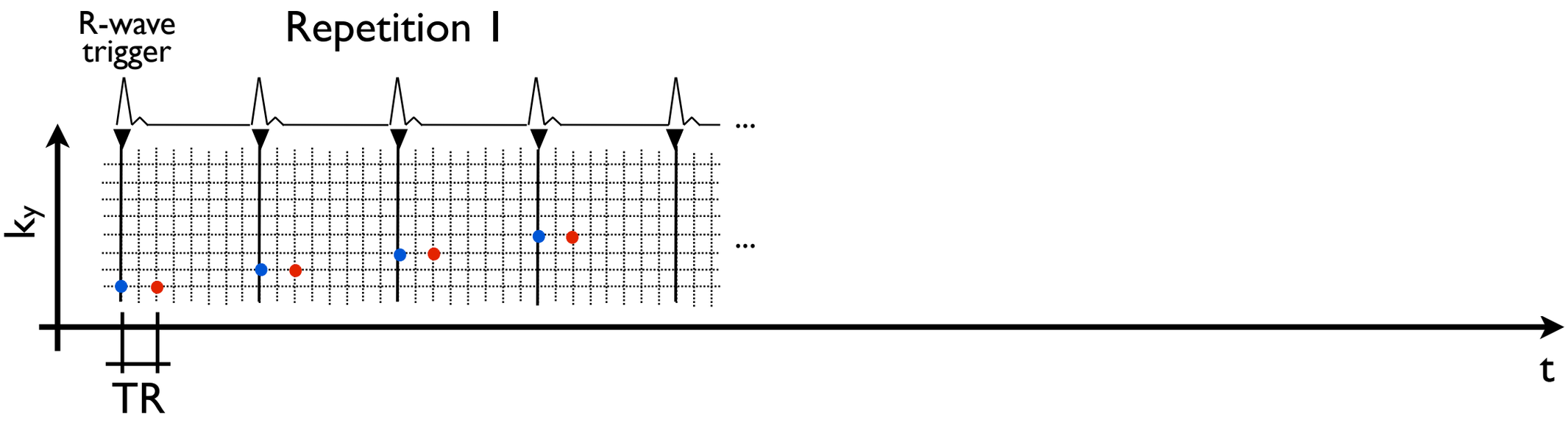
Basic cine



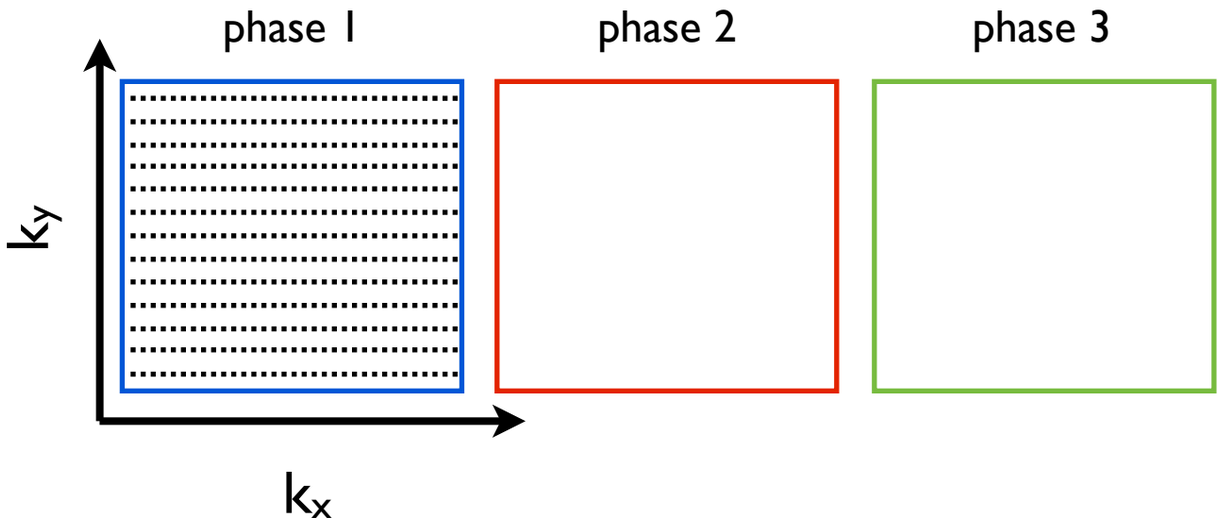


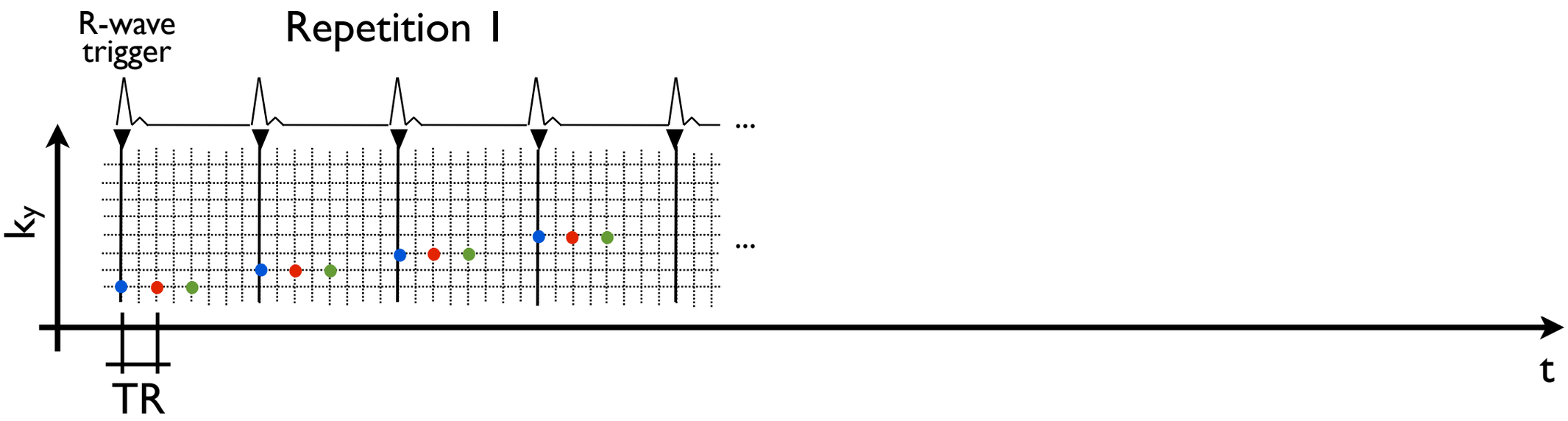
Basic cine



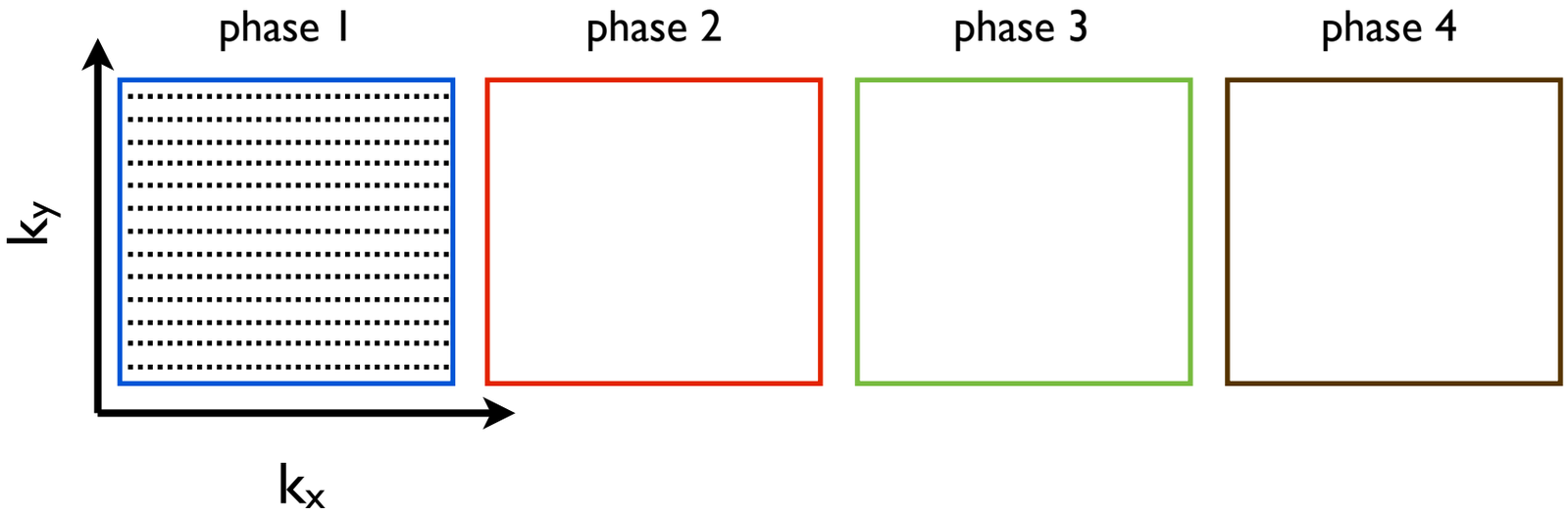


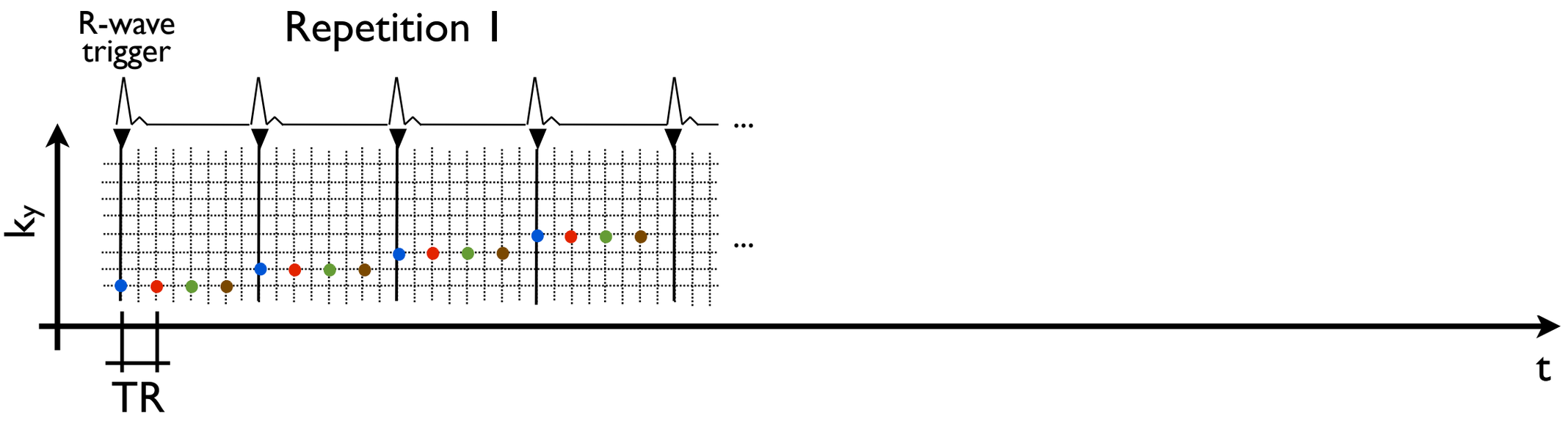
Basic cine


phase 1
phase 2
phase 3
k_y
k_x

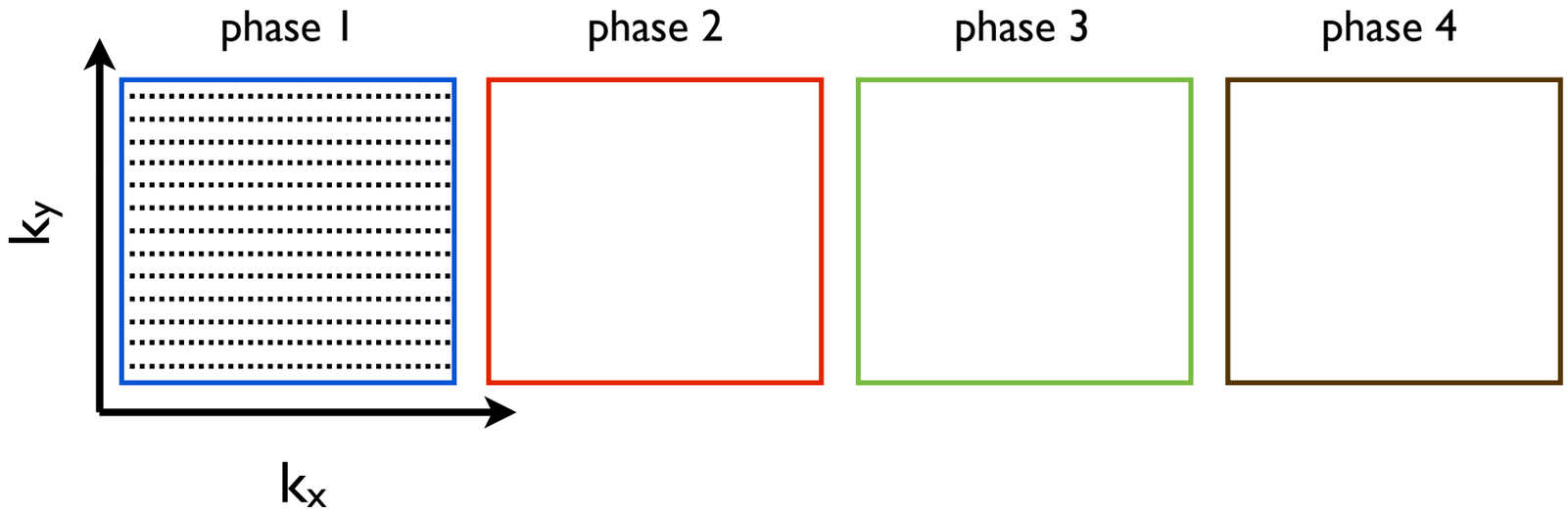

R-wave trigger
Repetition 1
...
...
k_y
TR
t

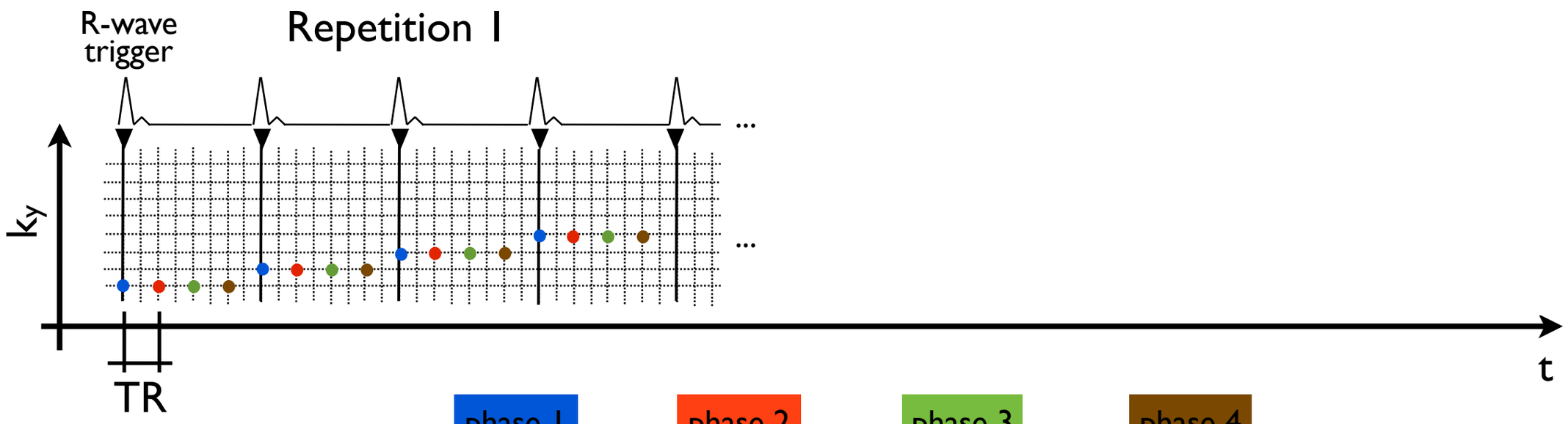
Basic cine

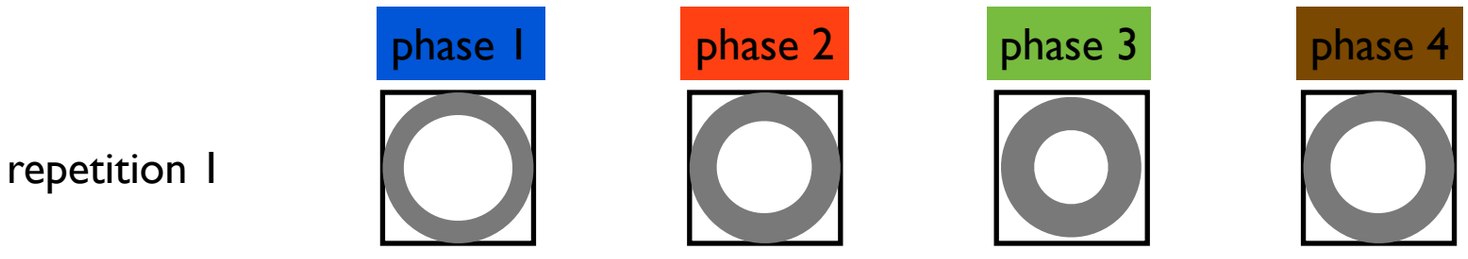

phase 1
phase 2
phase 3
phase 4
k_y
k_x


R-wave trigger
Repetition 1
...
...
k_y
t
TR

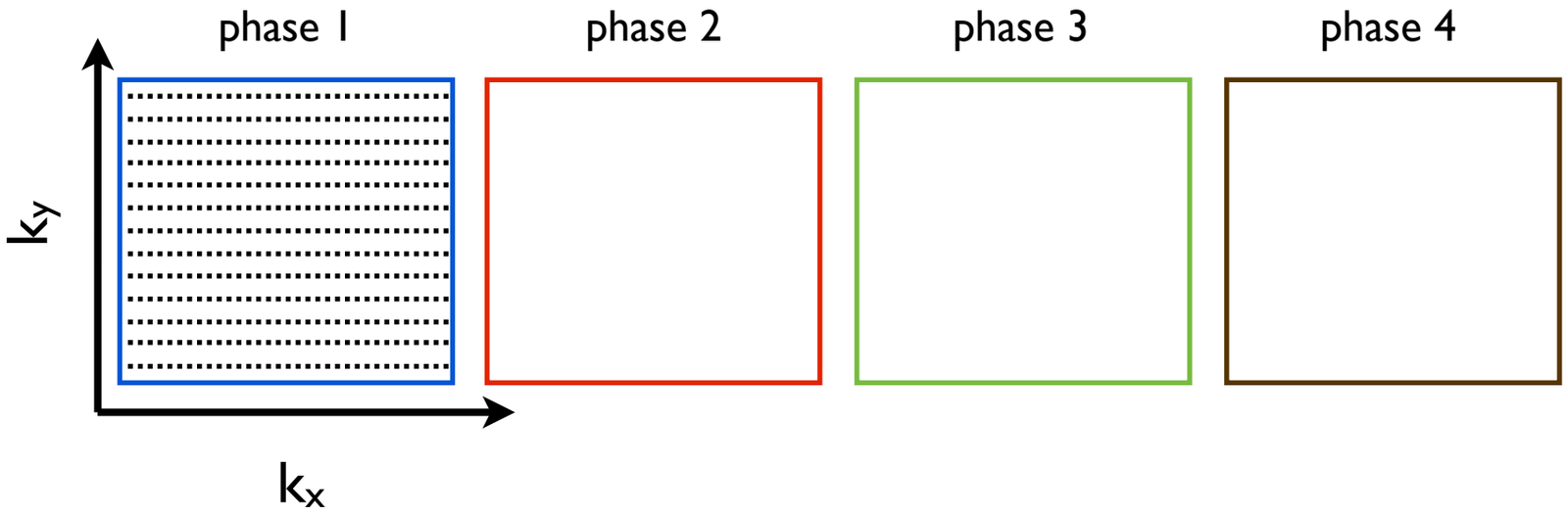
Basic cine

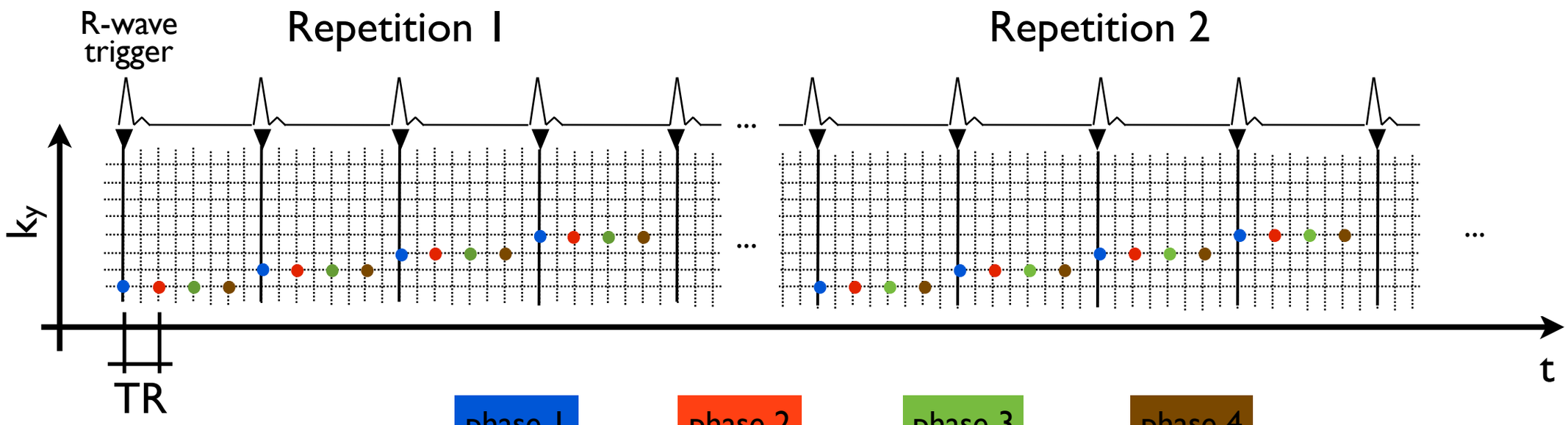

phase 1
phase 2
phase 3
phase 4
k_y
k_x

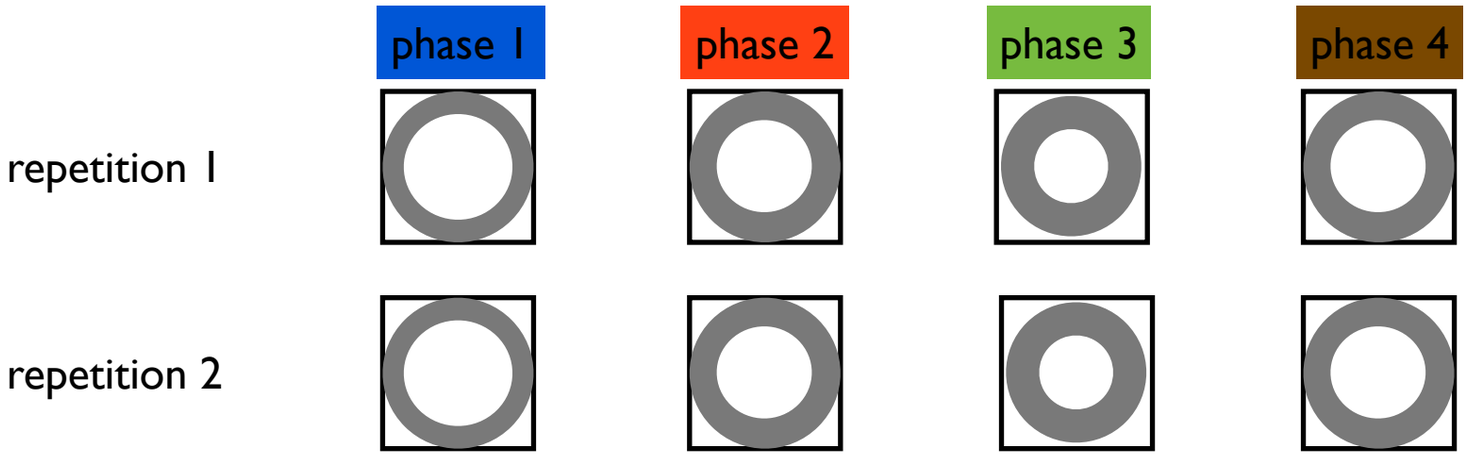

R-wave trigger
Repetition 1
...
...
k_y
TR
t


phase 1
phase 2
phase 3
phase 4
repetition 1

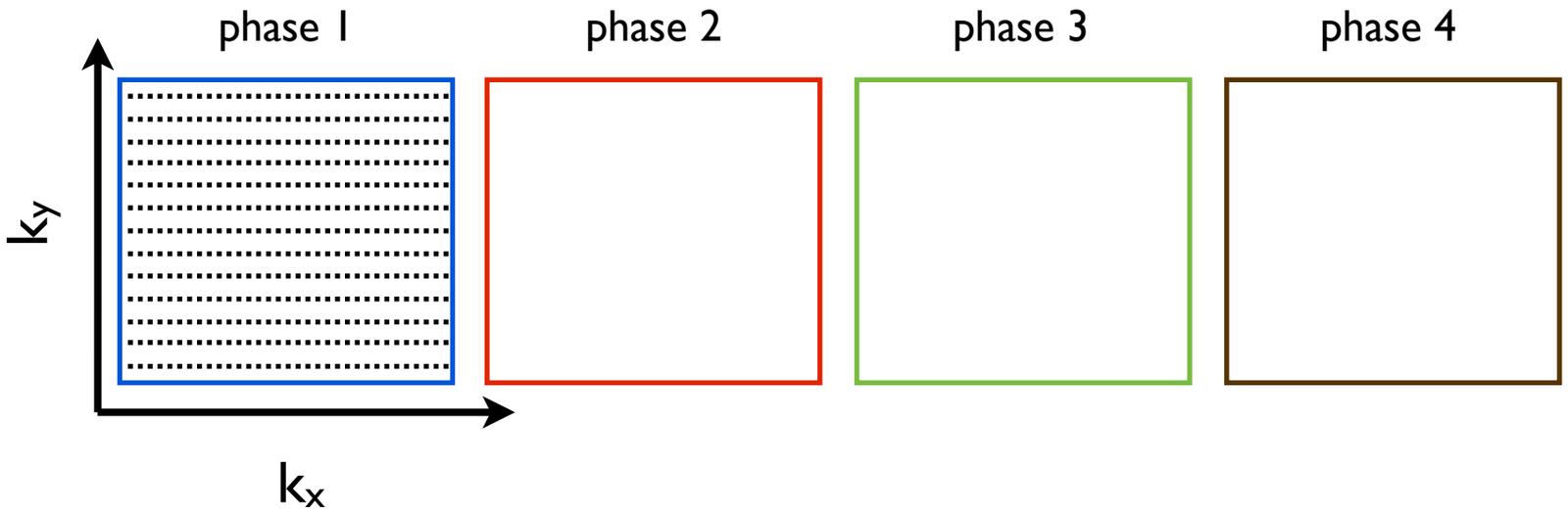
Basic cine

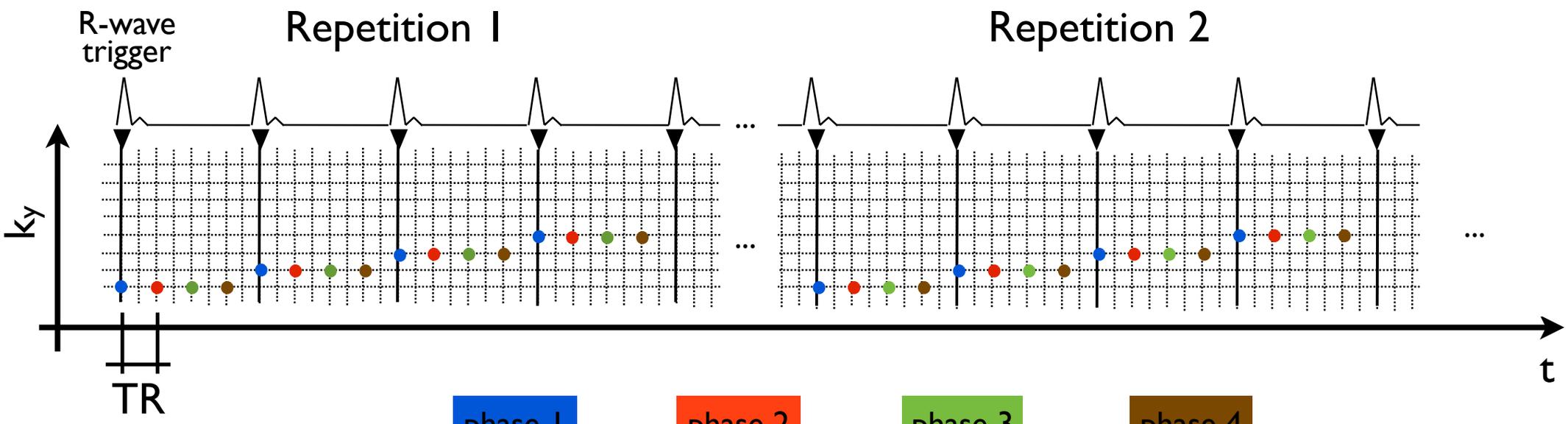

phase 1
phase 2
phase 3
phase 4
k_y
k_x

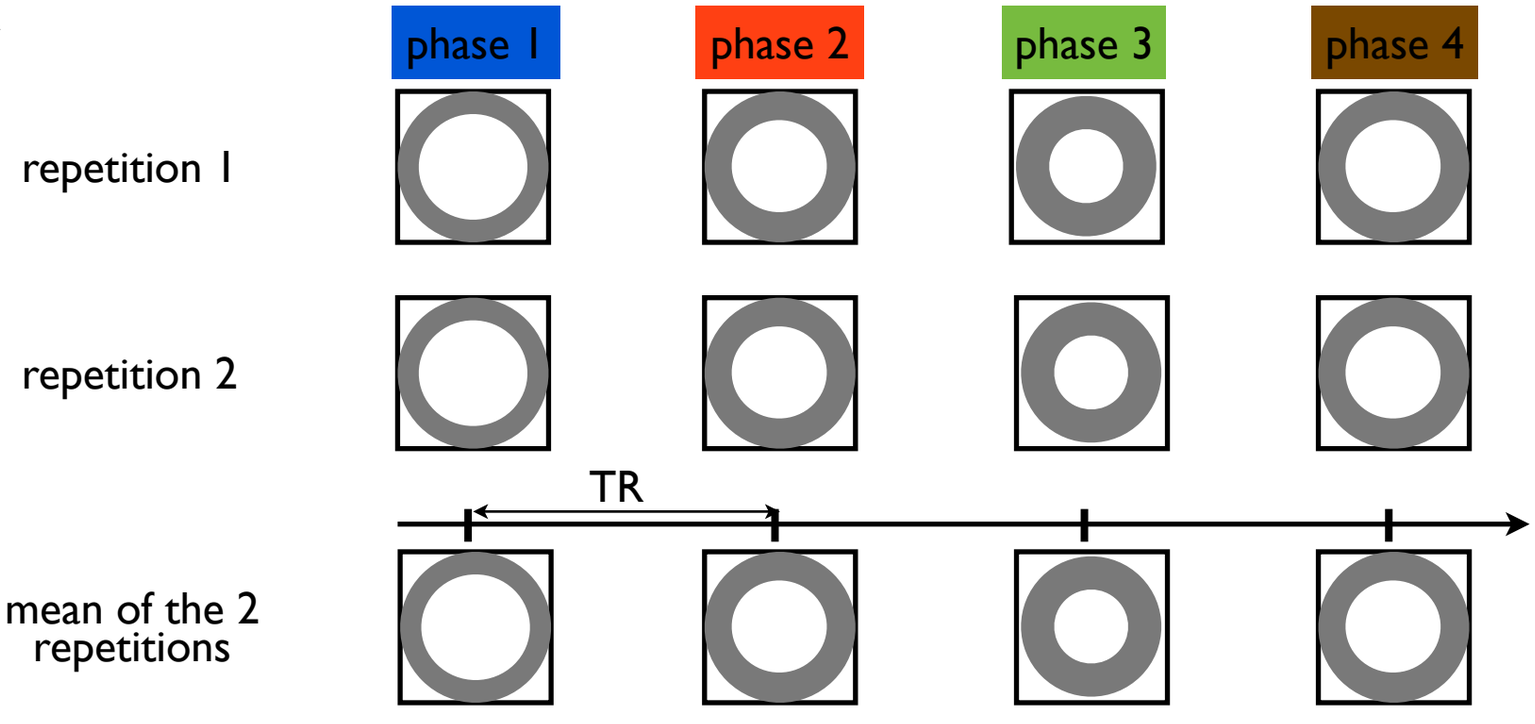

R-wave trigger
Repetition 1
Repetition 2
...
...
k_y
TR
t


phase 1
phase 2
phase 3
phase 4
repetition 1
repetition 2

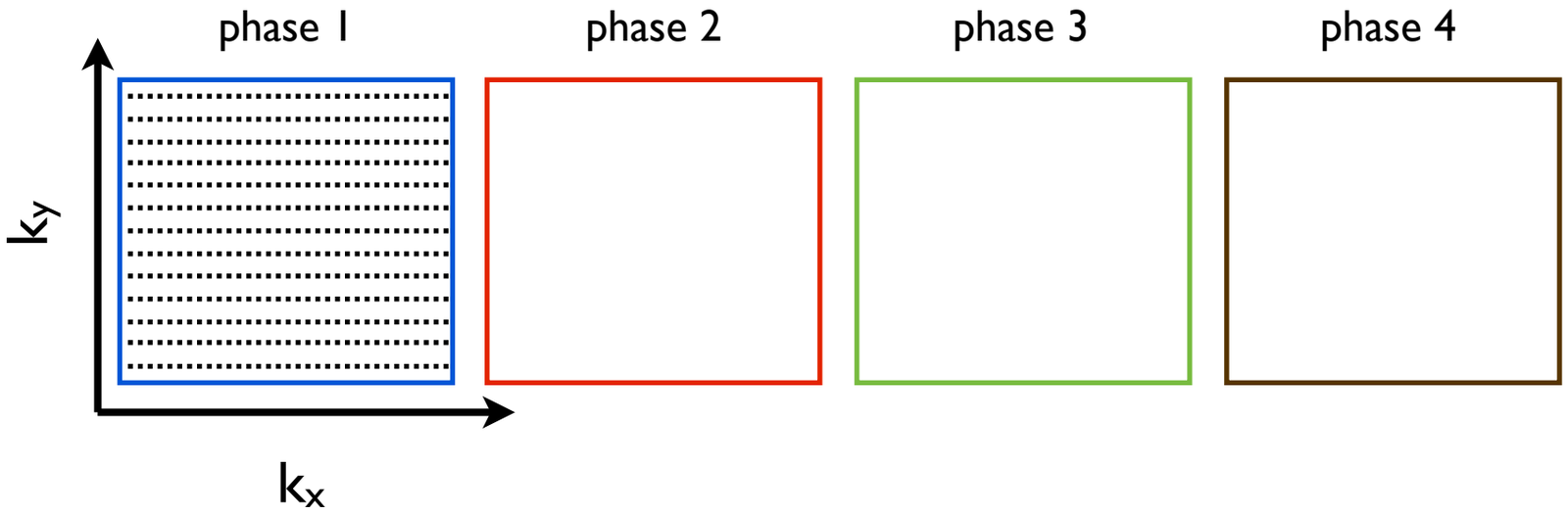
Basic cine

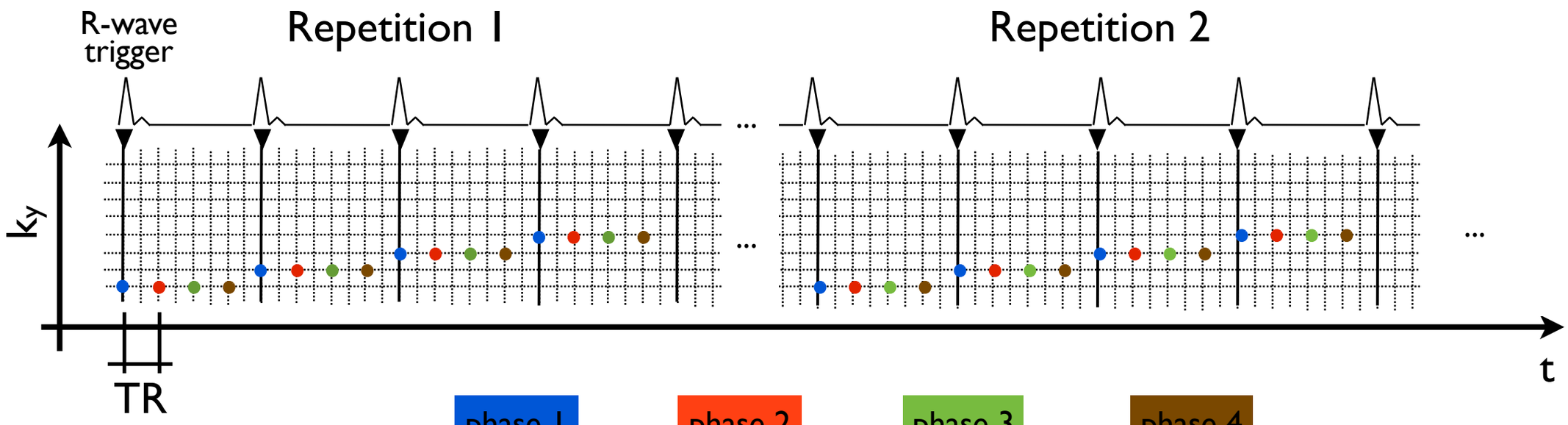

phase 1
phase 2
phase 3
phase 4
k_y
k_x

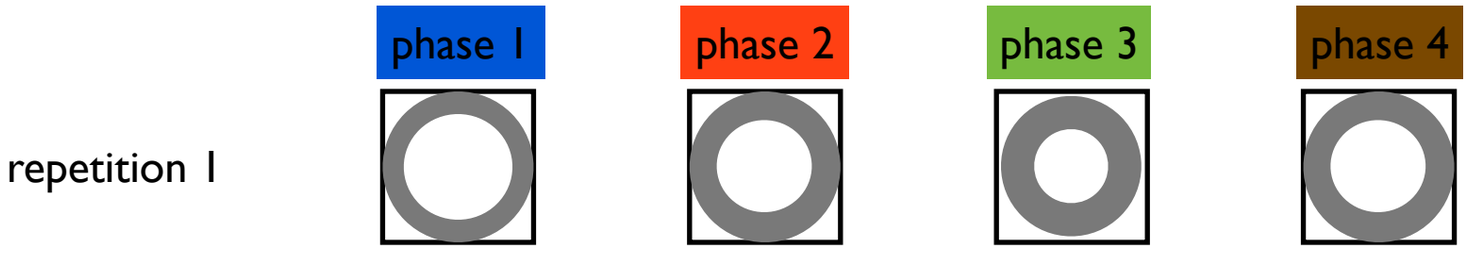

R-wave trigger
Repetition 1
Repetition 2
...
...
k_y
t
TR


phase 1
phase 2
phase 3
phase 4
repetition 1
repetition 2
TR
mean of the 2 repetitions

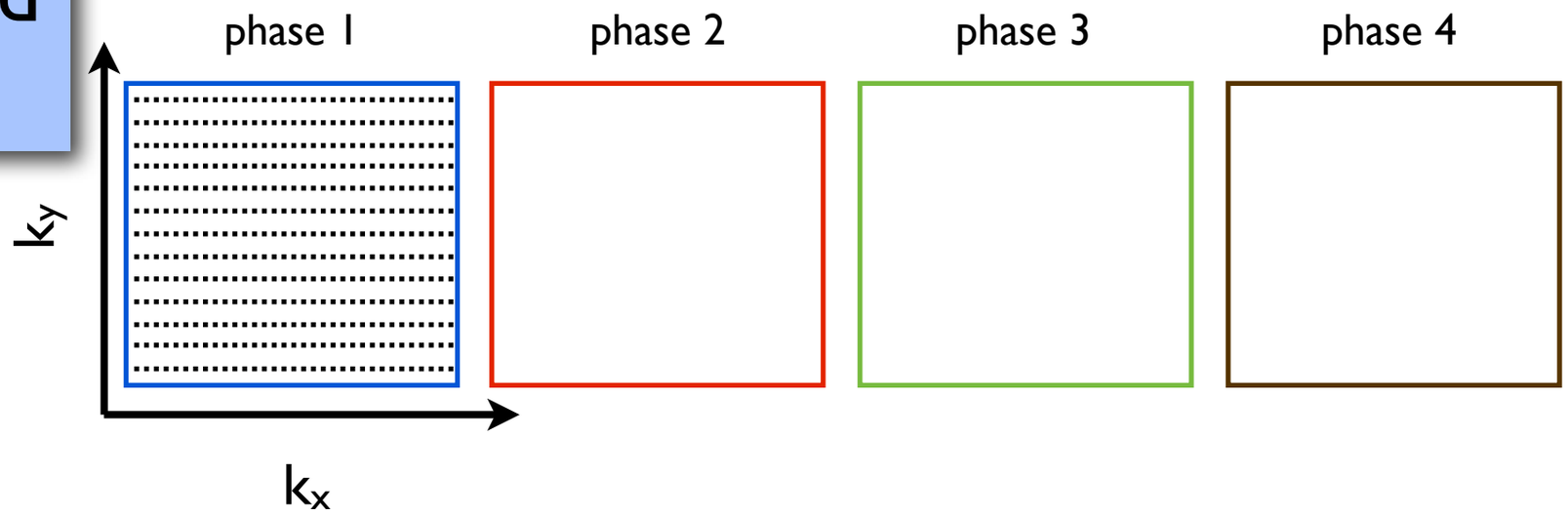
Basic cine

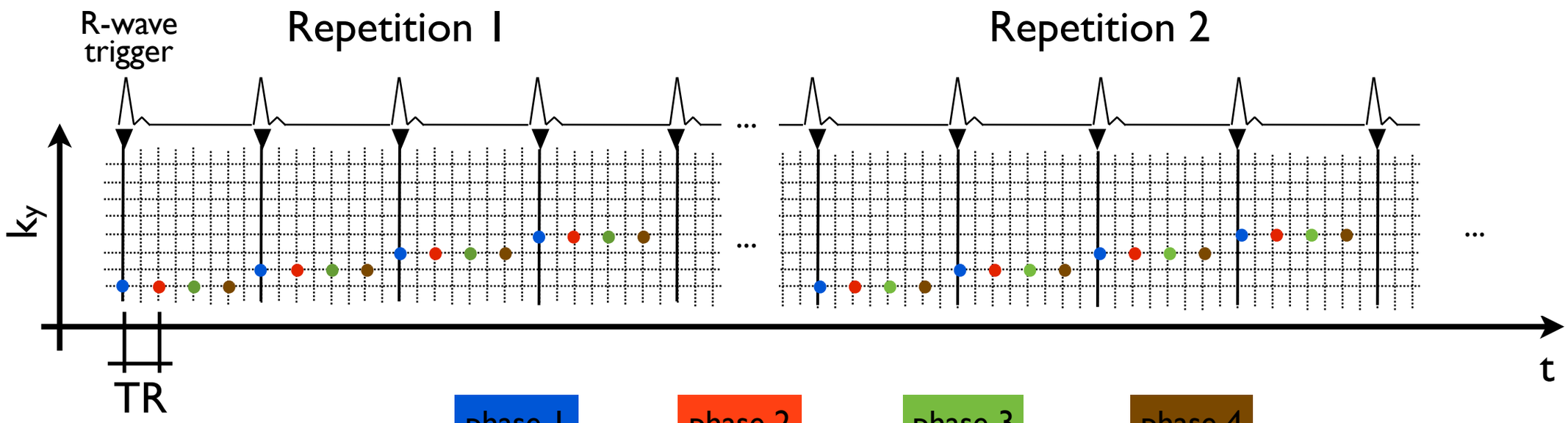

phase 1
phase 2
phase 3
phase 4
k_y
k_x

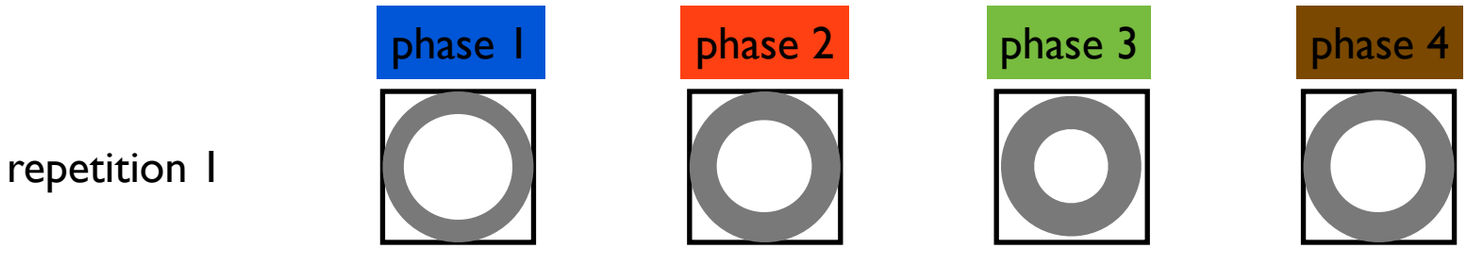

R-wave trigger
Repetition 1
Repetition 2
...
...
...
k_y
t
TR


phase 1
phase 2
phase 3
phase 4
repetition 1

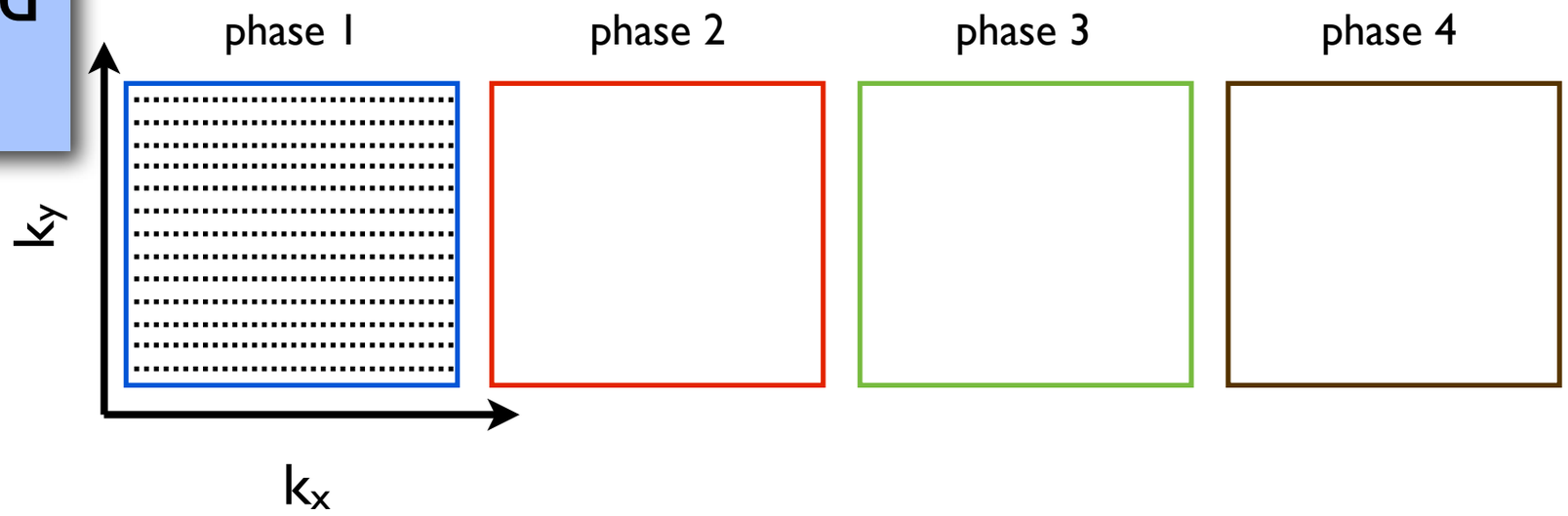
Interleaved cine

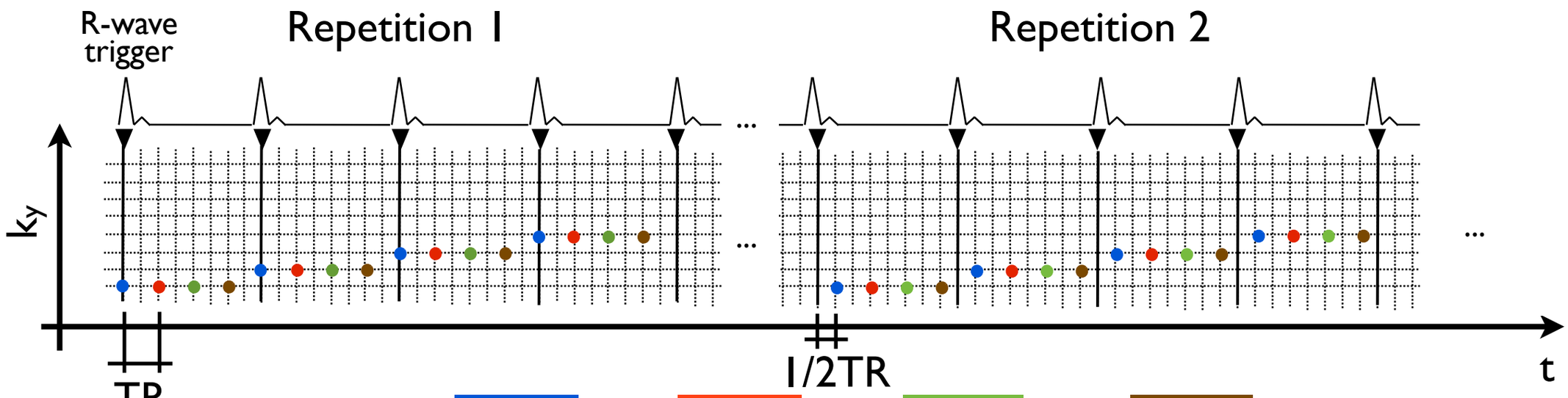


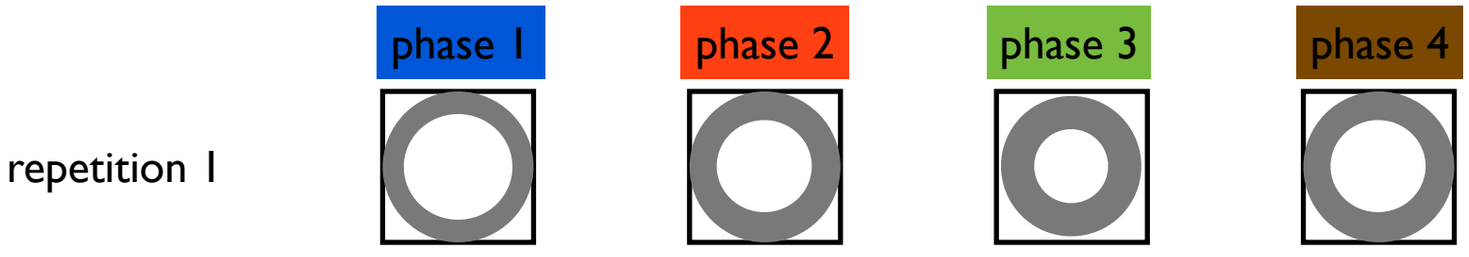




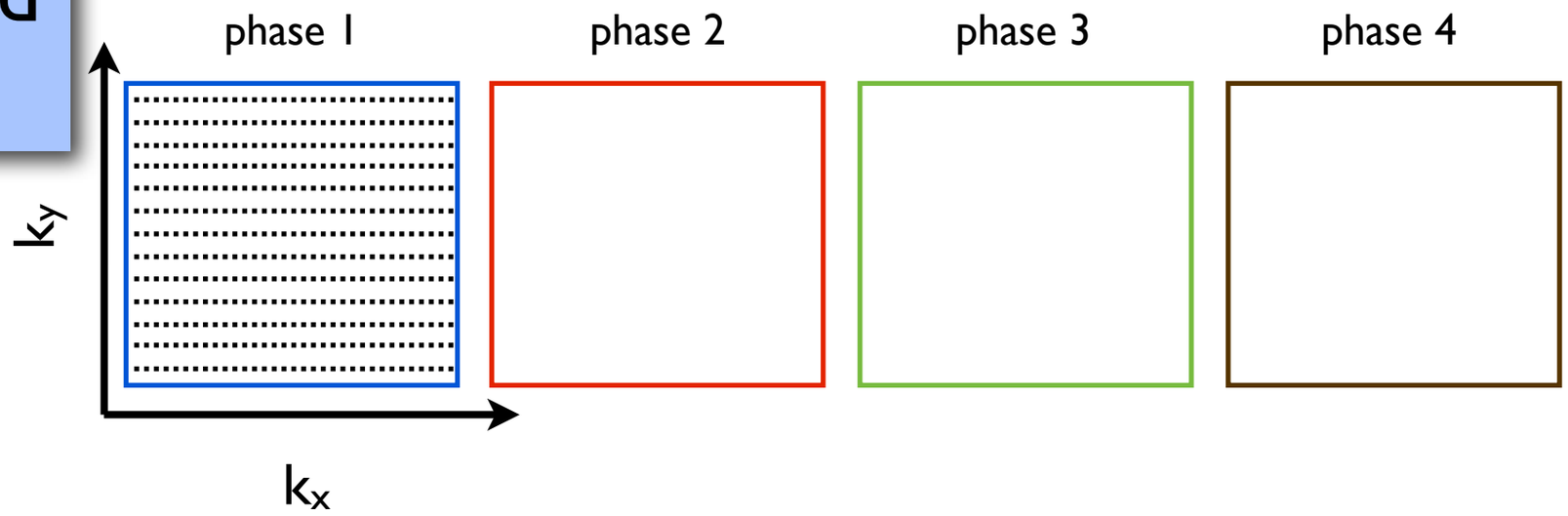
Interleaved cine

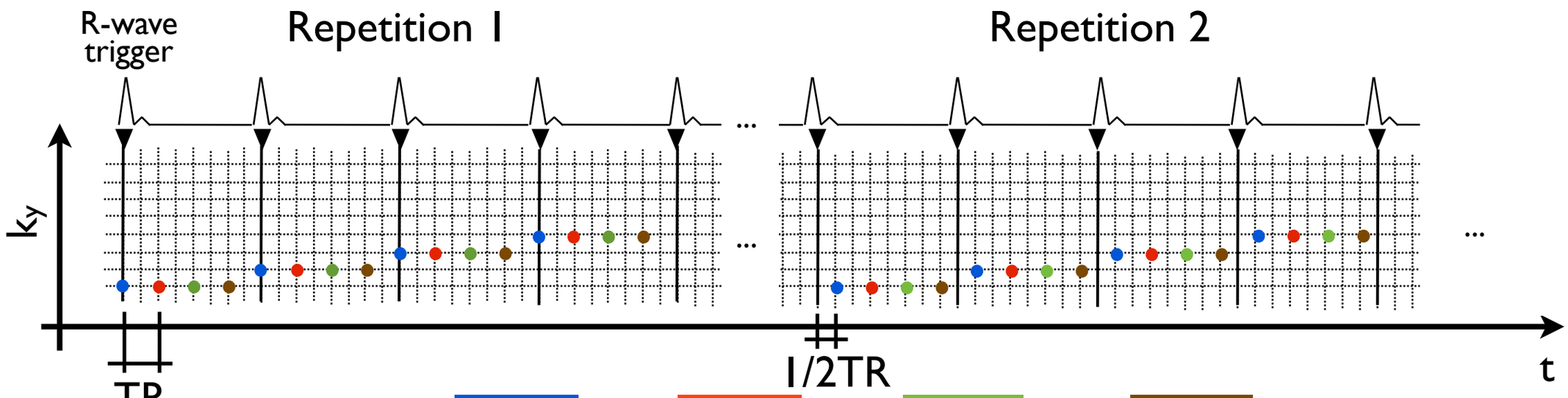


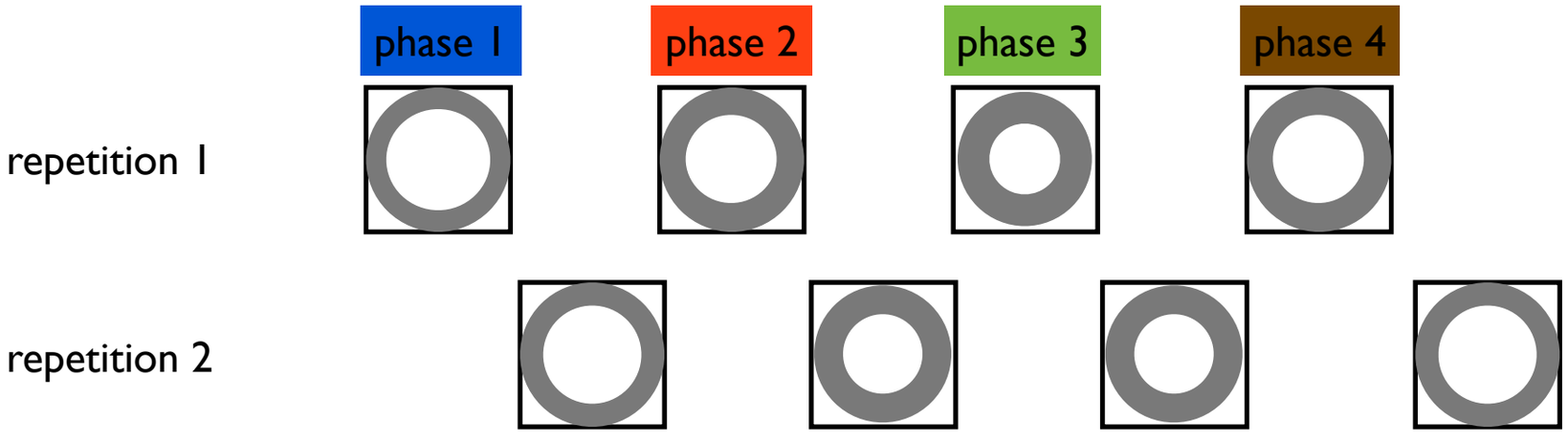




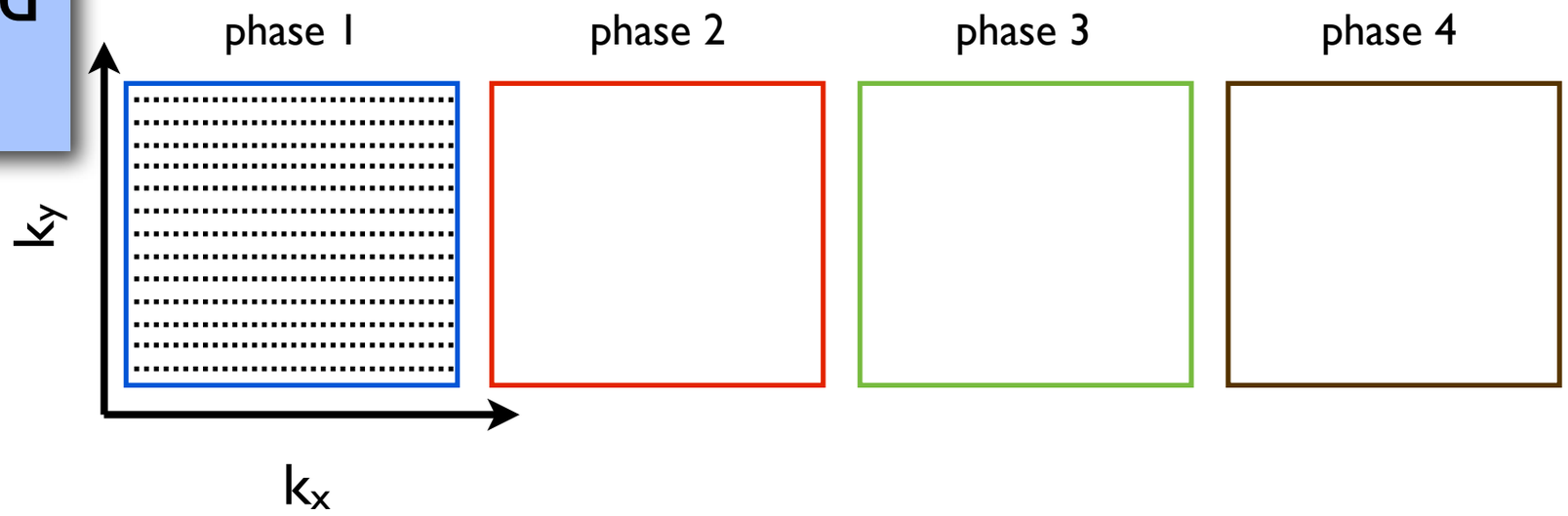
Interleaved cine

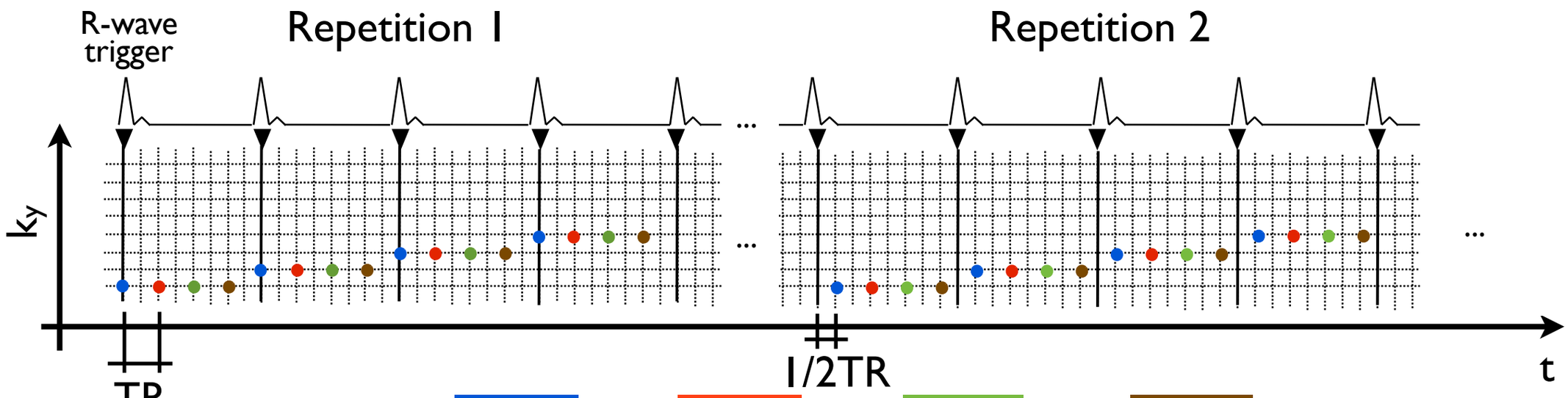


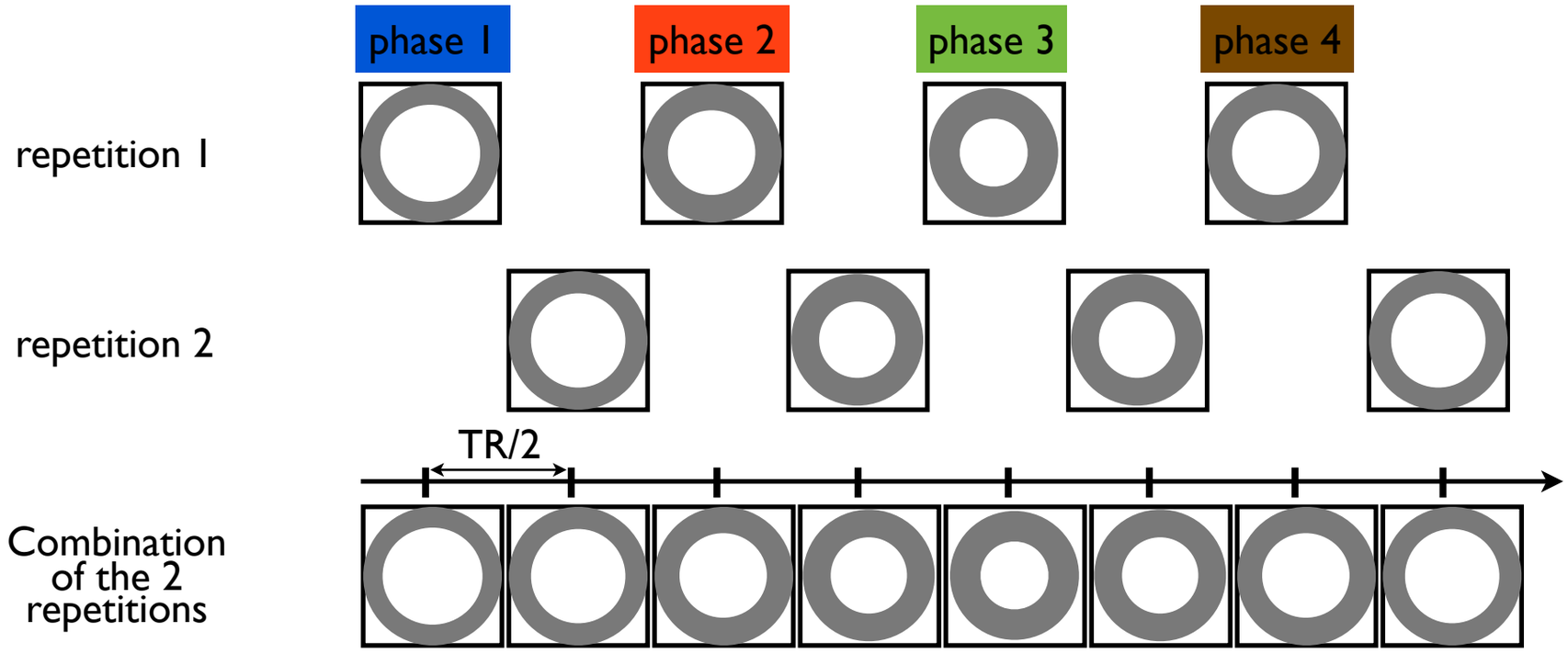




Interleaved cine







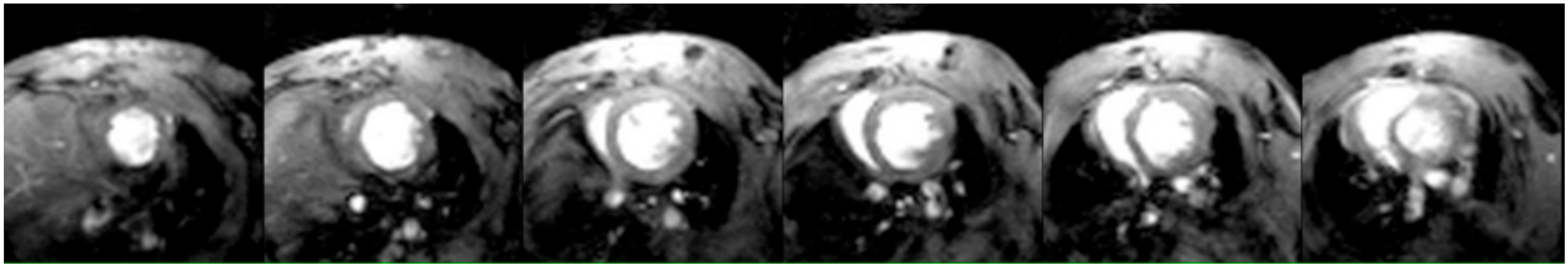
First results

Basic sequence (TR=13.5ms)

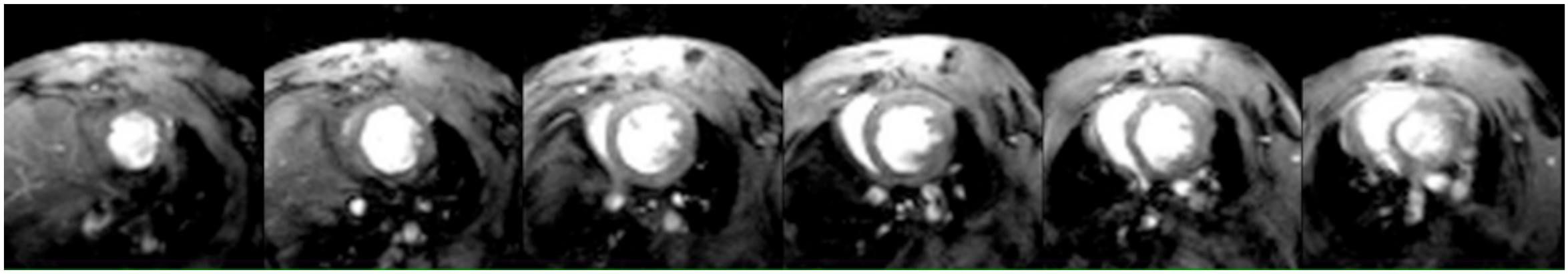
Interleaved cine (TR=6.8ms)

First results

Basic sequence (TR=13.5ms)



Interleaved cine (TR=6.8ms)



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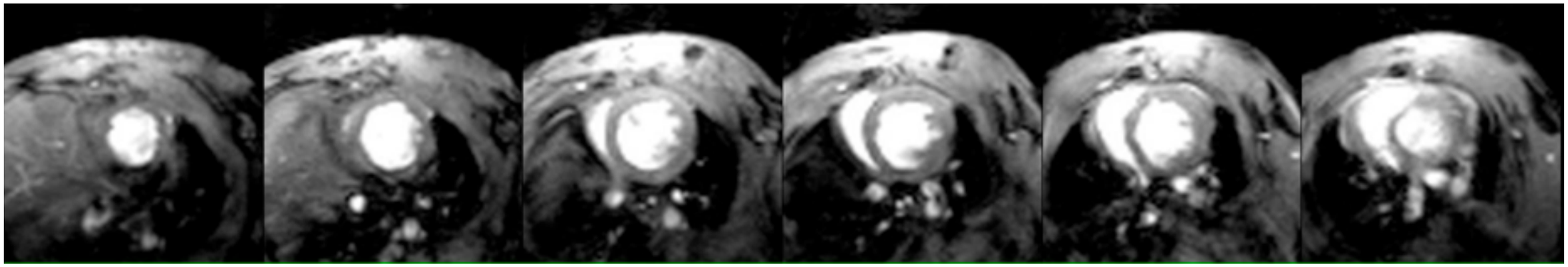
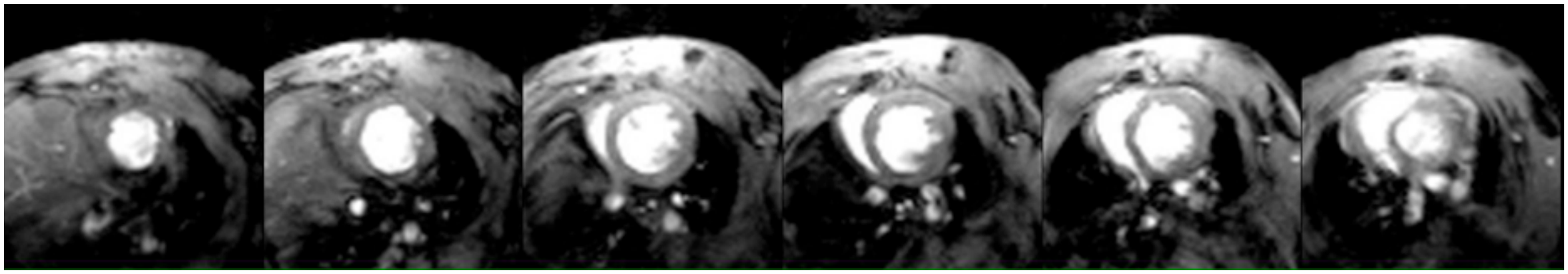


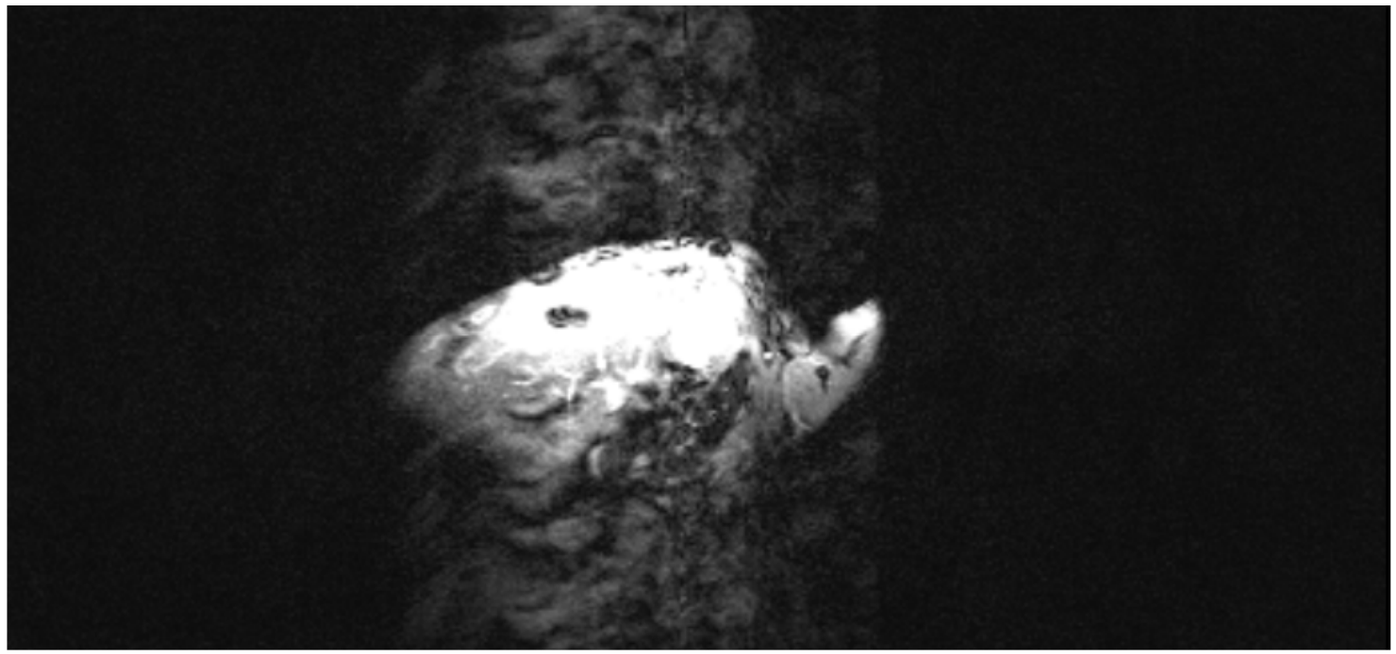
Interleaved cine (TR=6.8ms)



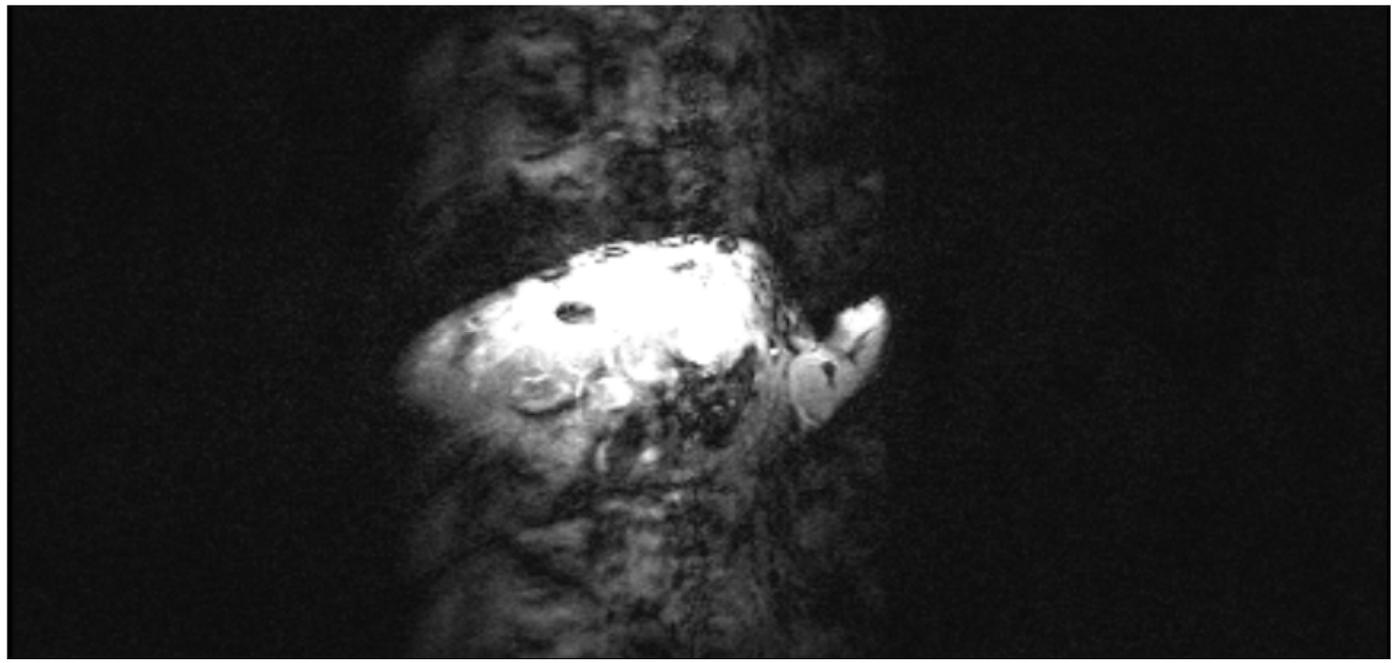
“Flickering” artifact due to combination of images with different artifacts (flow)

Flickering artifact

Phase 1 - rep 1



Phase 1 - rep 2

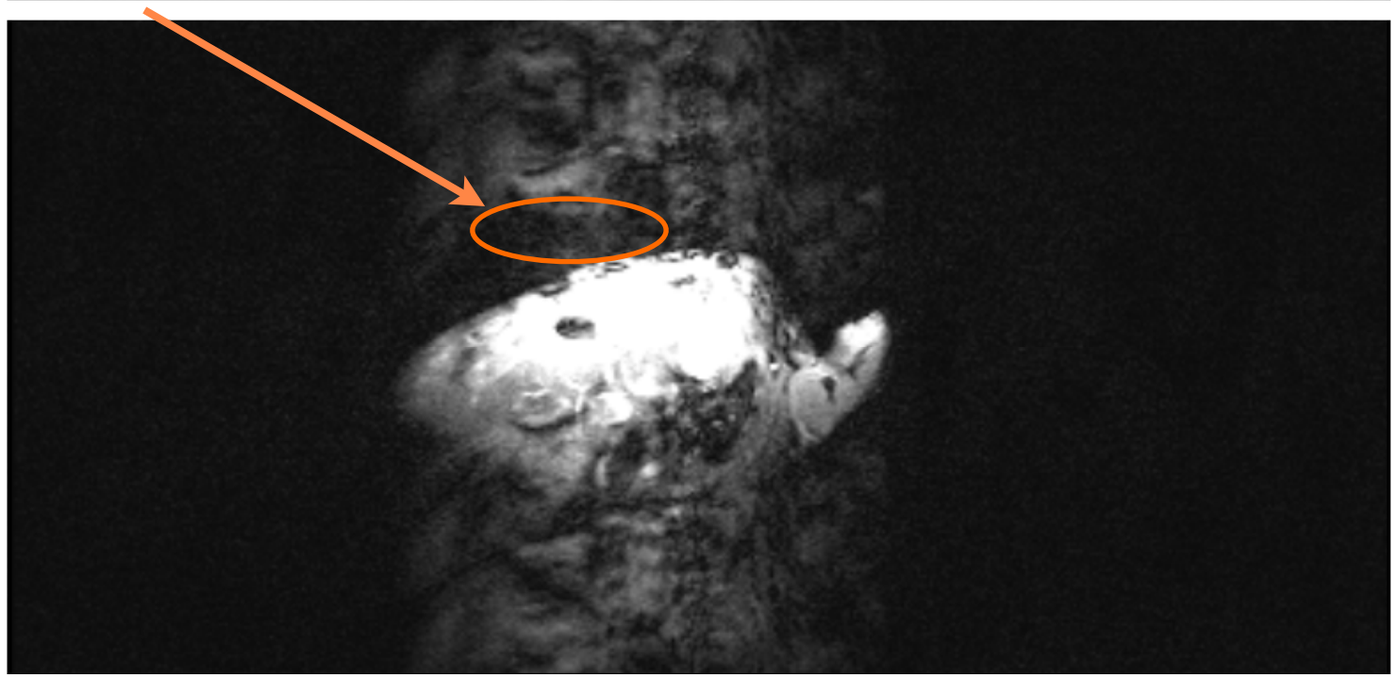


WW/WL set to see ghosting artifacts

Flickering artifact

Phase 1 - rep 1

Phase 1 - rep 2



WW/WL set to see ghosting artifacts

Image enhancement

Variational model

$$J(s) = \sum_n \|f_n - s_n\|_2^2 + \lambda \sum_n \|\hat{s}_n\|_1$$

n: temporal indice
^: Fourier transform

Image enhancement

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n: temporal indice

^: Fourier transform

Case 1:

original

After soft thresh.

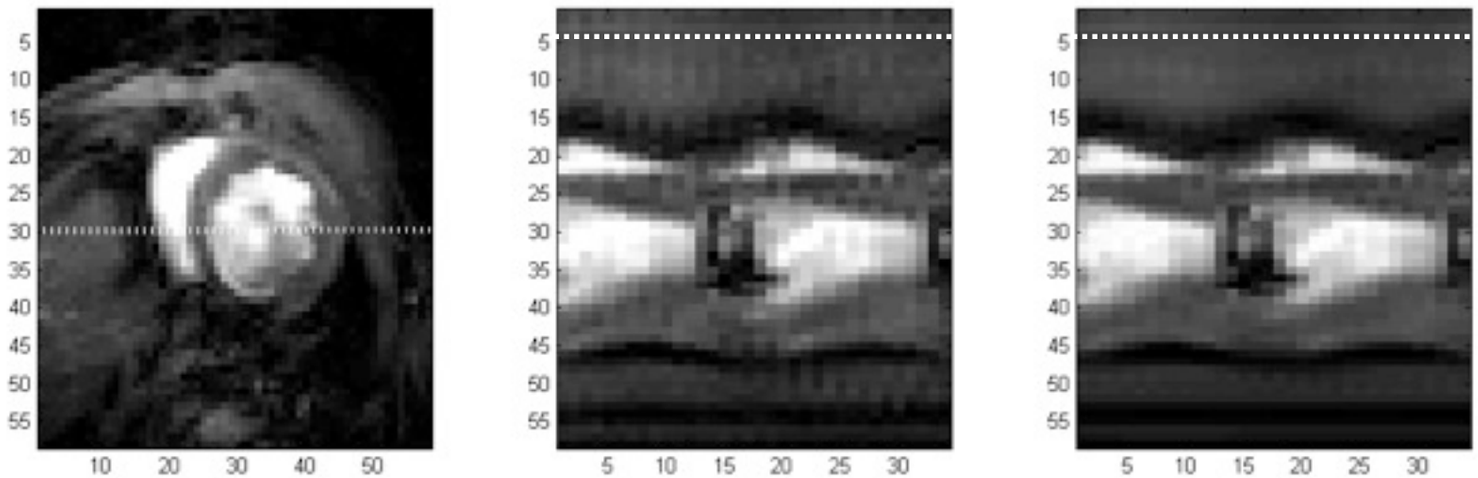

Image enhancement

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original

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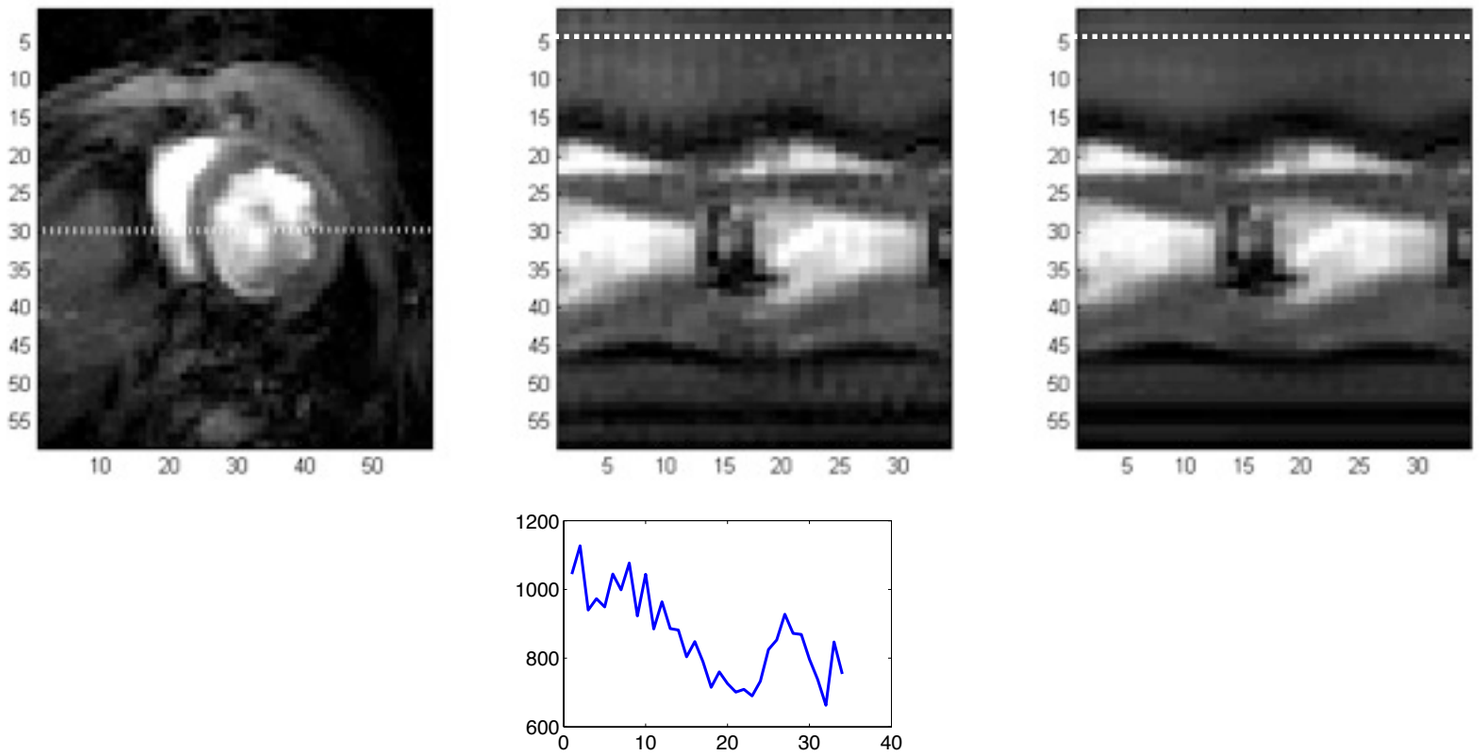

Image enhancement

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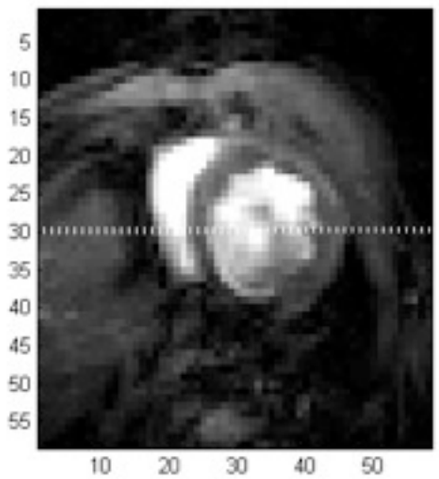
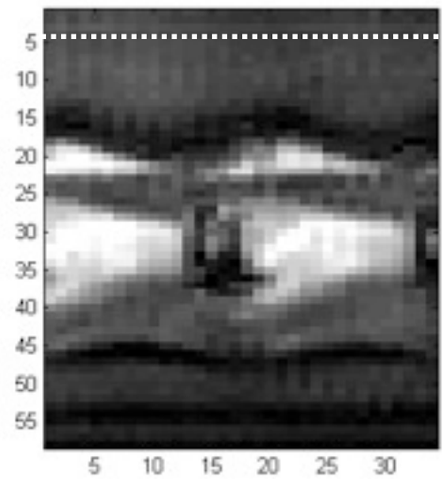
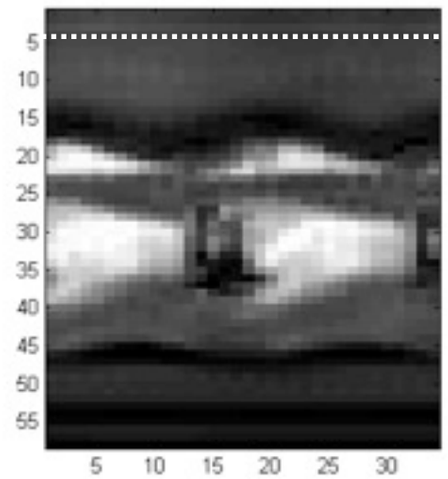
Case 1:

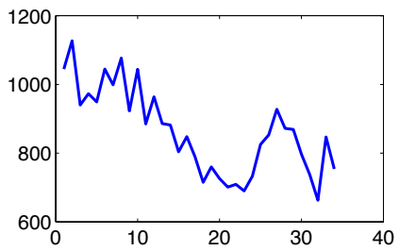


original



After soft thresh.





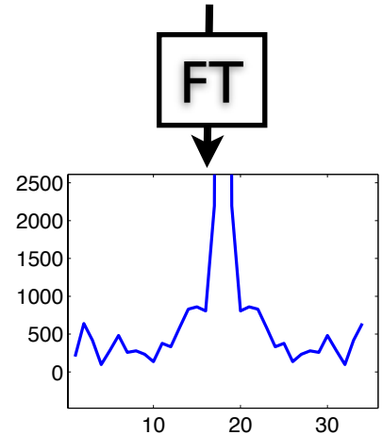


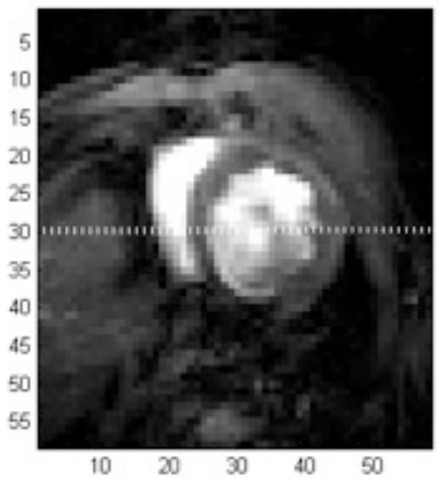
Image enhancement

Variational model $$J(s) = \sum_n \|f_n - s_n\|_2^2 + \lambda \sum_n \|\hat{s}_n\|_1$$

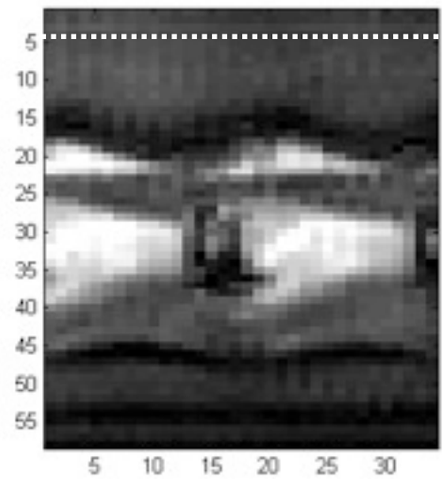
n: temporal indice

^: Fourier transform

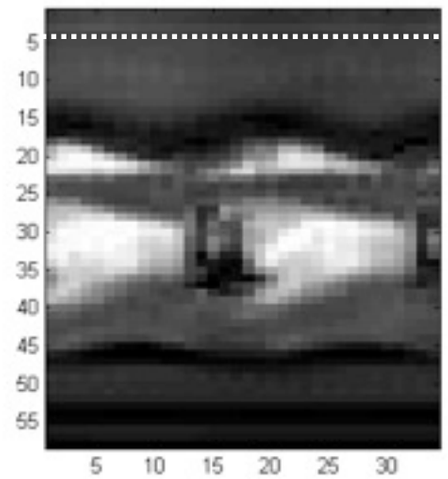
Case 1:

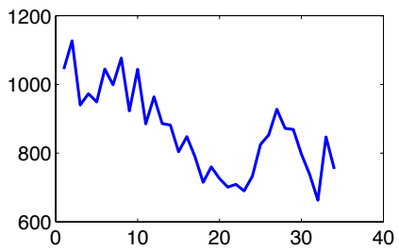


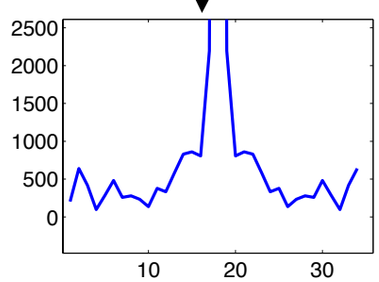
original

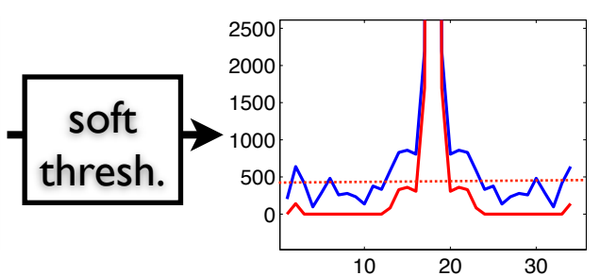


After soft thresh.









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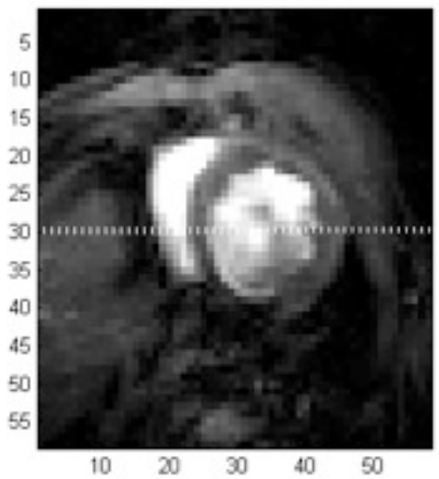

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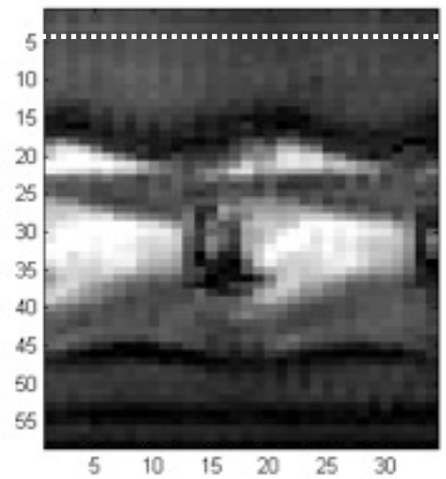

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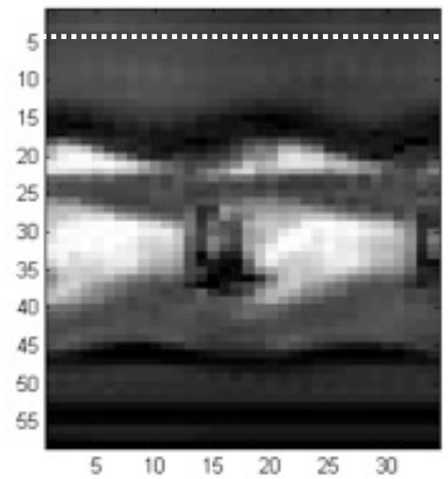

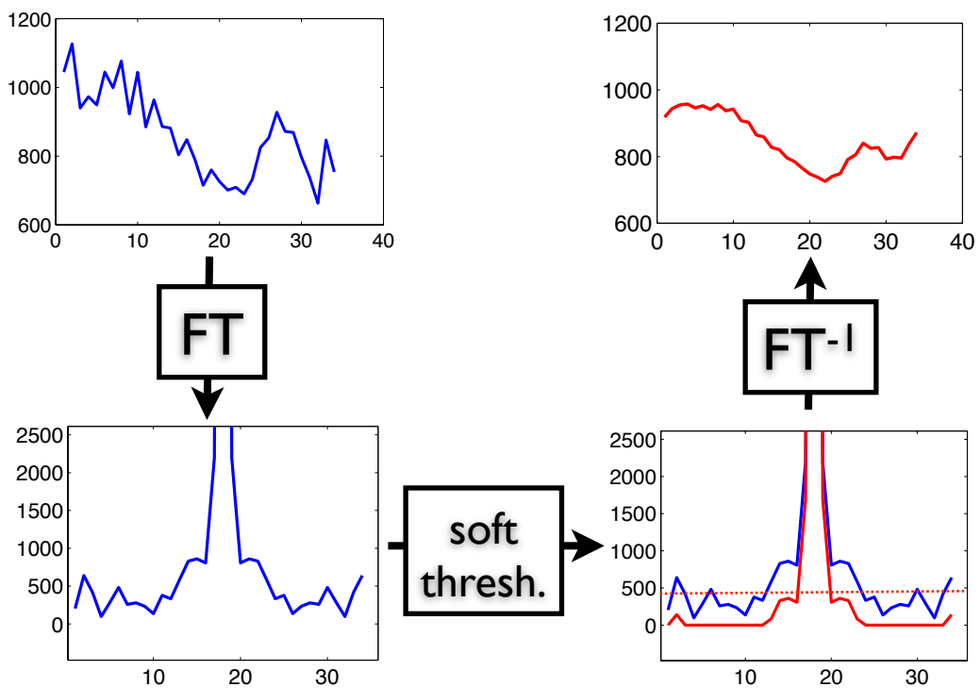

Image enhancement

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Case 2:

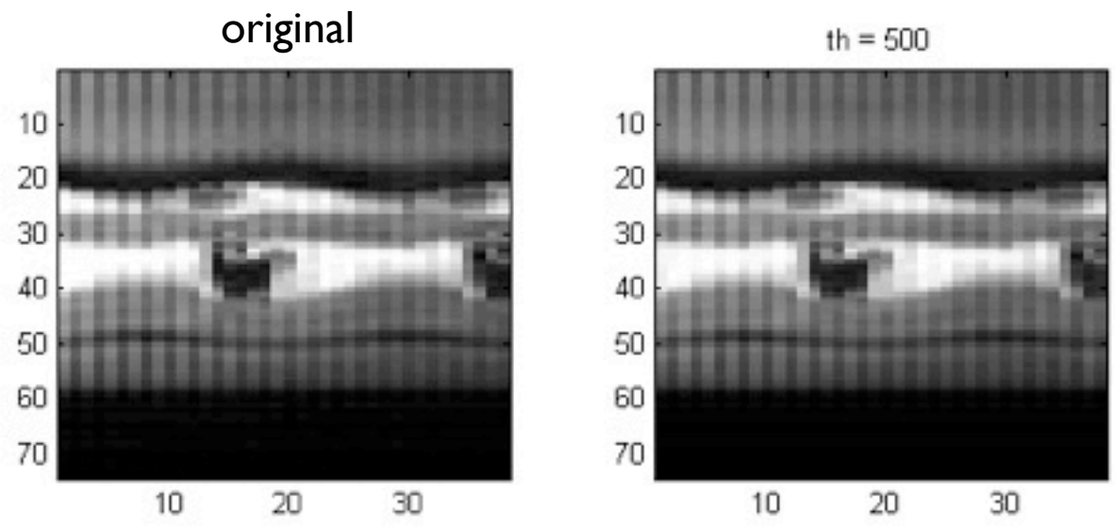

Image enhancement

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^: Fourier transform

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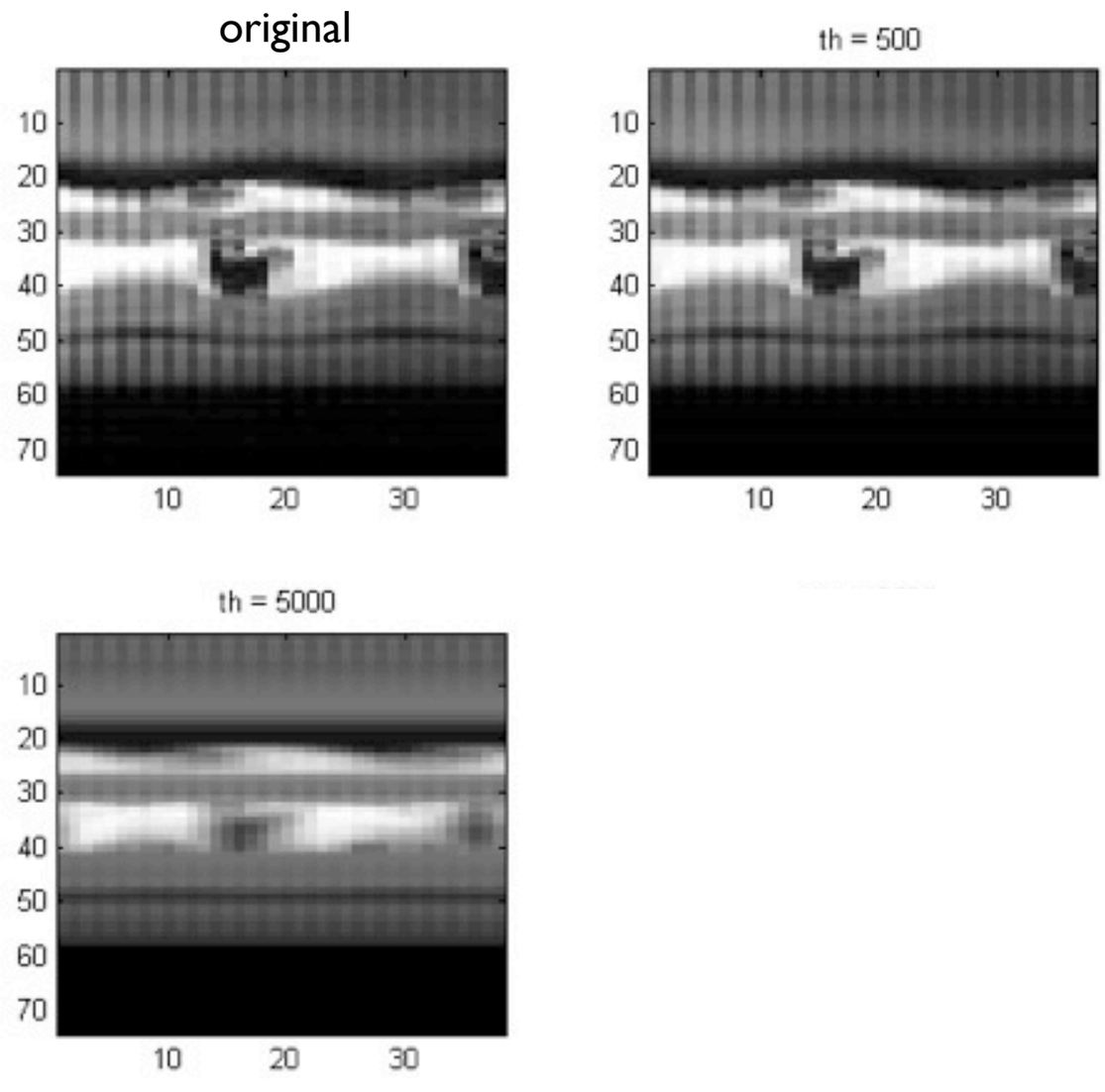

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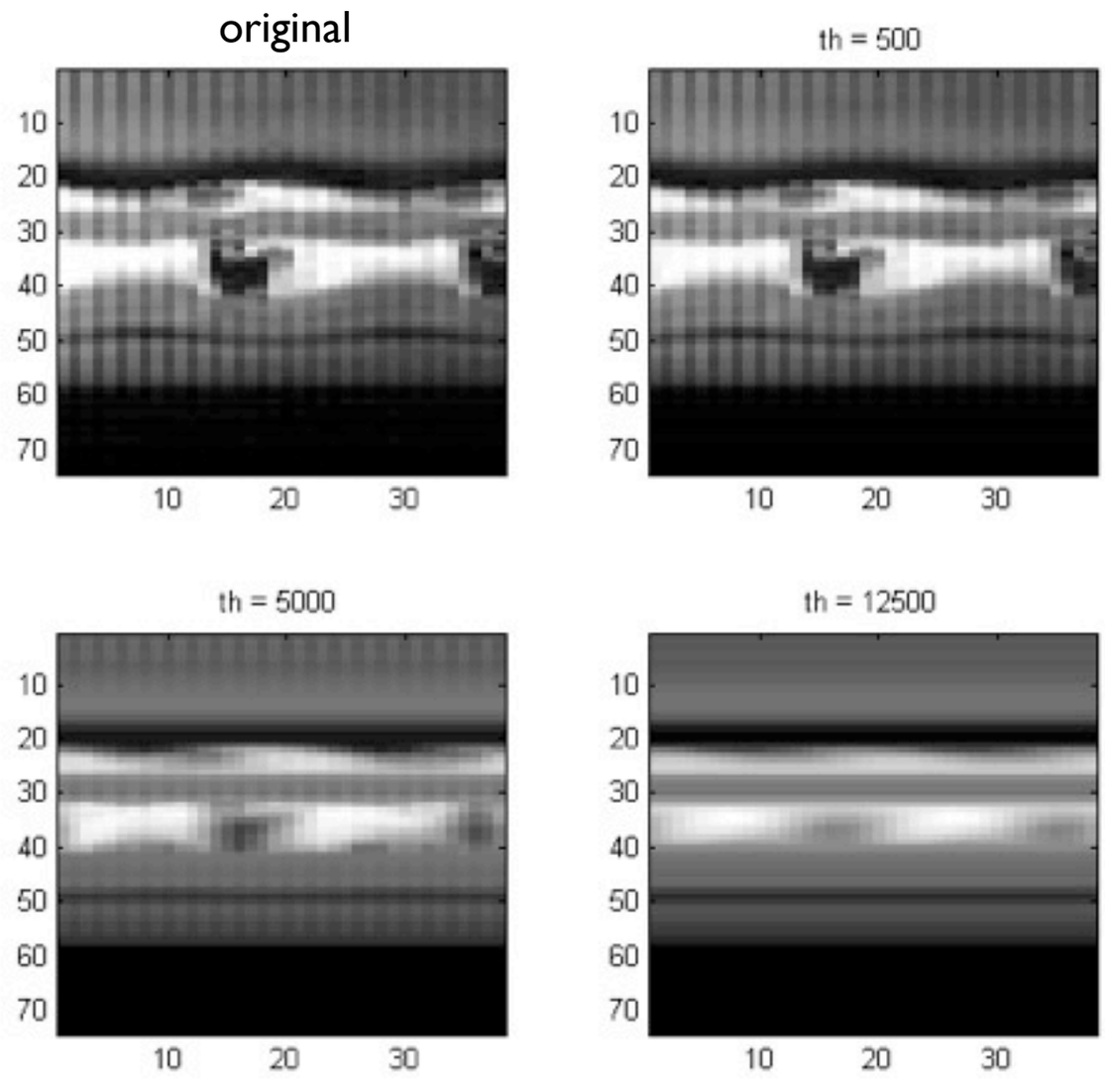
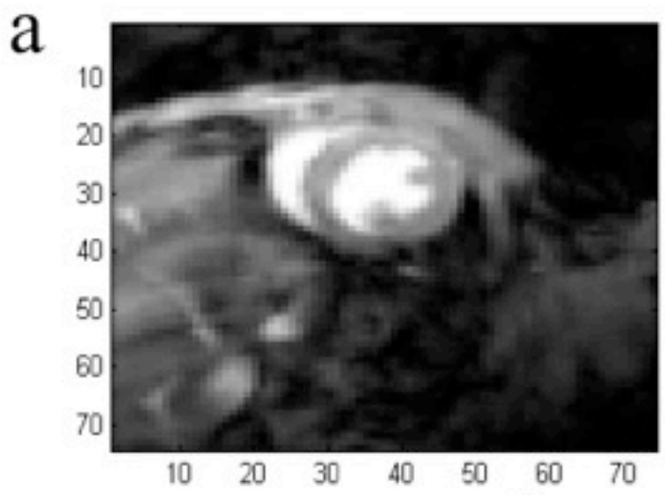
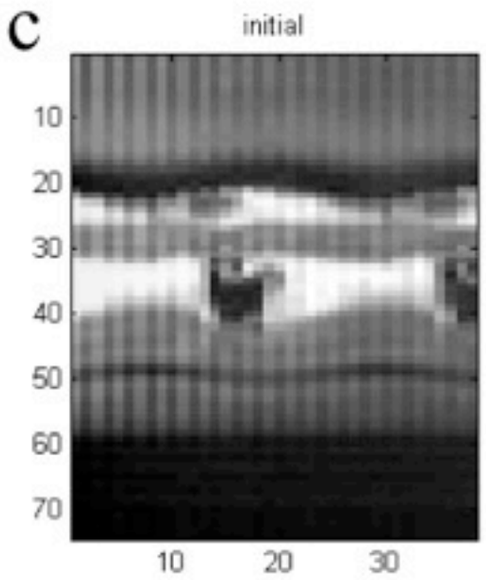


Image enhancement

Variational model $J(s, A, \omega, \phi) = \sum_n \|f_n - A\sin(\omega n + \phi) - s_n\|_2^2 + \lambda \sum_n \|\hat{s}_n\|_1$

n: temporal indice
^: Fourier transform





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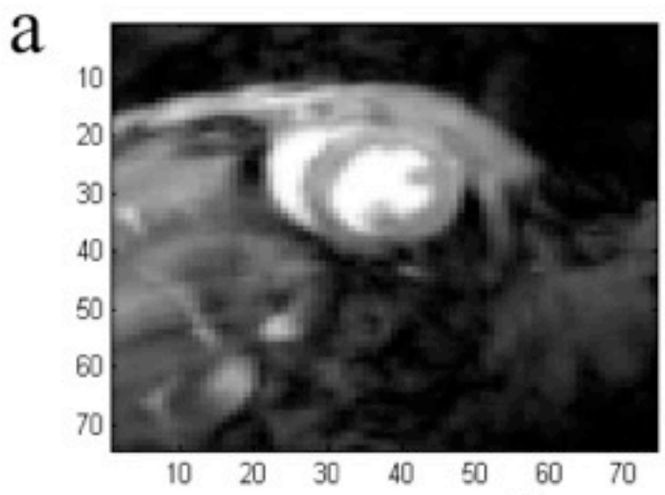

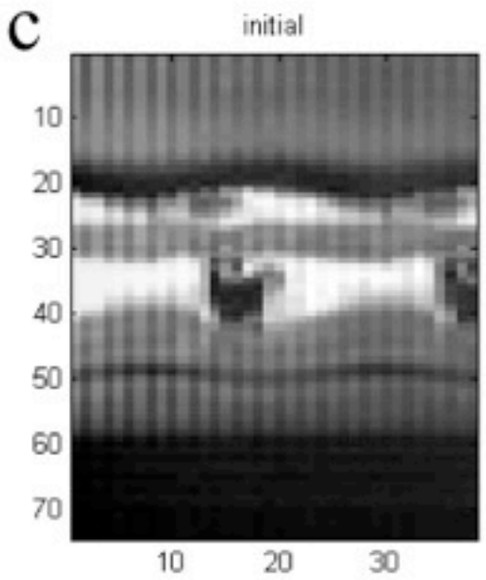

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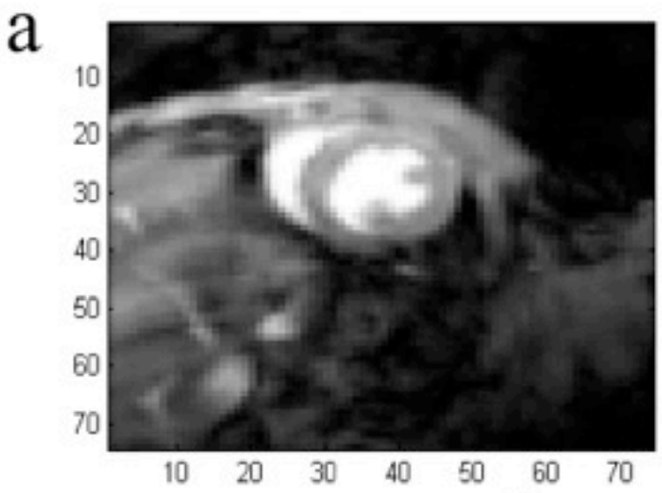

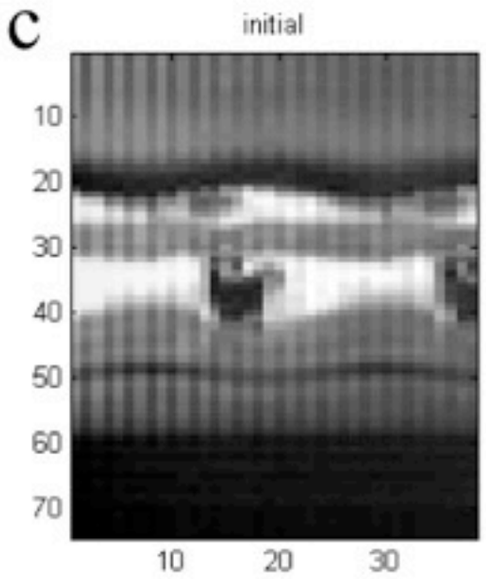

Step 1 $\mu_n = \frac{1}{N_x}\sum_x \frac{1}{N_y}\sum_y f_n(x, y)$

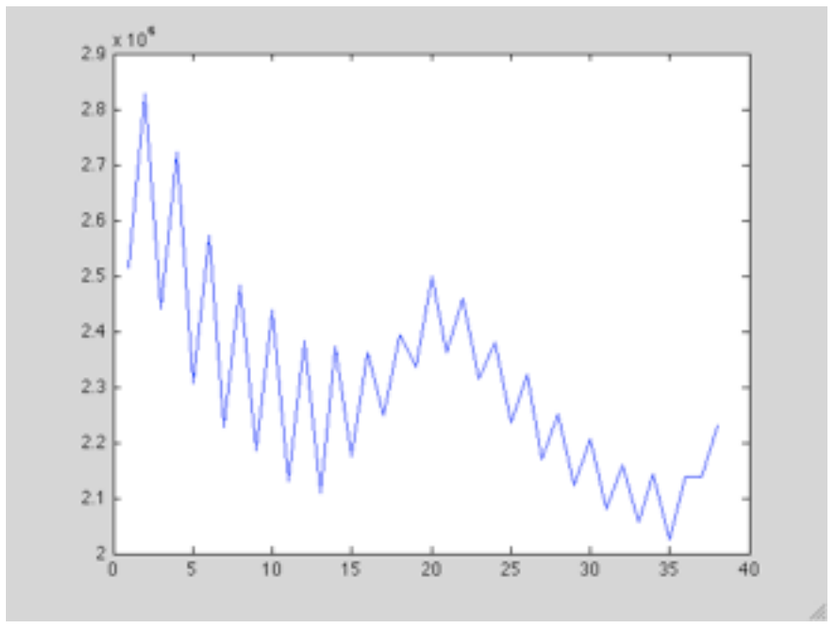

Image enhancement

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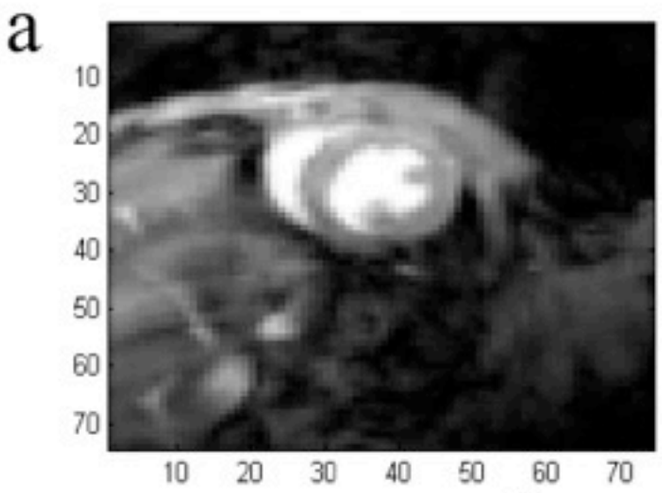

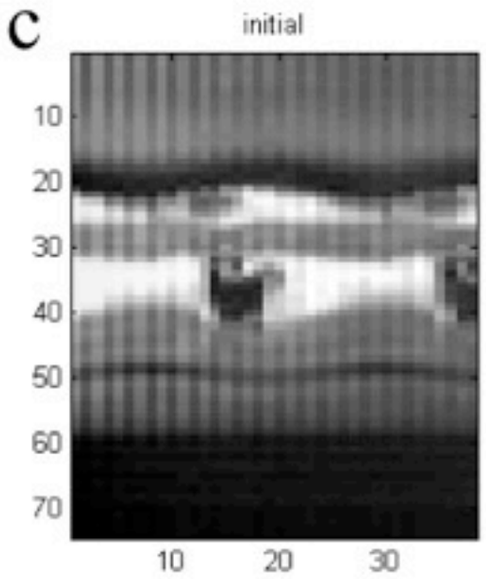

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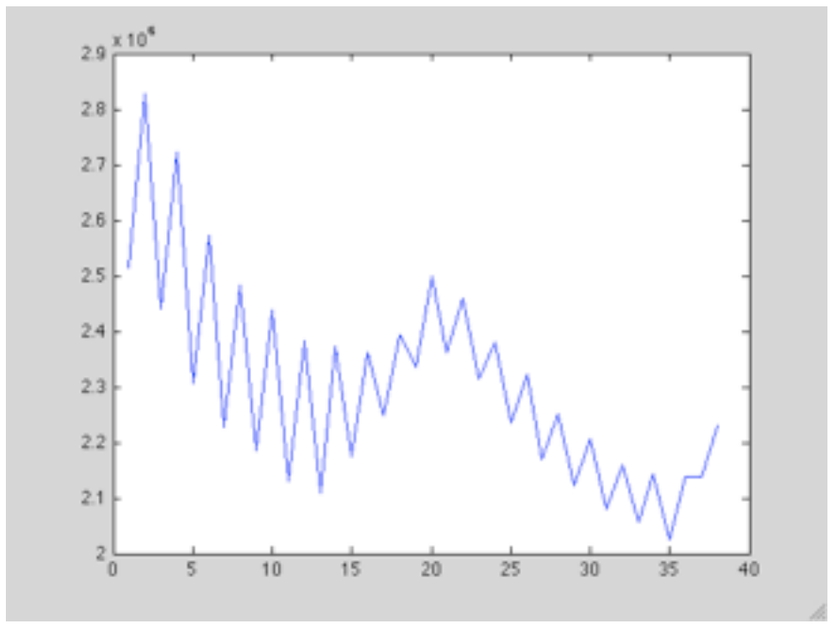

fit ω, ϕ

Image enhancement

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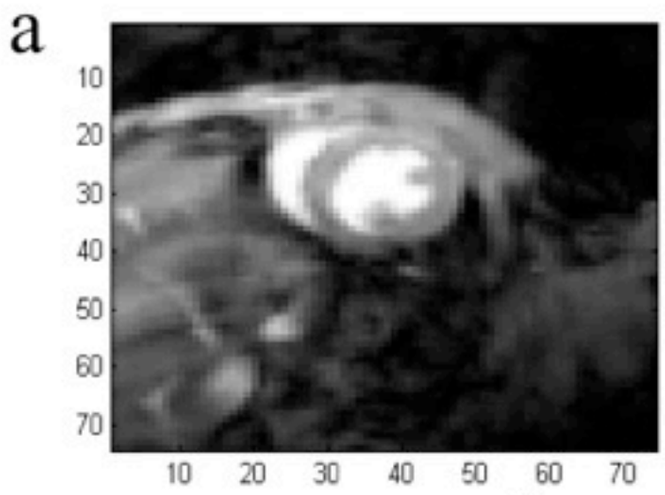

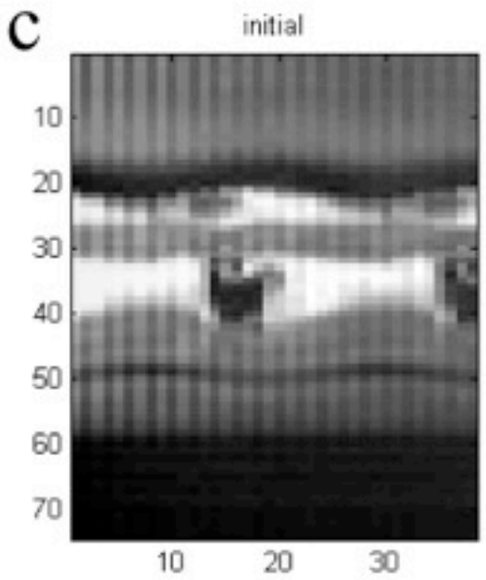

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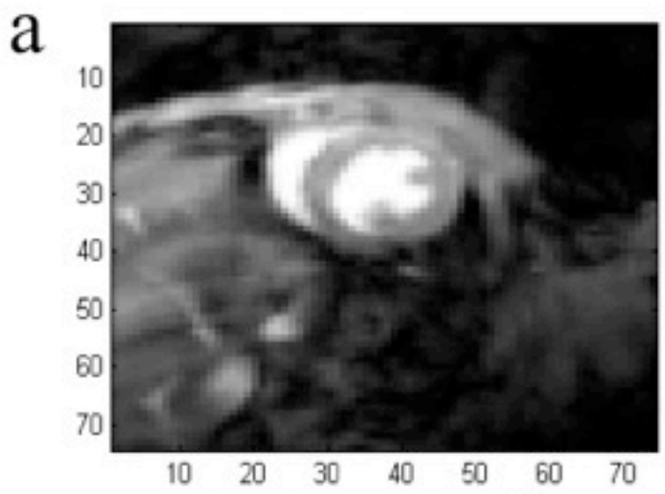

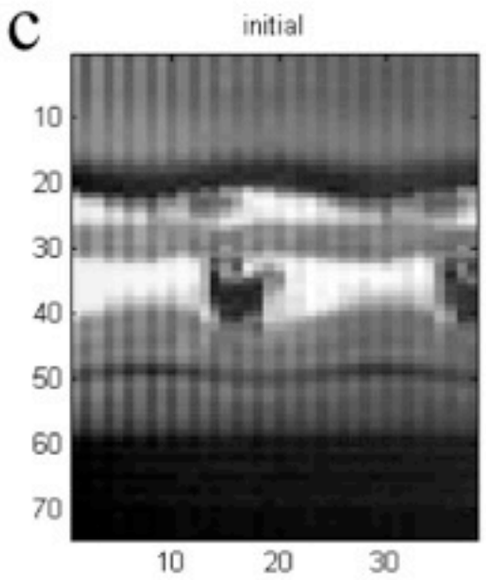

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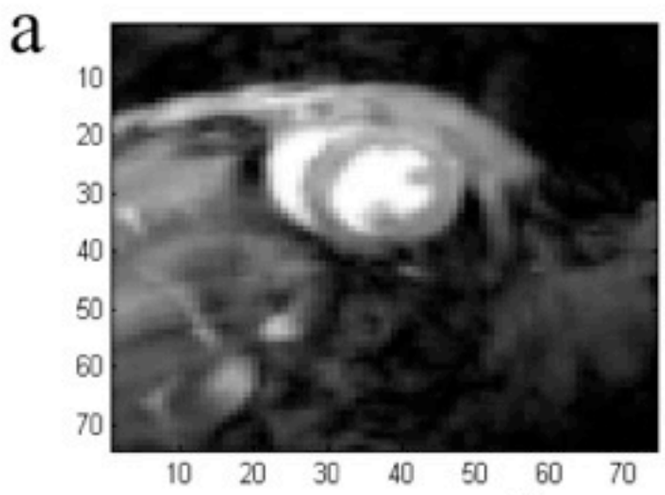

Step 2: fit A(*x*,*y*)

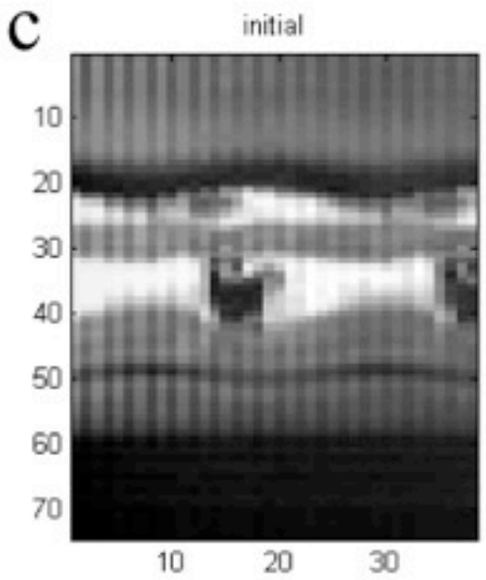

Image enhancement

Variational model $J(s, A, \omega, \phi) = \sum_n \|f_n - A\sin(\omega n + \phi) - s_n\|_2^2 + \lambda \sum_n \|\hat{s}_n\|_1$

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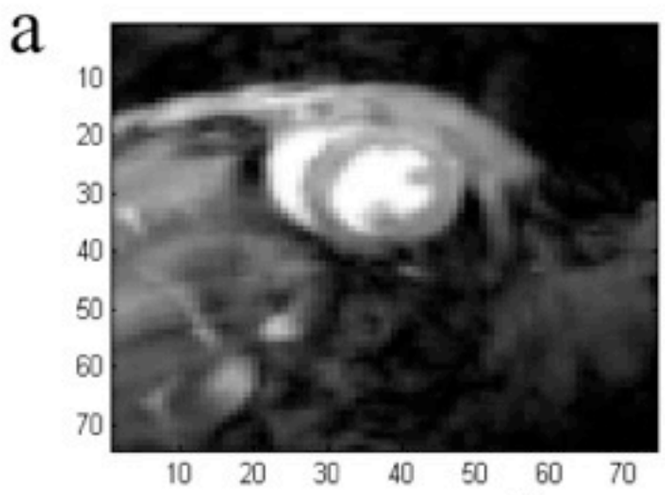

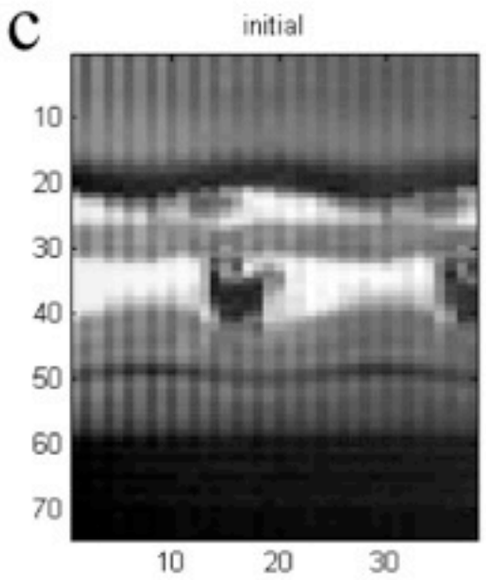

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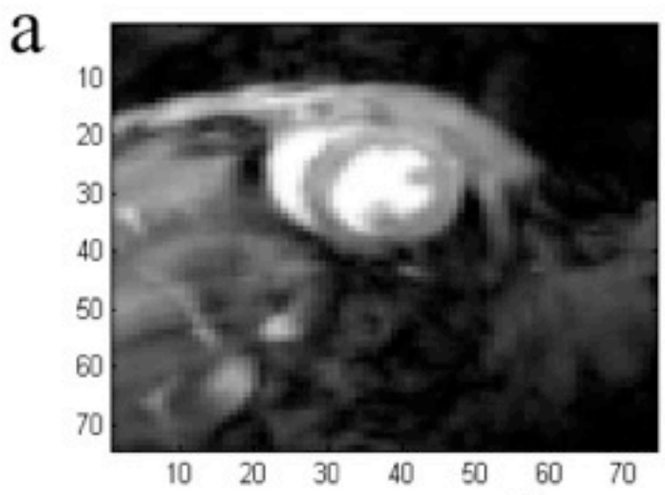

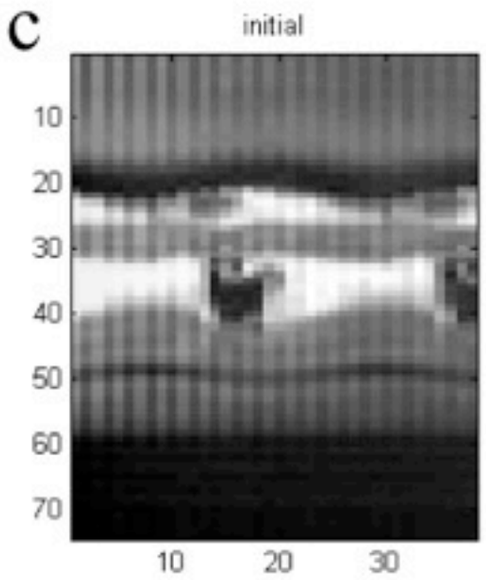

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$$A(x,y) = \frac{\sum_n f_n(x,y)\sin(\omega n + \phi)}{\sum_n \sin^2(\omega n + \phi)}$$

Image enhancement

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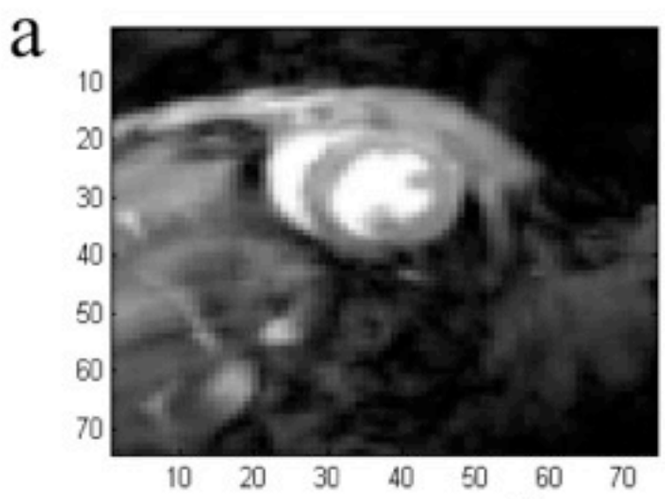

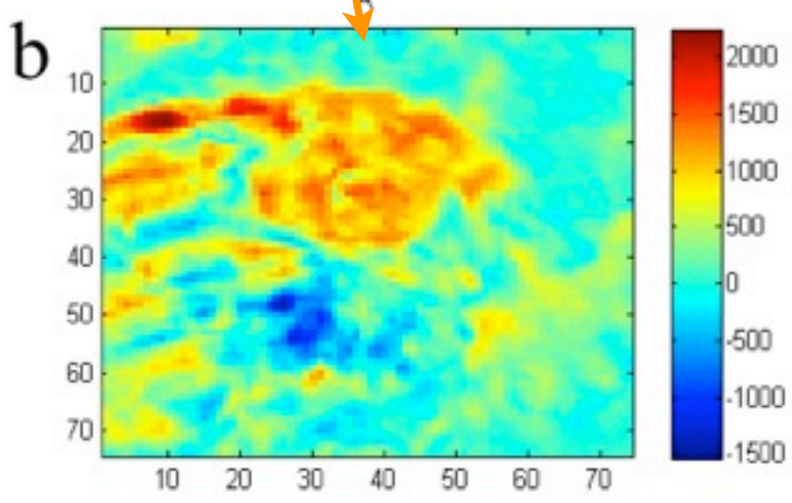

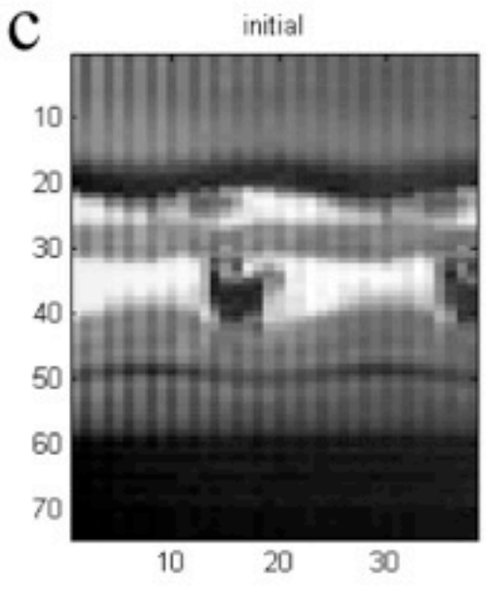

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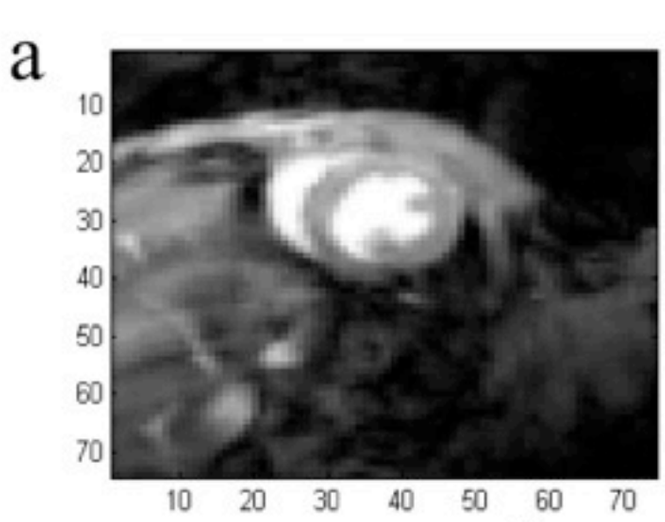

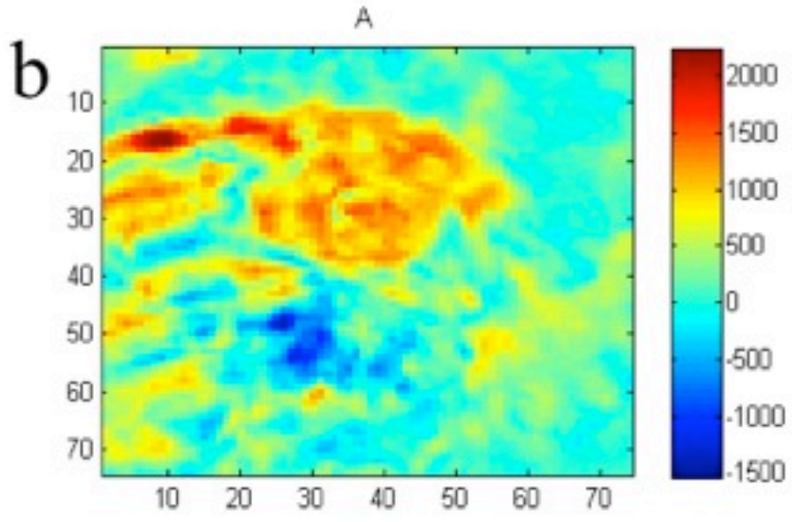

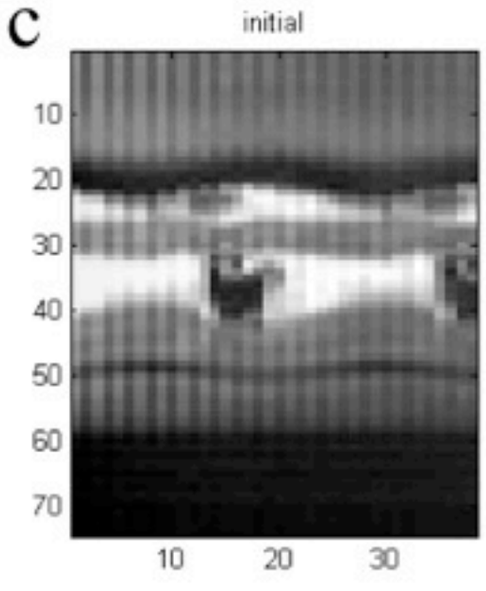

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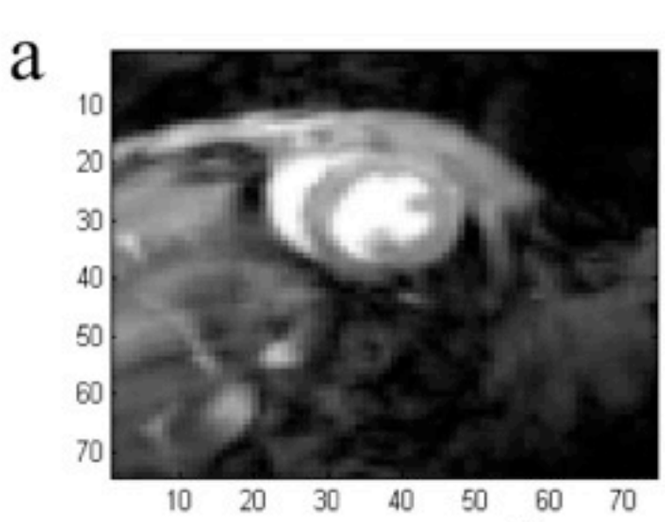

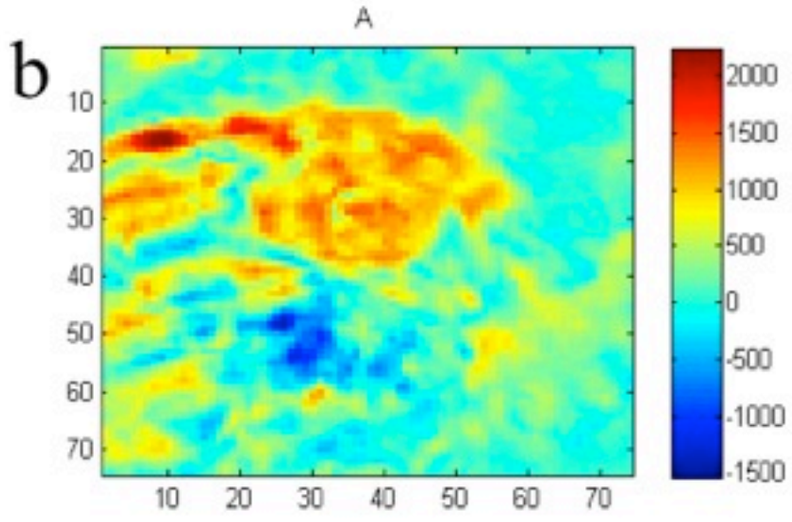

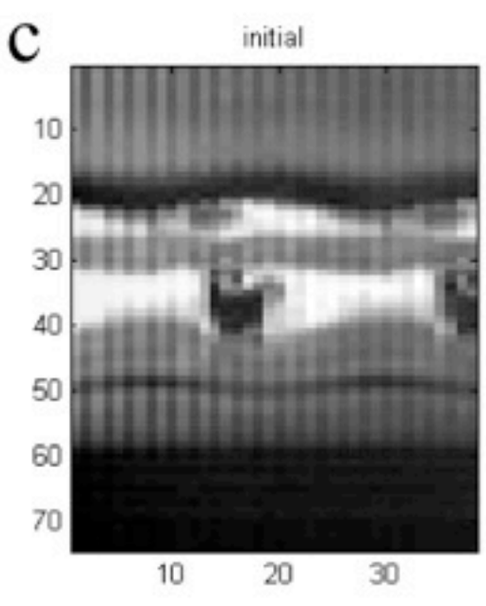

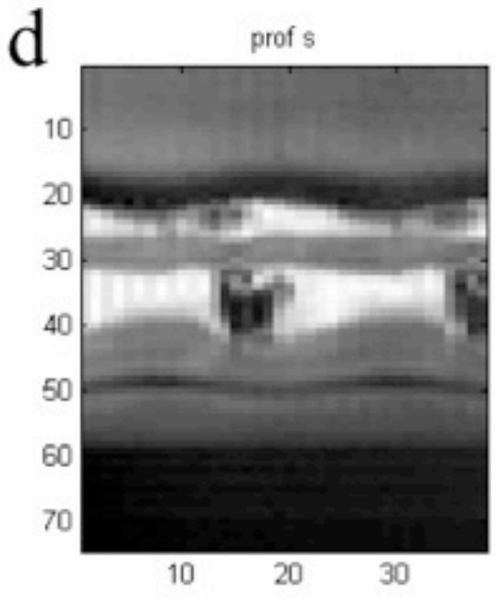

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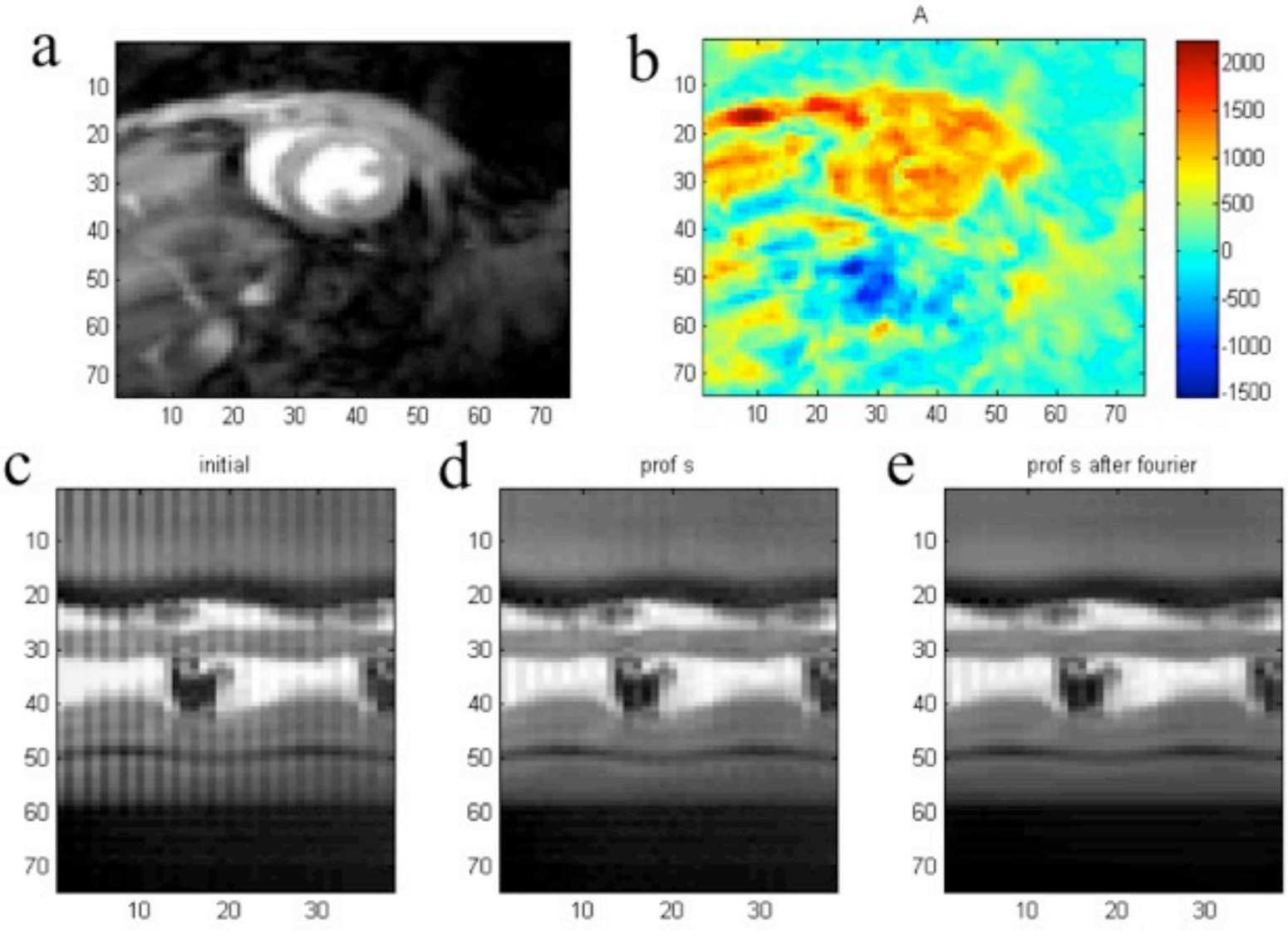
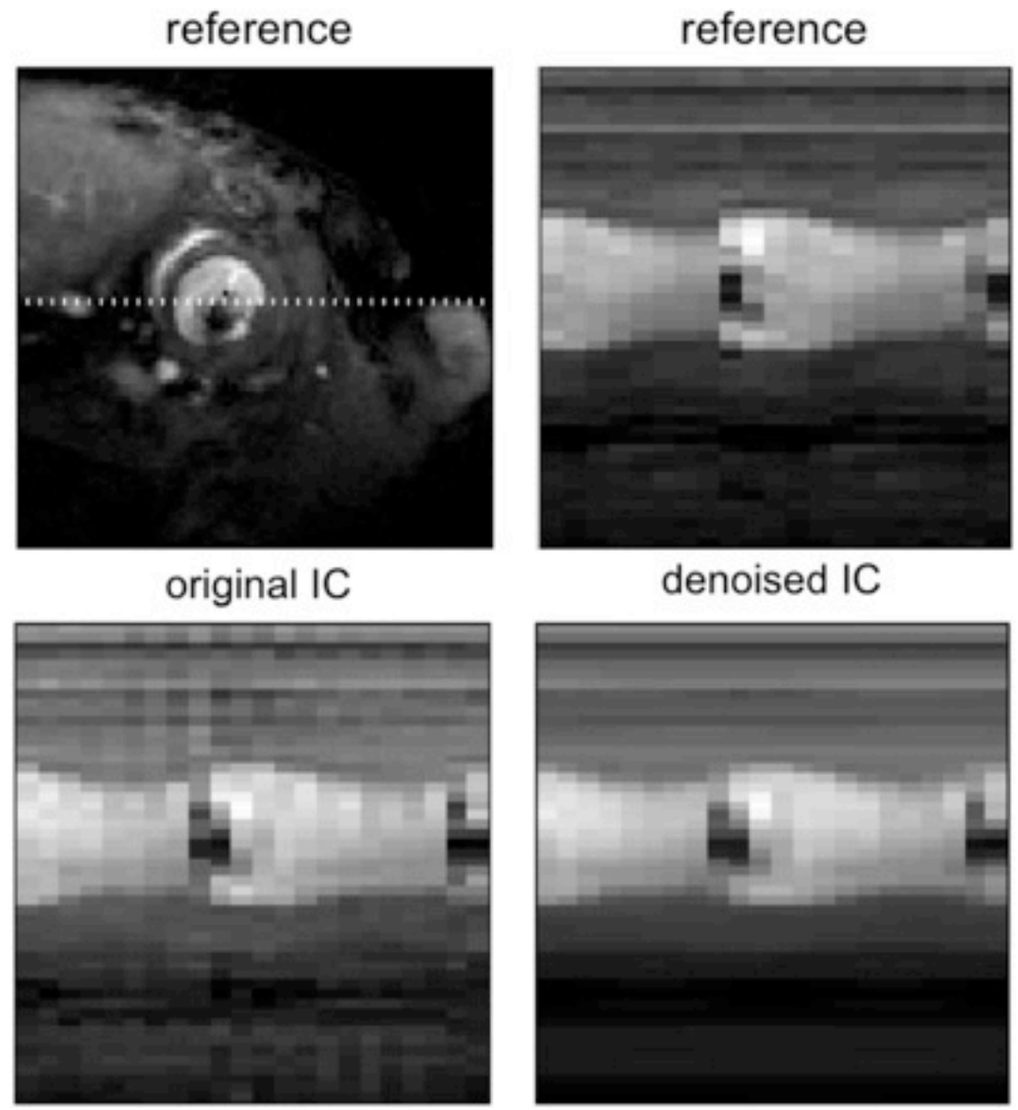


Denoising evaluation

Reference:
Basic cine TR 13.5 ms - 2 averages

Interleaved cine:
TR 27 ms - 2 repetitions (no average)
final TR = 13.5 ms

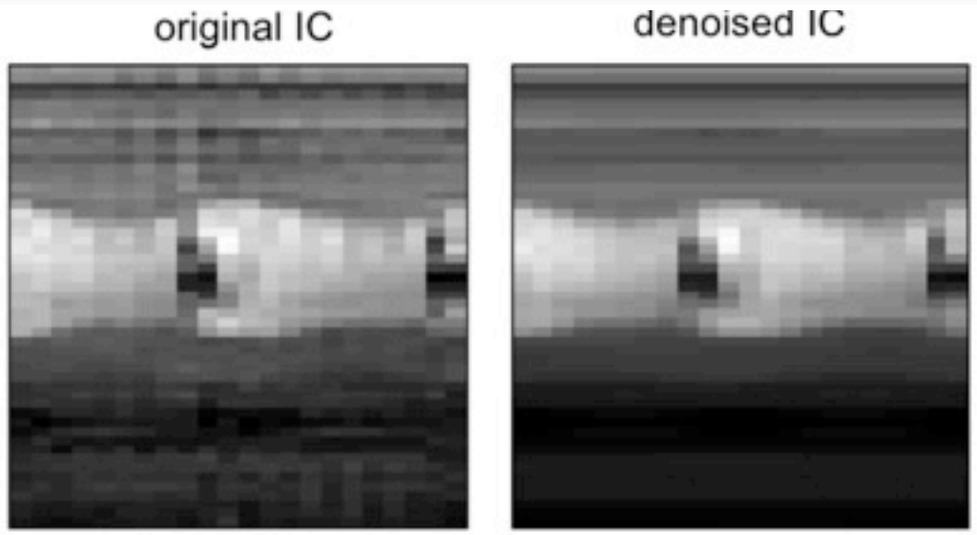


2 evaluation indices :

Energy E $$E = \sum \left| \frac{\partial}{\partial t} \| I - I_{ref} \|^2 \right|$$

Noise reduction $$10 \log \frac{E_{denoised}}{E_{original}}$$

Denoising evaluation



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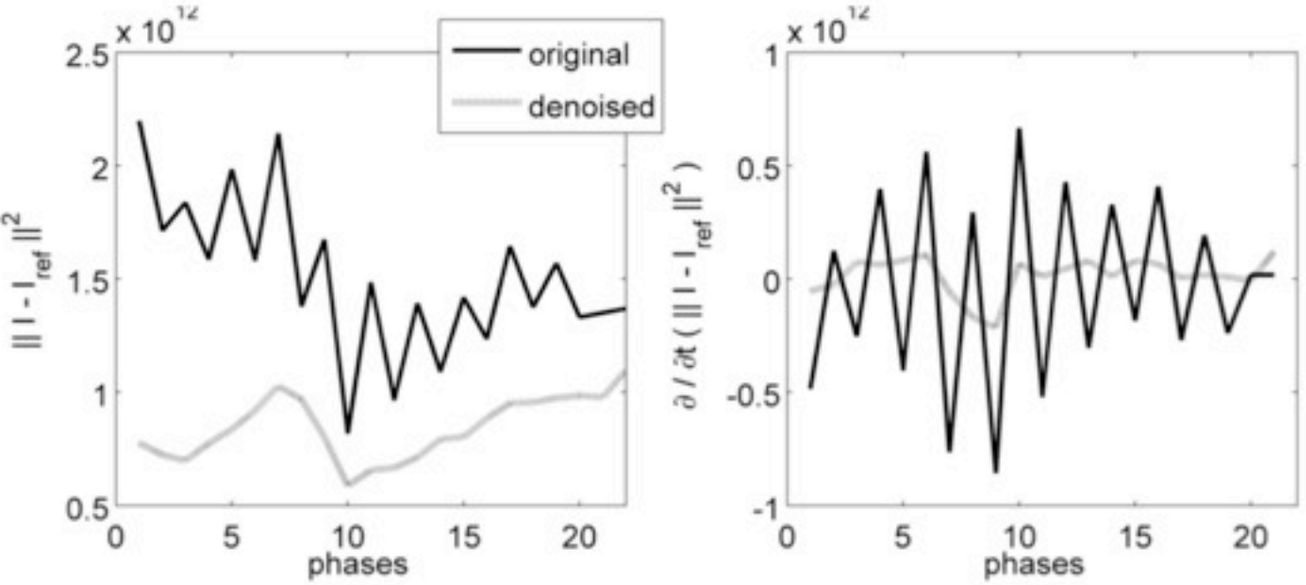

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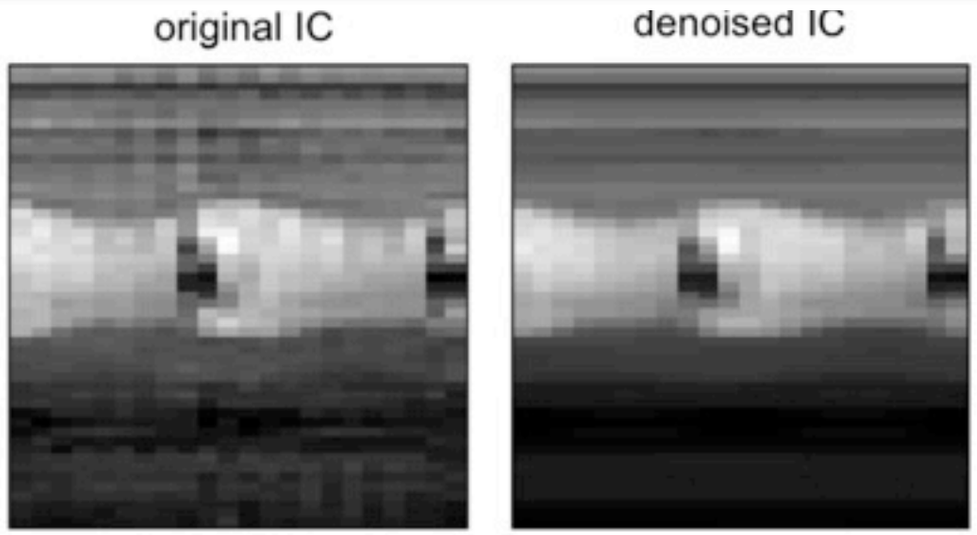

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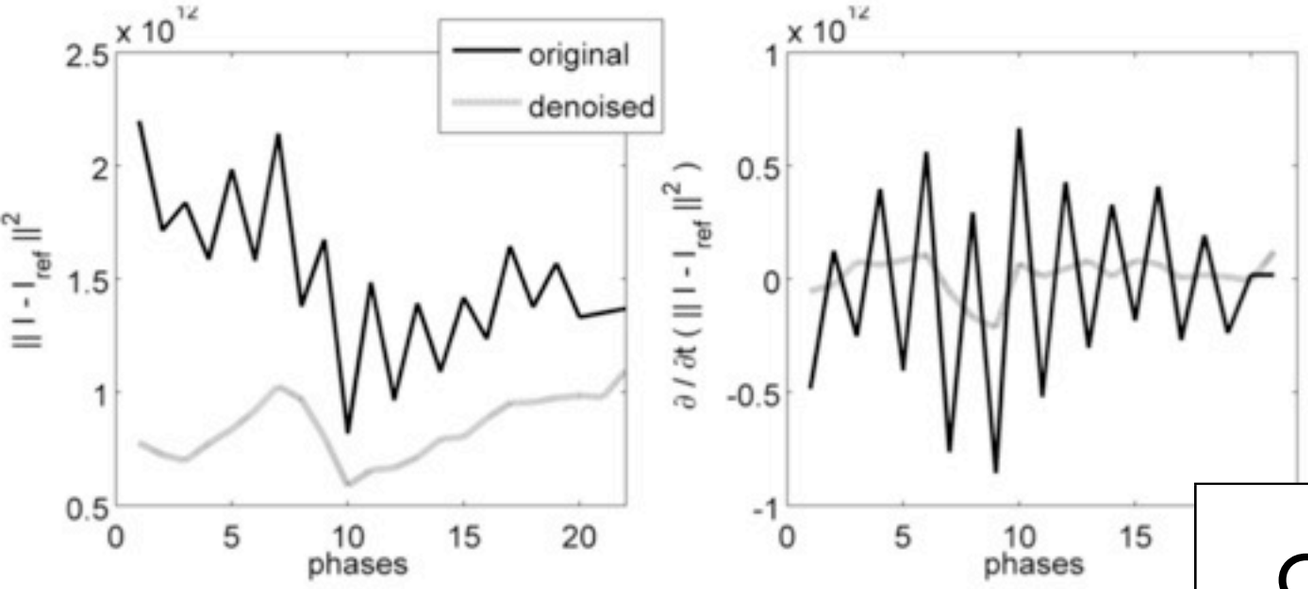


Noise reduction (n=8):

	E	Noise reduction
Original IC	$2.11\pm2.88 * 10^{24}$	-
Soft threshold only	$4.37\pm6.12 * 10^{23}$	-6.0±2.2 dB
Complete model	$1.24\pm1.58 * 10^{23}$	-10.4±3.8 dB

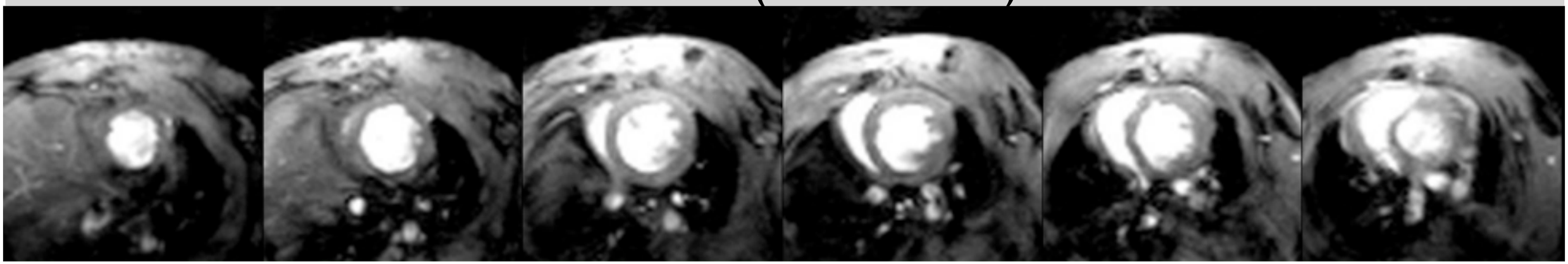
Final result

Basic cine (TR=13.5 ms)

Original images

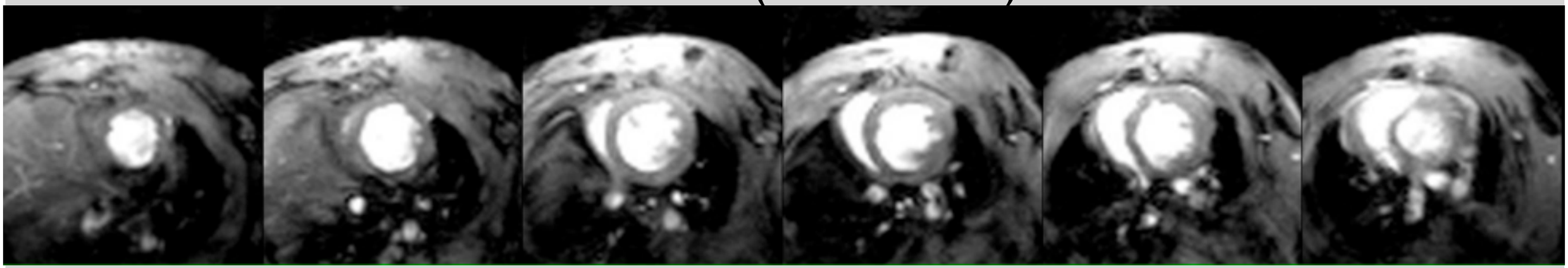
Final result

Basic cine (TR=13.5 ms)

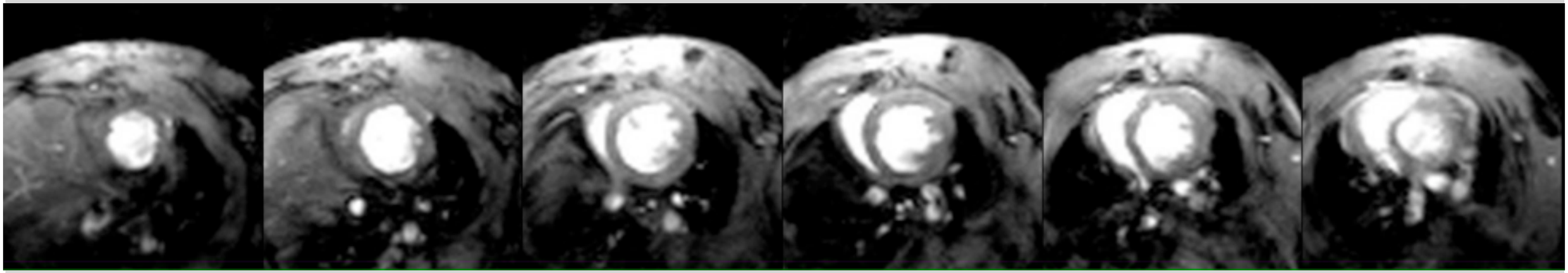


Final result

Basic cine (TR=13.5 ms)



Interleaved cine (TR=6.8 ms)



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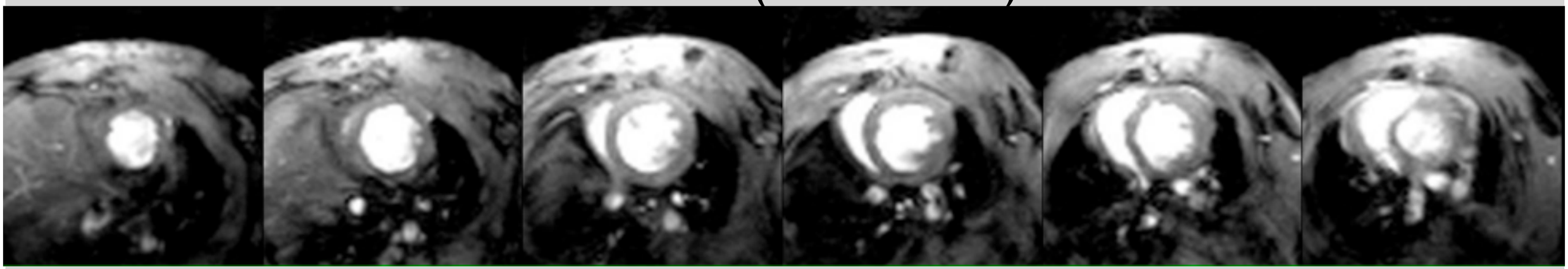

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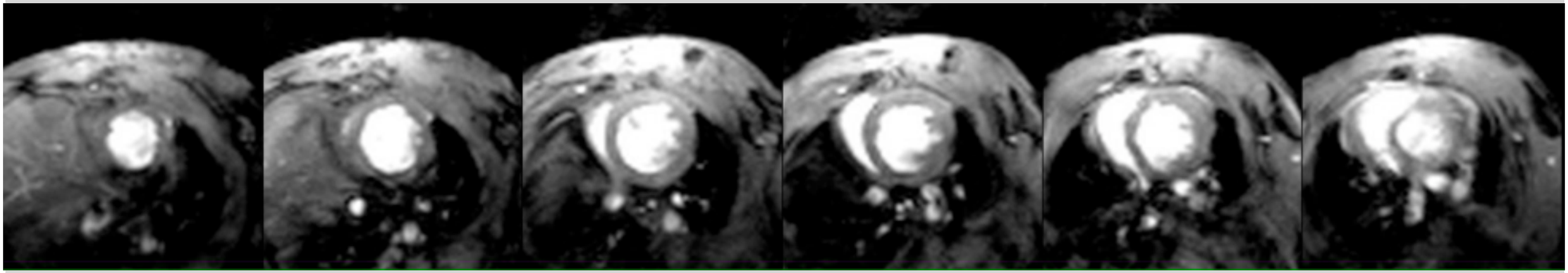
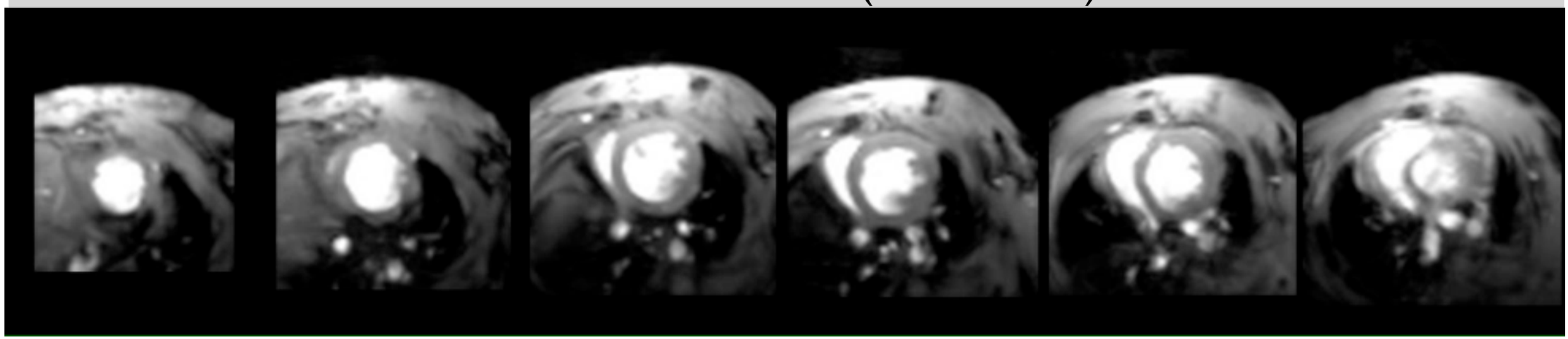


After enhancement (TR=6.8 ms)



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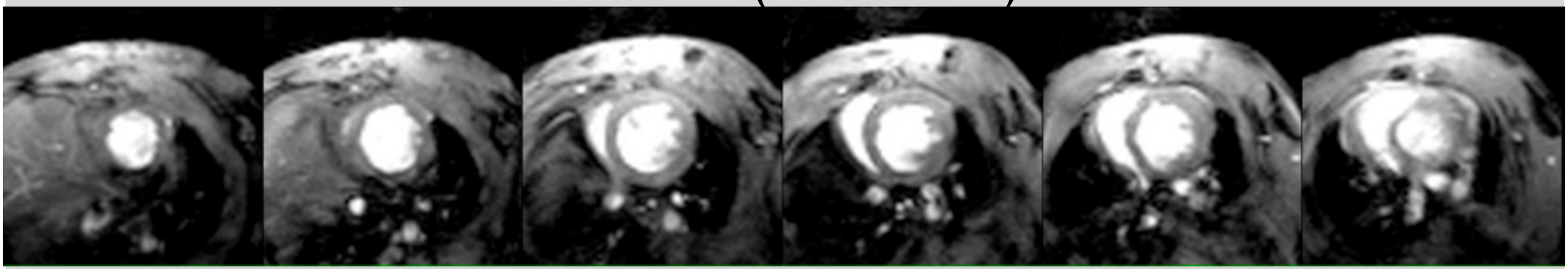

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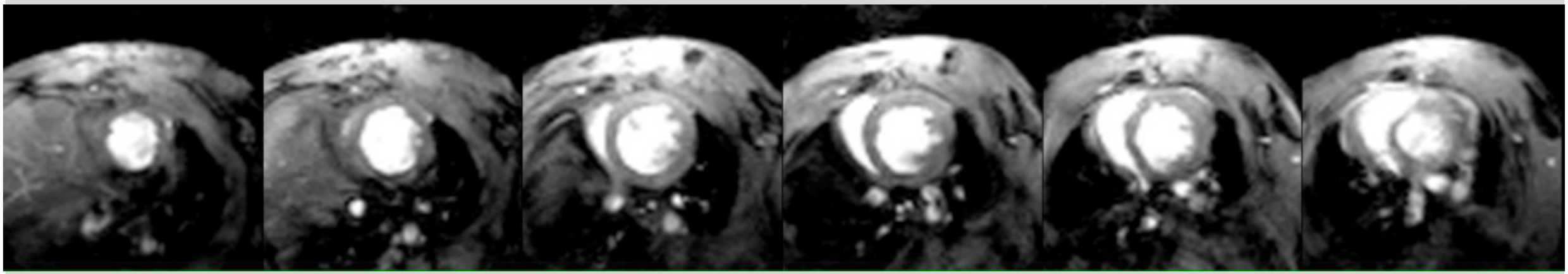

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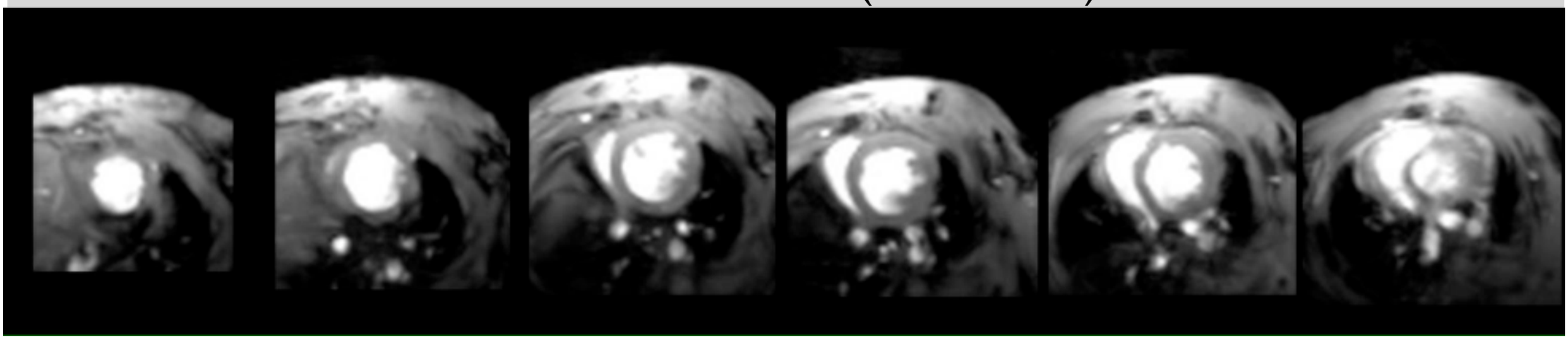


Tool to achieve sufficient temporal resolution for mice imaging (< 9 ms)

Applications in cardiac research

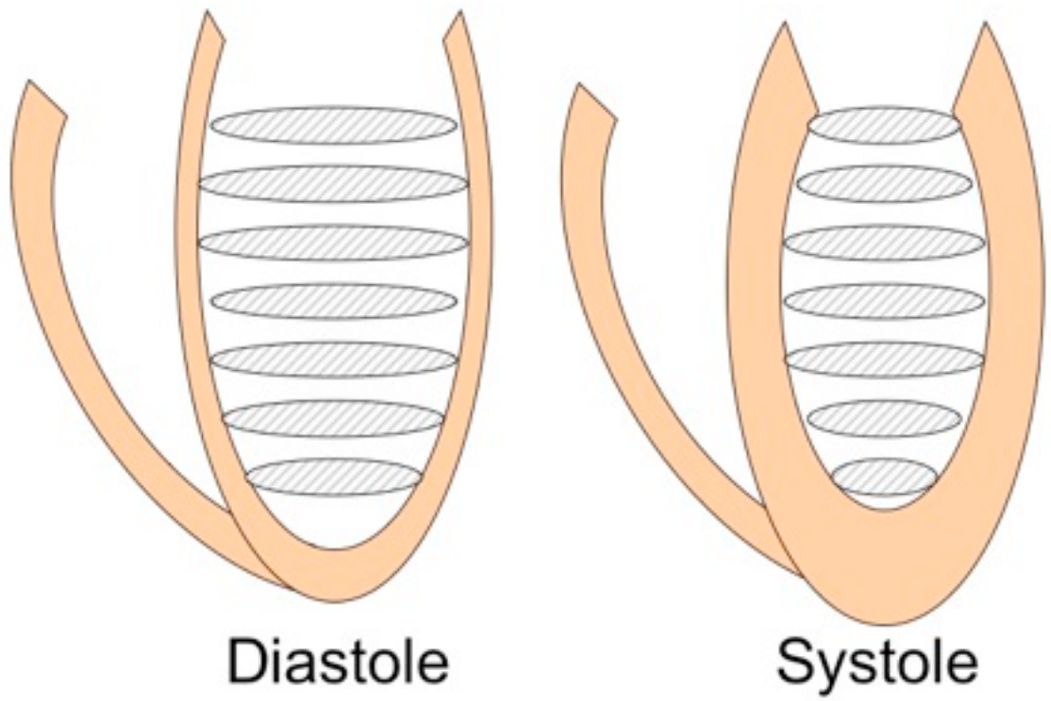
Multi-slices short axis cine to evaluate:

Heart mass

$$(LV + RV)_{mass} = \gamma \cdot \text{Slice thickness} \cdot \sum_{\text{all slices}} [\text{epi area} - (\text{LV endo area} + \text{RV endo area})]$$

γ is the specific gravity of the myocardium, γ=1.055 g/cm^3

Cardiac function



End-diastolic volume
EDV

End-systolic volume
ESV

$$EF = \frac{EDV - ESV}{EDV}$$

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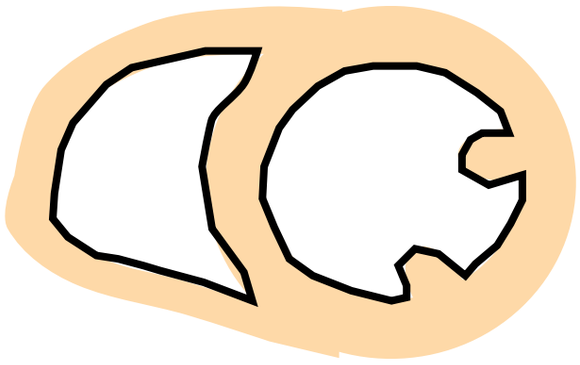

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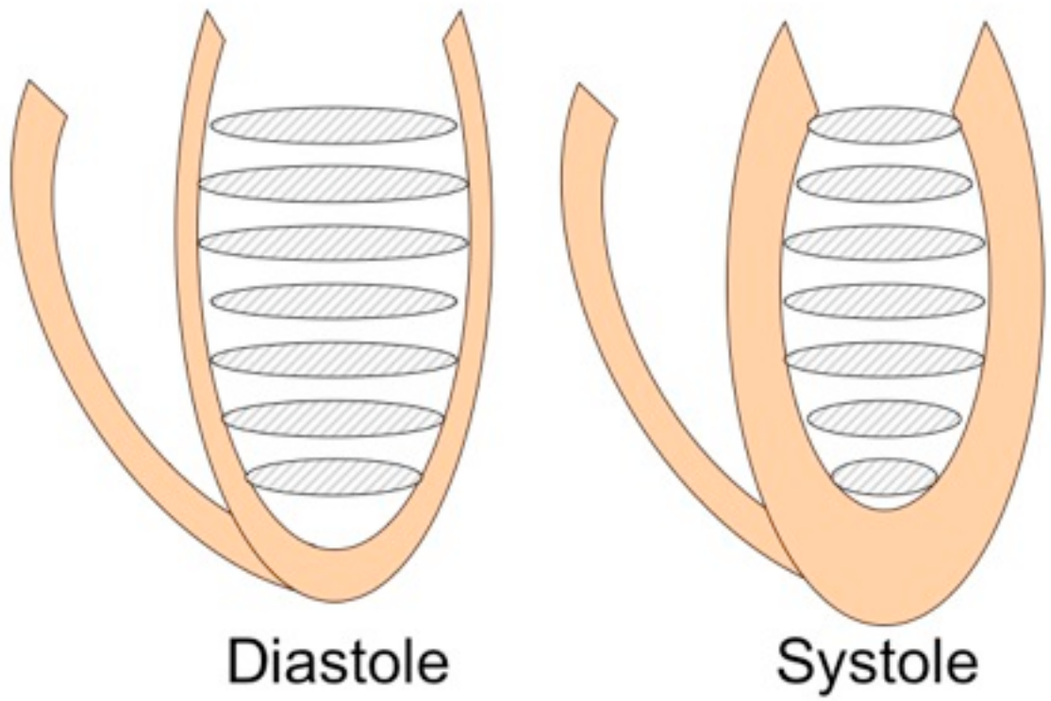

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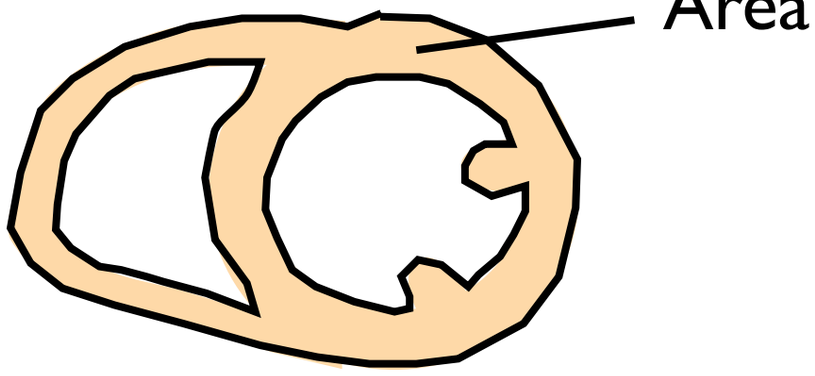

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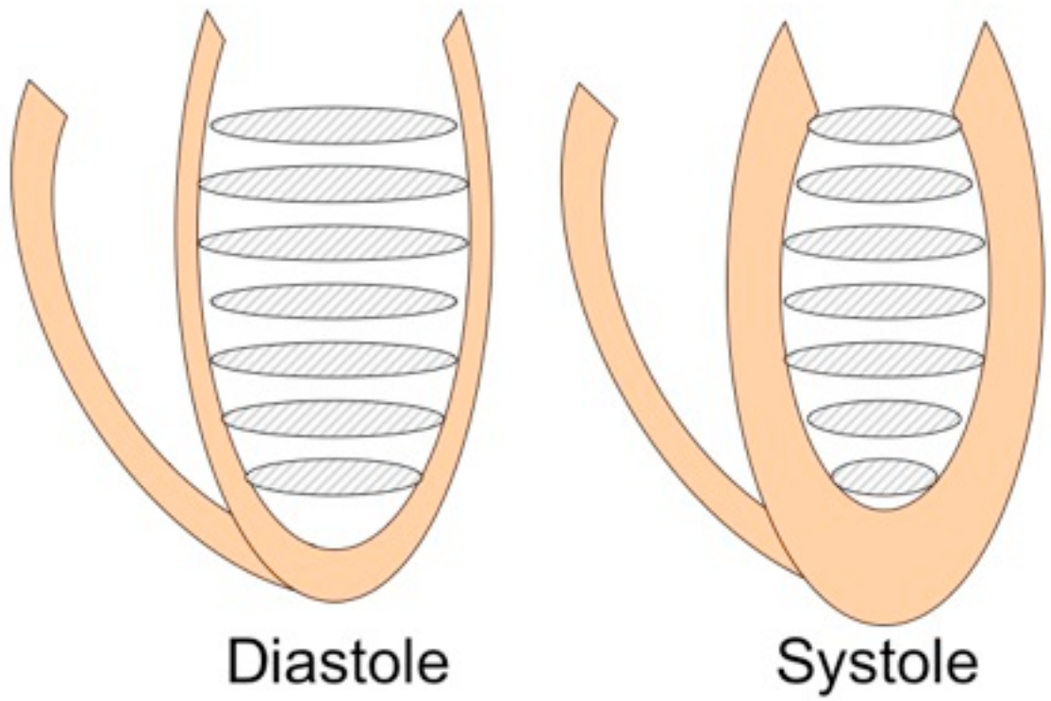

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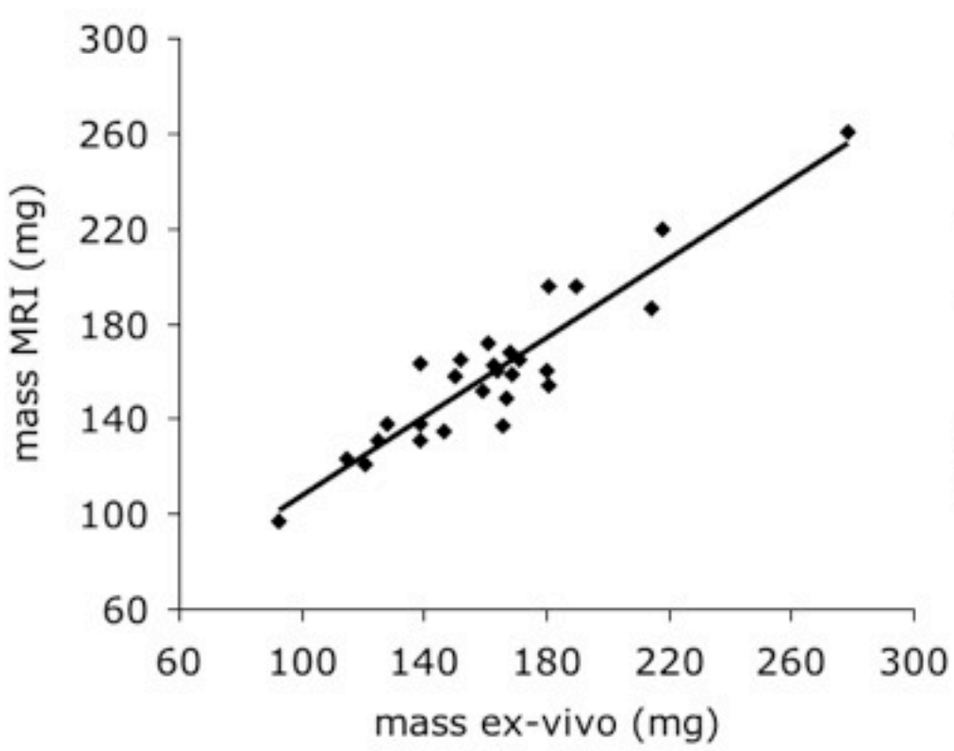
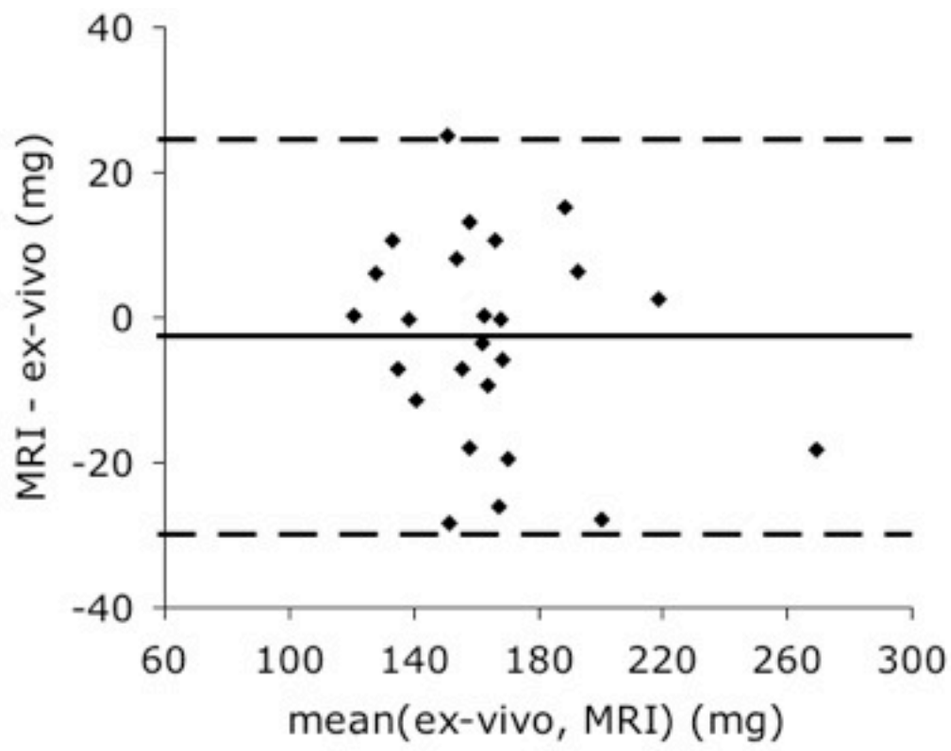
Diabetes - Cardiac hypertrophy

- Transgenic mice developing cardiac hypertrophy (n=23)
- Wild type mice (n=4)



$y = 0.829x + 25.1$, $R^2 = 0.89$ (n=27)



bias = 2.62 mg
1.96 SD = 27.15 mg

Yang et al.[1] obtained 1.96 SD = 15 mg on a dedicated scanner (4.7 T)

[1] Yang, Circulation 109(9):1161, 2004

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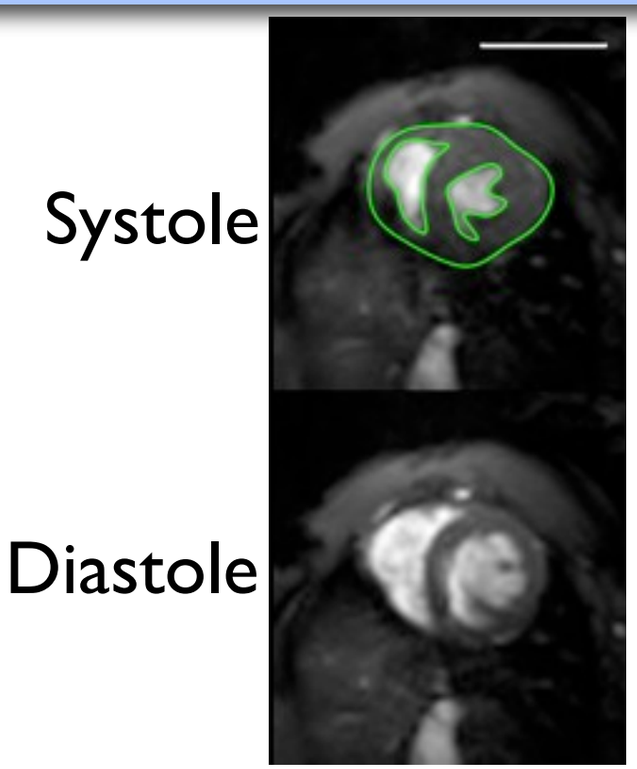

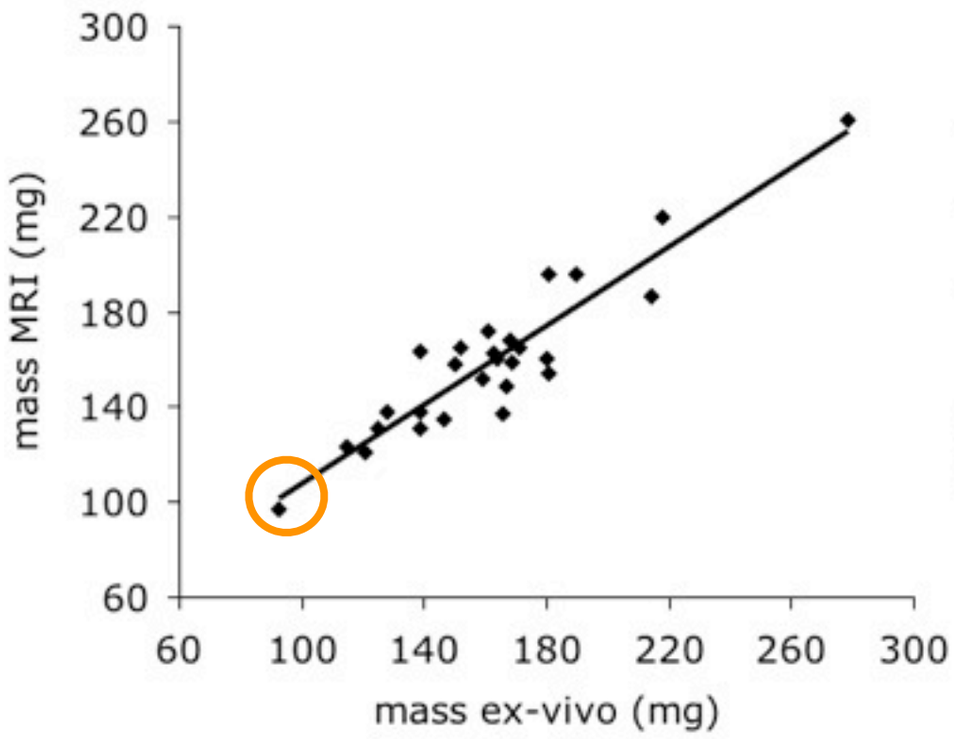

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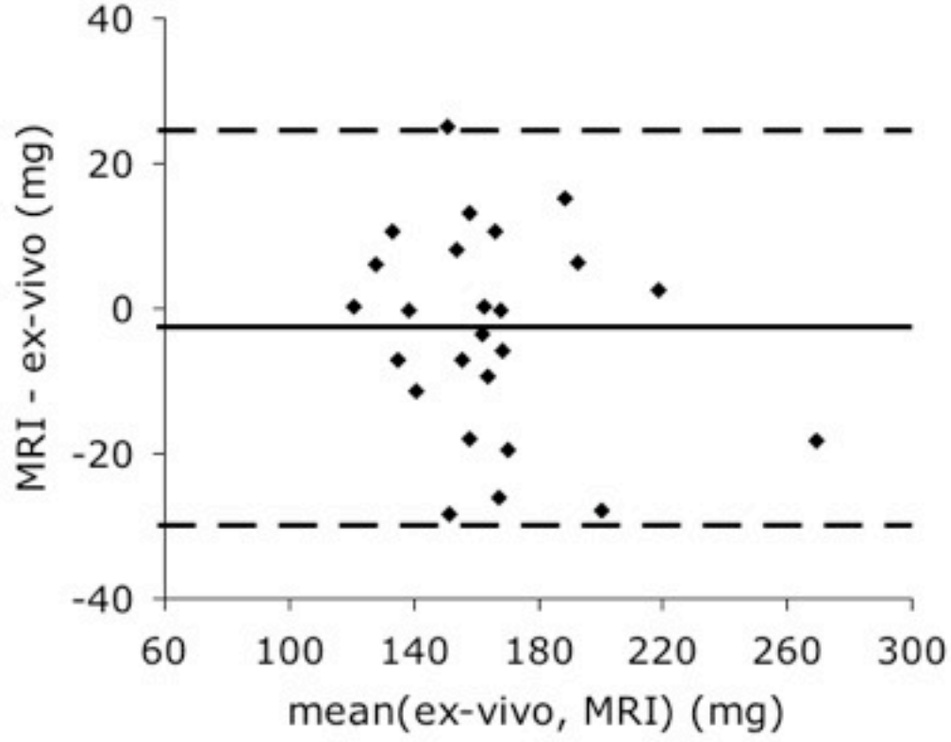

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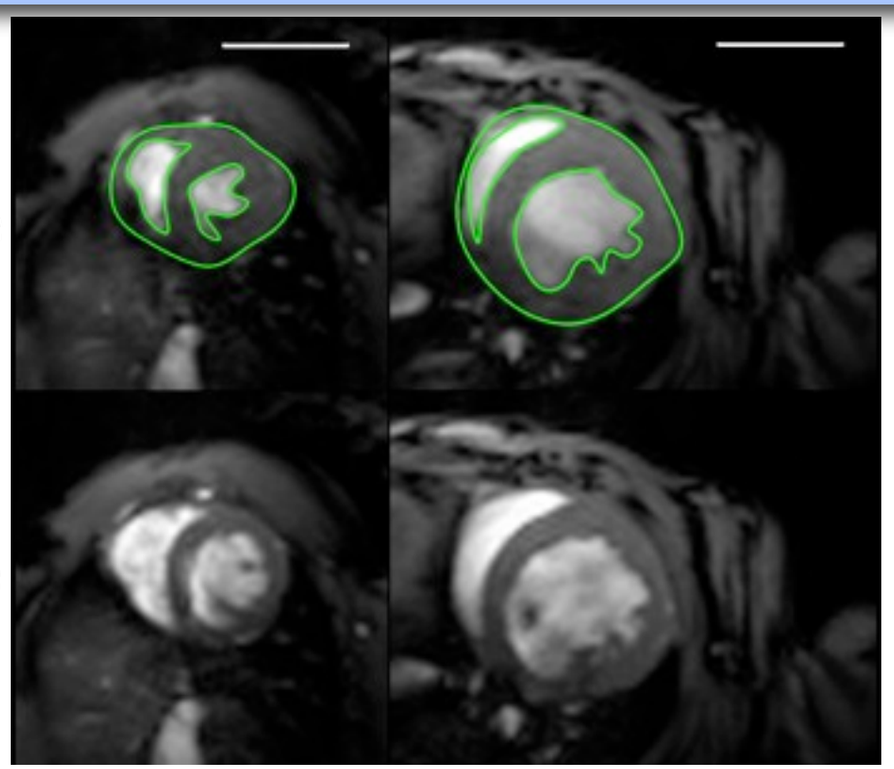
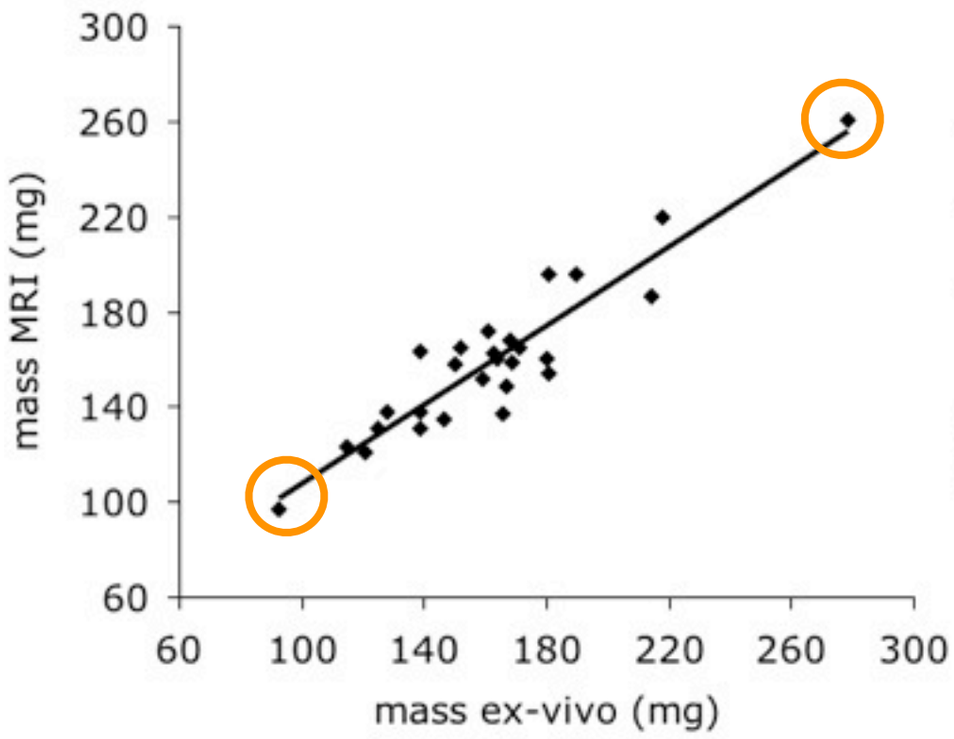


bar: 5mm



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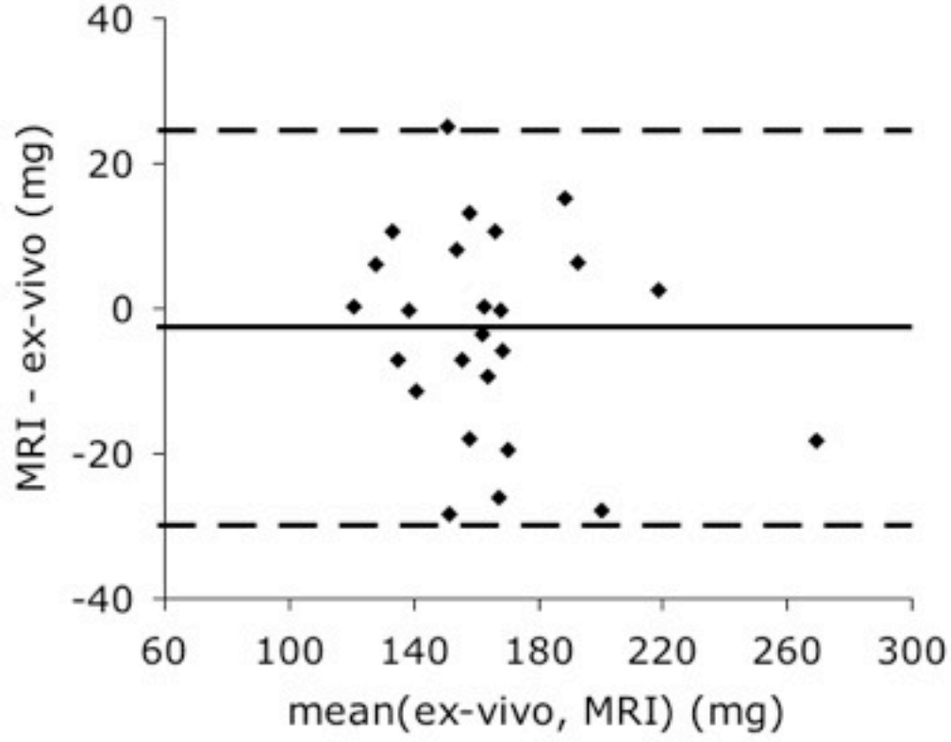

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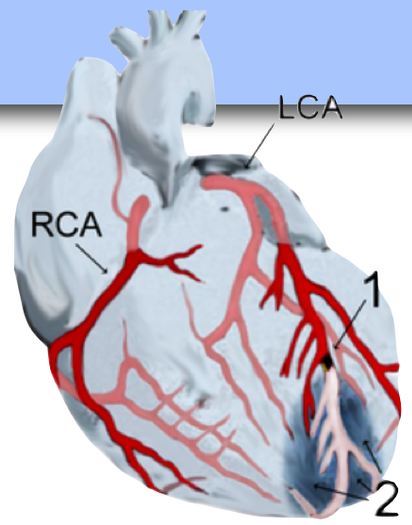
Infarction - Function impairment

WT: Control mice C57/BL6 WT n=4
MI: C57/BL6 with complete ligation of LAD, 24h after surgery (n=3)

Evaluate effect of drug on infarct size and heart failure



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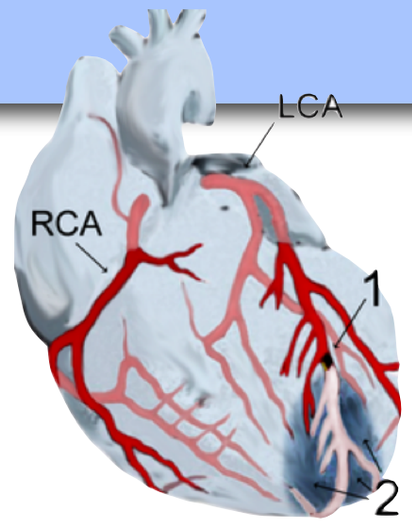
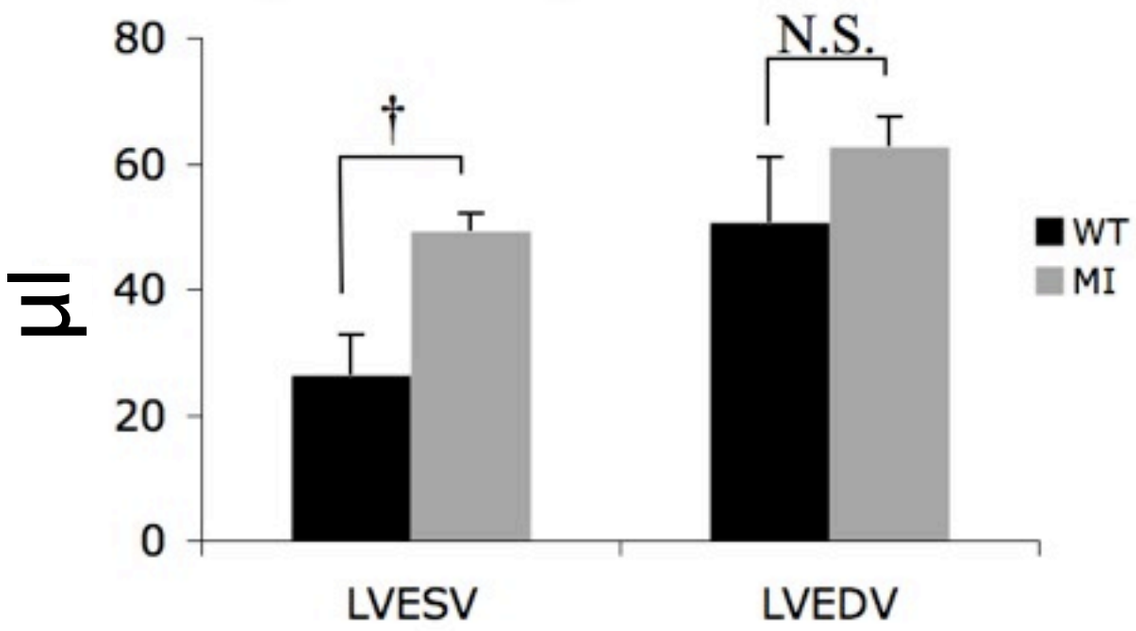
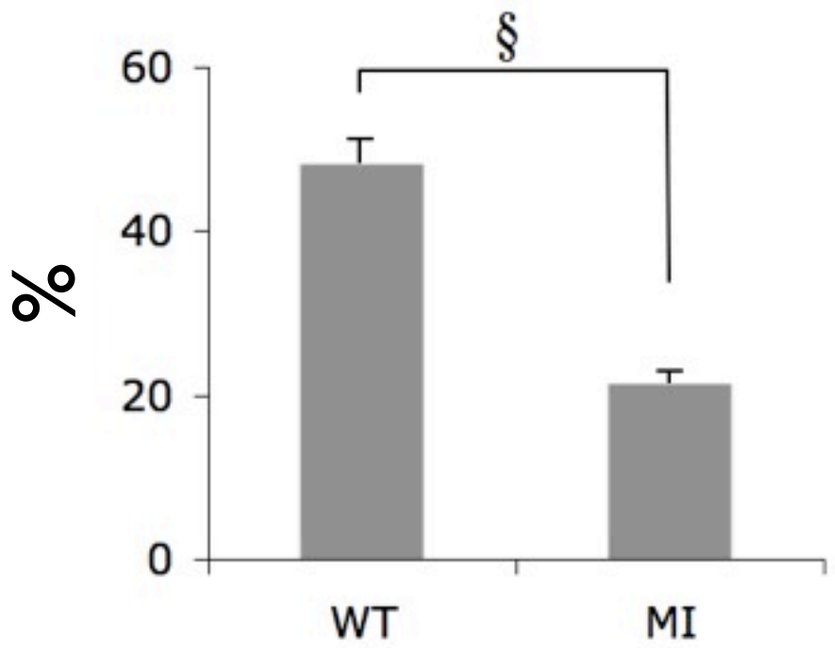


Basic cine (TR=13.5ms)



EF



* p<0.05,
§ p<0.01,
† p<0.001

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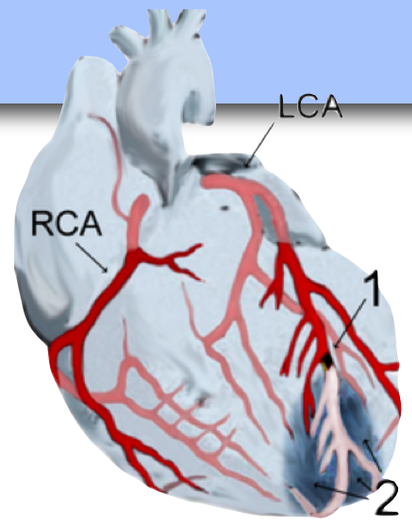
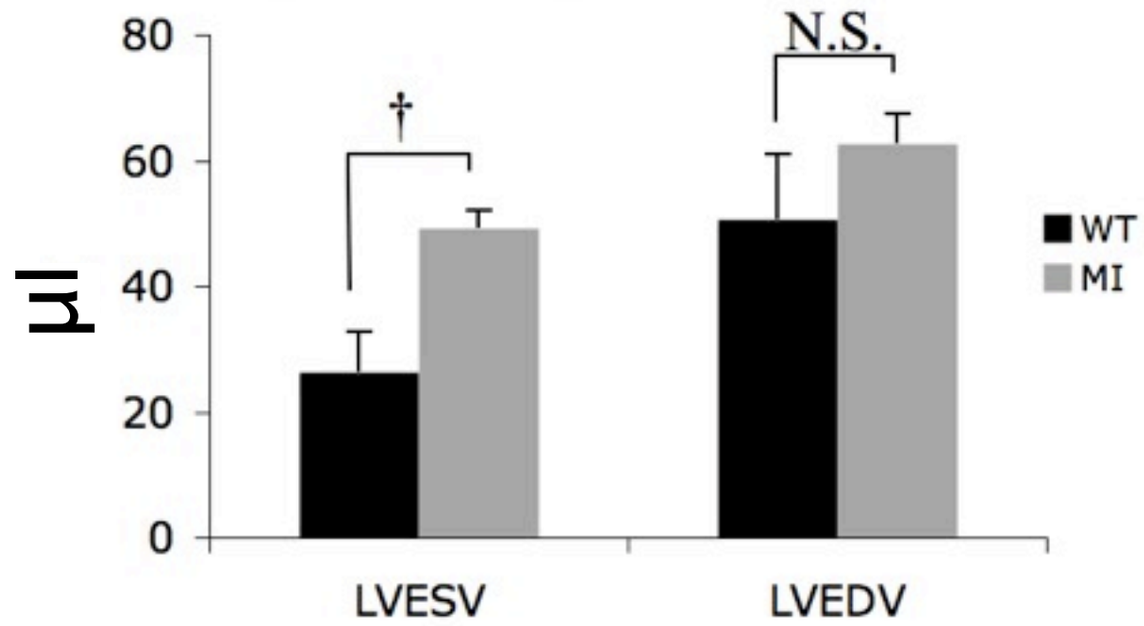
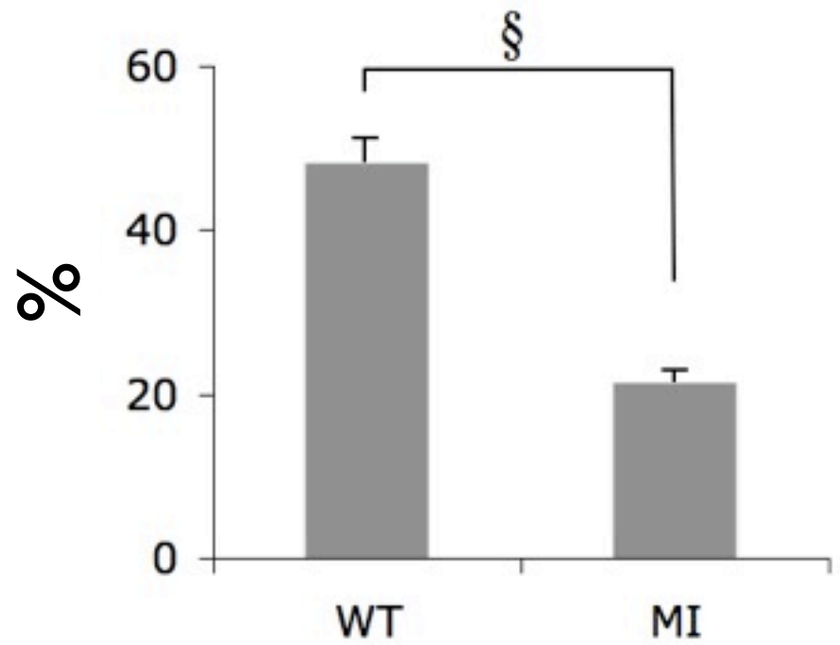
MI: C57/BL6 with complete ligation of LAD, 24h after surgery (n=3)

Evaluate effect of drug on infarct size and heart failure



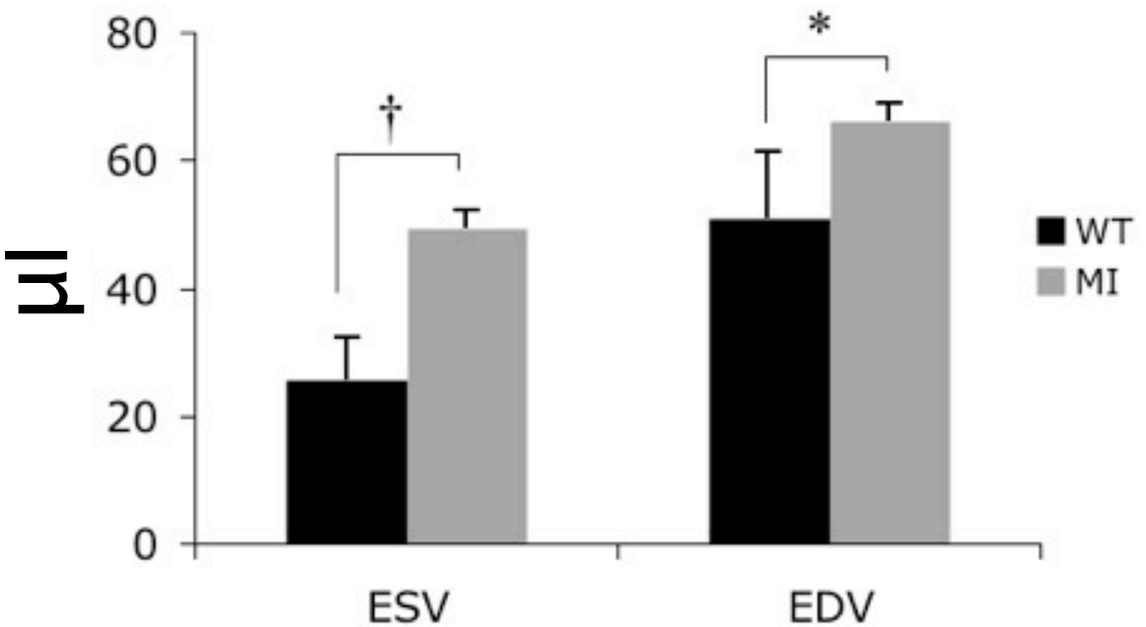
Basic cine (TR=13.5ms)

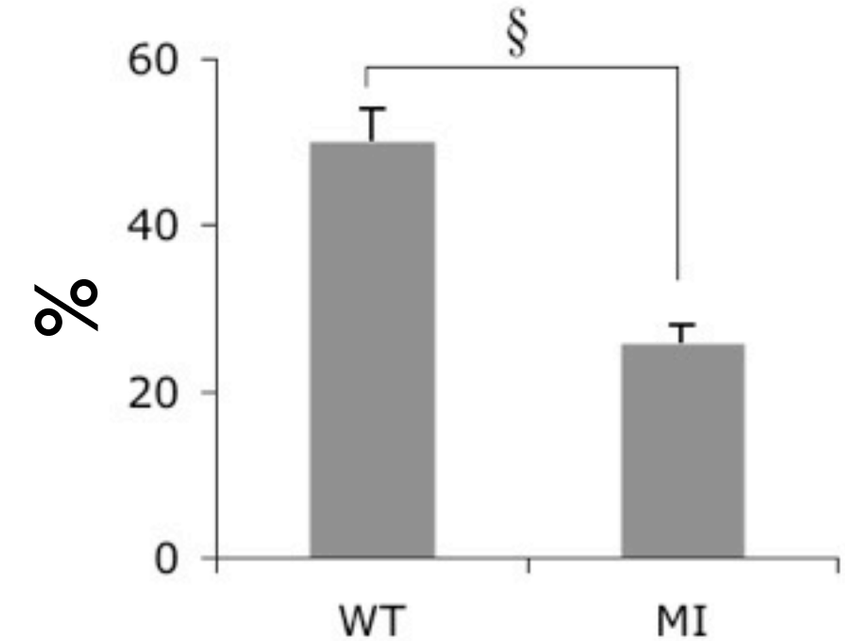




* p<0.05,
§ p<0.01,
† p<0.001

Interleaved cine (TR=6.8ms)

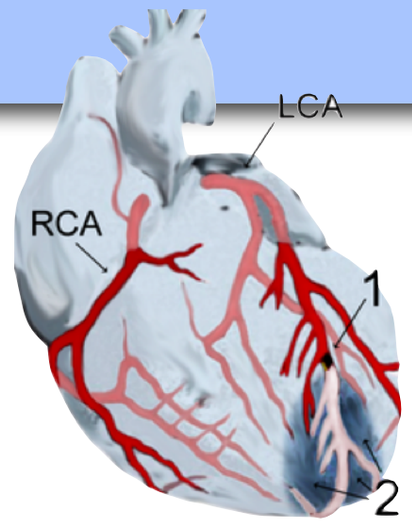




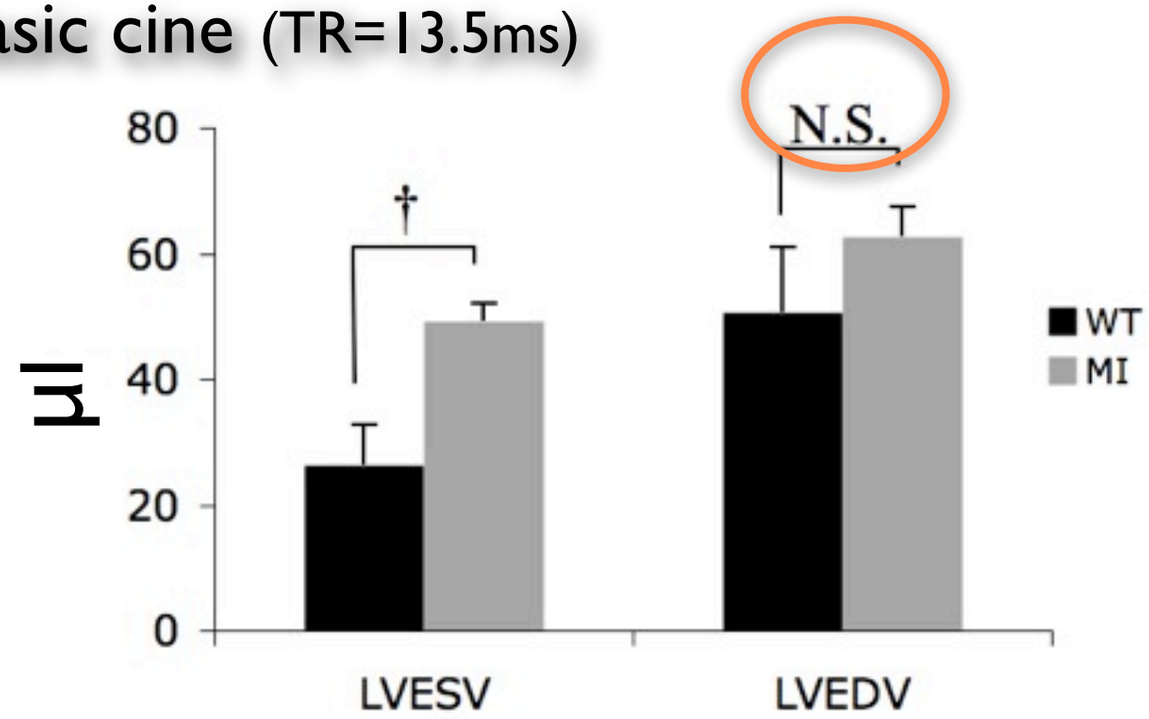
Infarction - Function impairment

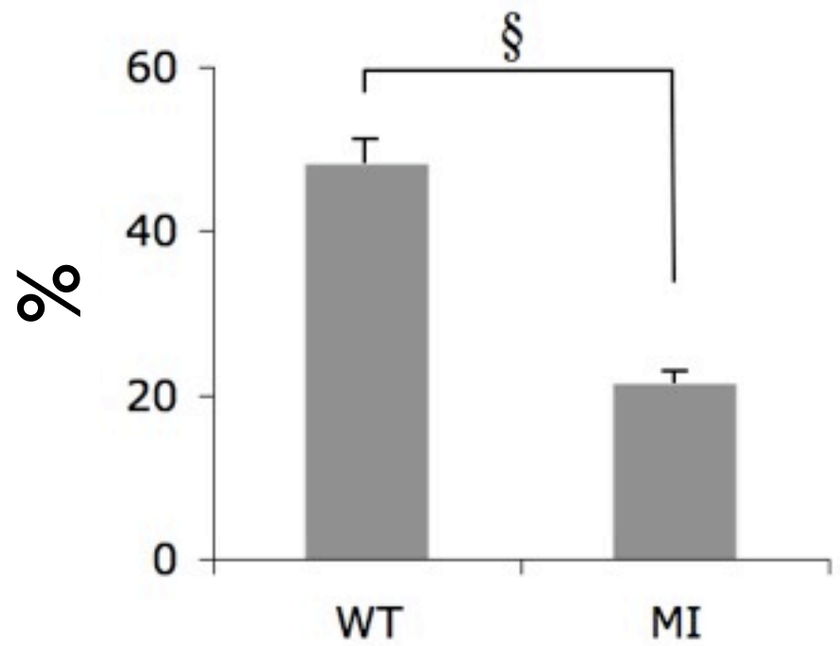
WT: Control mice C57/BL6 WT n=4
MI: C57/BL6 with complete ligation of LAD, 24h after surgery (n=3)

Evaluate effect of drug on infarct size and heart failure



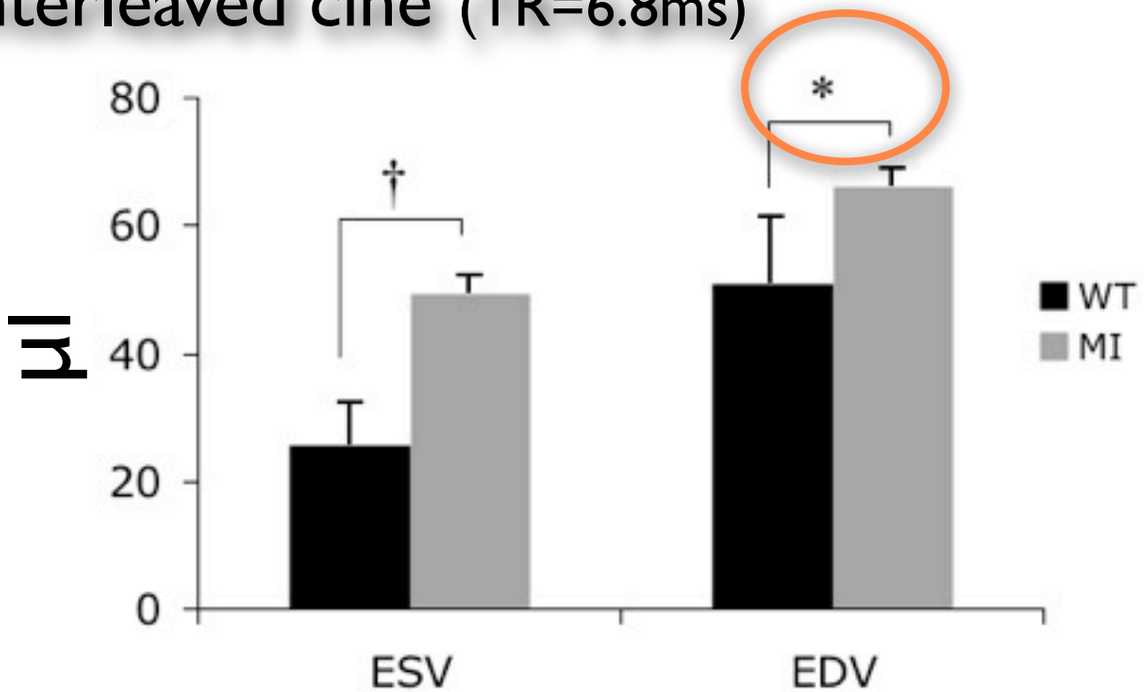
Basic cine (TR=13.5ms)

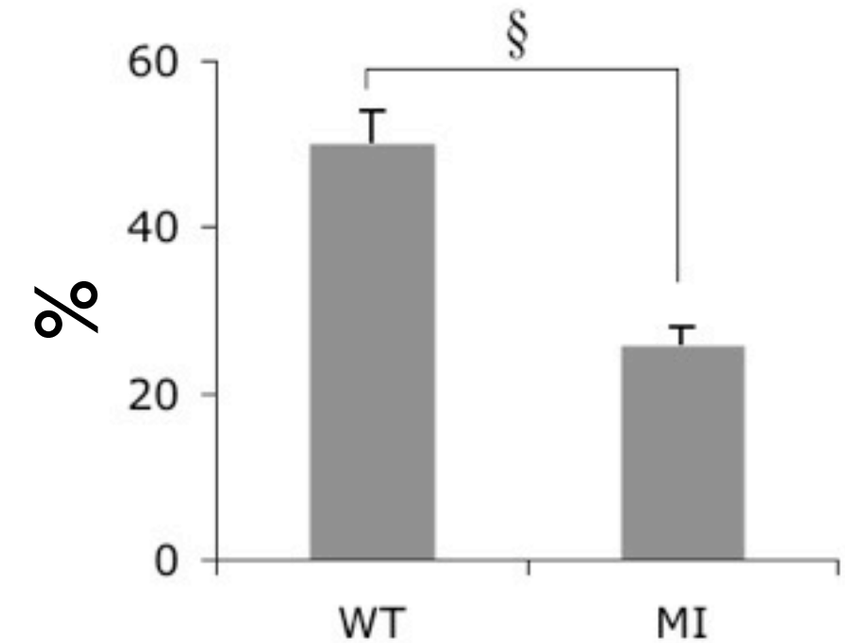




* p<0.05,
§ p<0.01,
† p<0.001

Interleaved cine (TR=6.8ms)

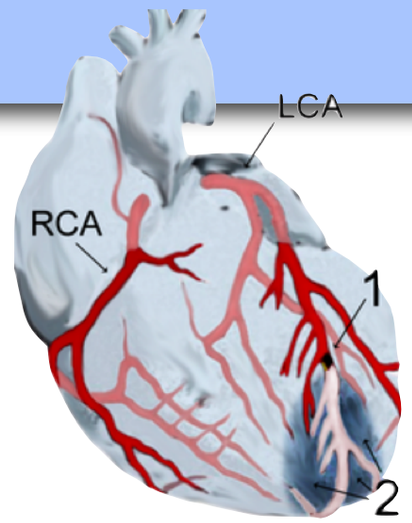




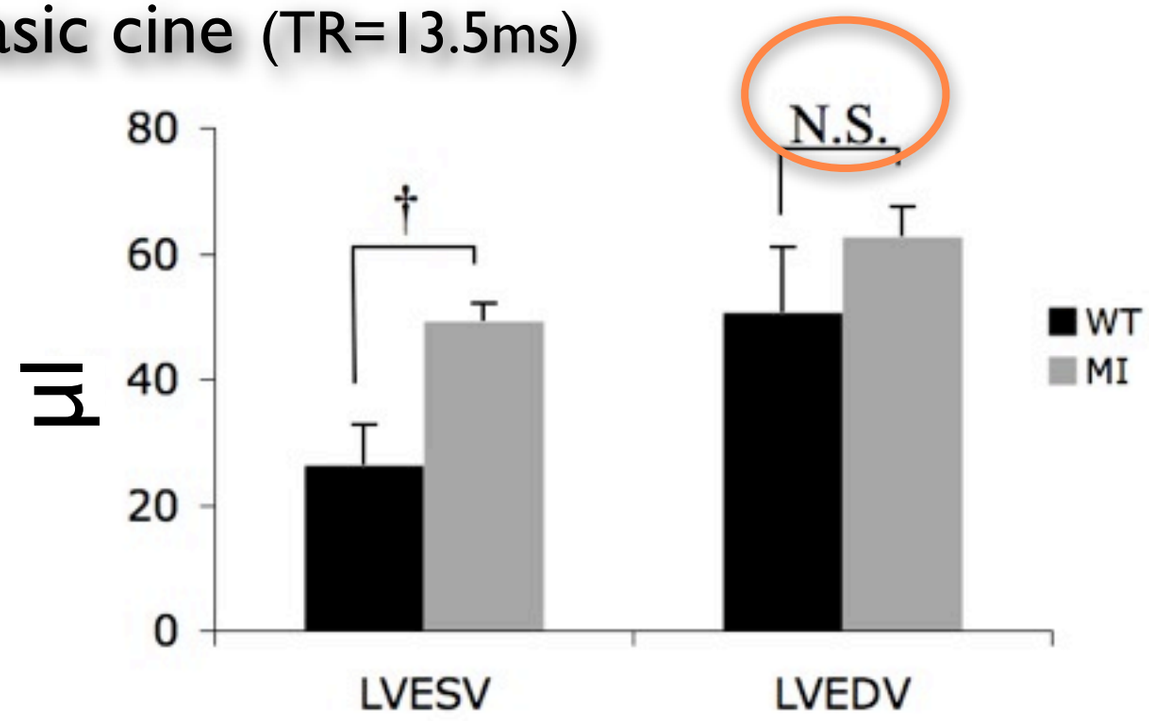
Infarction - Function impairment

WT: Control mice C57/BL6 WT n=4
MI: C57/BL6 with complete ligation of LAD, 24h after surgery (n=3)

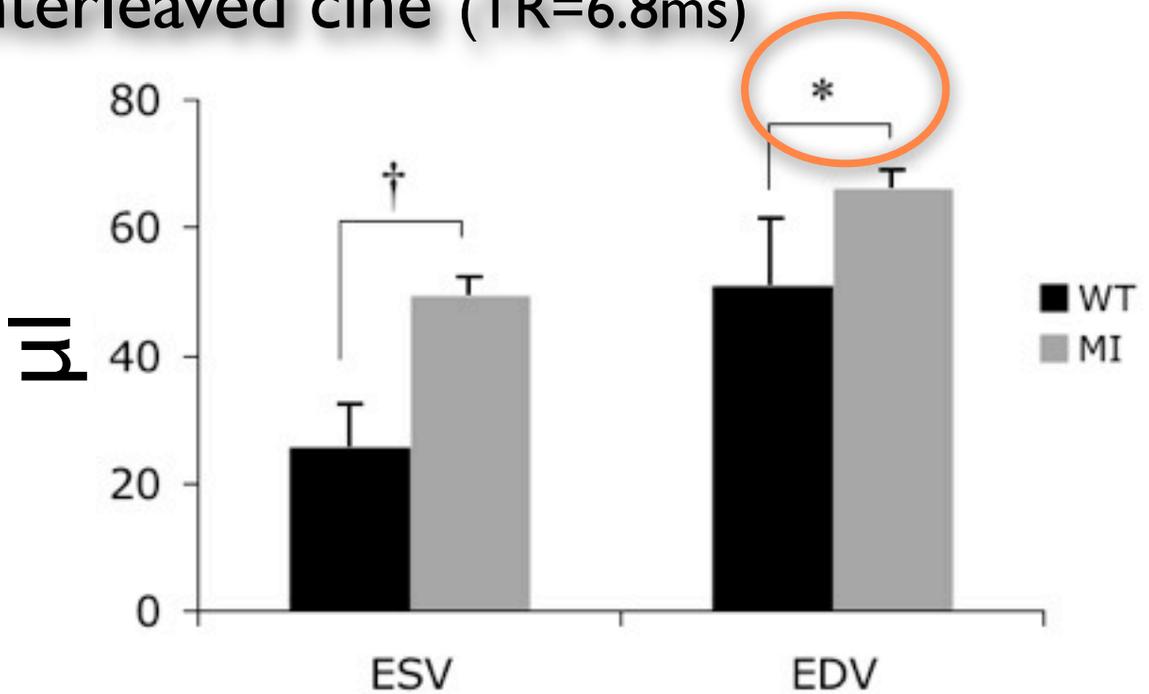
Evaluate effect of drug on infarct size and heart failure



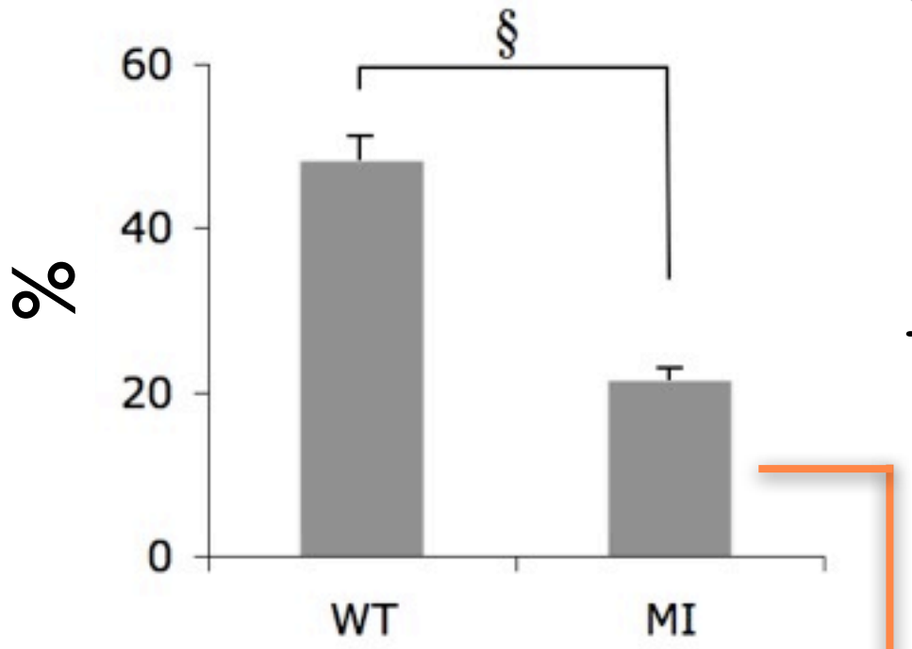
Basic cine (TR=13.5ms)

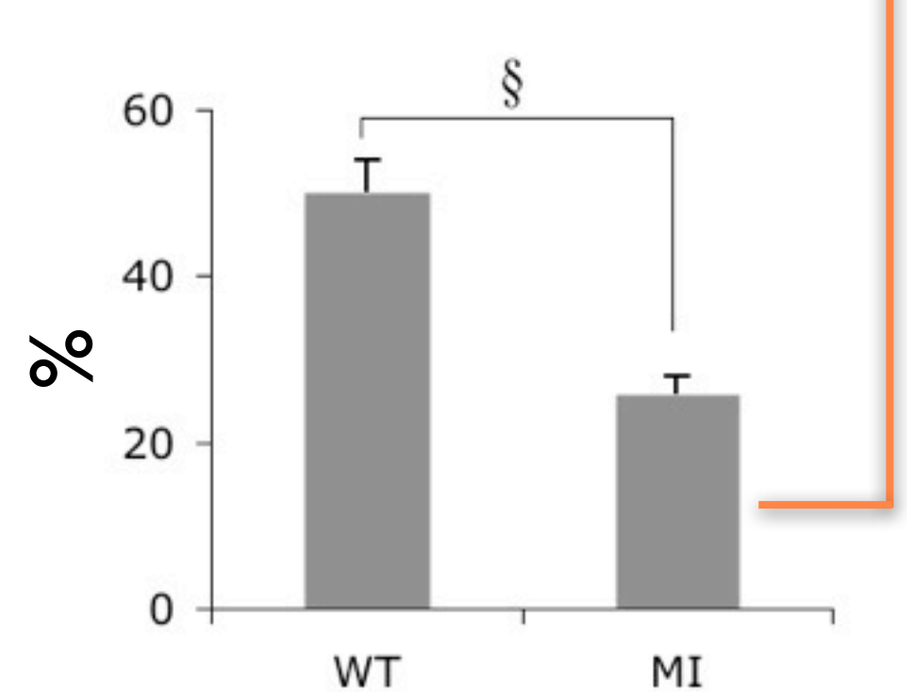


Interleaved cine (TR=6.8ms)



EF





* p<0.05,
§ p<0.01,
† p<0.001

*

Conclusions

- Interleaved cine
  - Same total acquisition time as basic cine
  - Data sampling at different time points (no slidding window)
- Denoising algorithm and temporal regularization
  - Fast and non-iterative
  - Works in image domain, still possible to use parallell imaging (SENSE or GRAPPA)
- Sequence available for cardiac assessment in mice
  - Already used in 2 large studies (diabetes, infarction)

Acknowledgments

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