



# MRI pulse design via discrete-valued optimal control

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# Motivation: Magnetic resonance imaging

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## Magnetic resonance imaging (MRI):

- popular for medical imaging (and spectroscopy)
- safe, radiation-free
- versatile
- simple image reconstruction (Fourier transform)
- **but:** complicated physics  
(compare CT: simple physics, complicated mathematics)

# MRI in a nutshell

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## Basic steps in MR scan:

- 1 magnetic field is applied, aligns proton spins
- 2 radio pulse at resonance frequency is absorbed by hydrogen nuclei, re-radiated over time at same frequency
- 3 decaying time-dependent signal is measured by receiver coil

## Fundamental principles of MRI:

- signal **amplitude** proportional to **hydrogen density**
- signal **frequency** proportional to **magnetic field strength**

# Spatial encoding

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## Problem:

- measured time-dependent signal is **composite** over whole volume, no spatial information

## Solution:

- use **spatially dependent magnetic fields** to map resonance frequency to spatial location

But: linear superposition of  $(x, y, z)$  fields is not unique

↪ **sequential application** of fields to encode  $(x, y, z)$  separately

# Spatial encoding

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## Slice selection ( $z$ ):

- use  $z$ -proportional magnetic field during RF **excitation**
- $\leadsto$  only thin slice has resonance at RF pulse frequency, contributes to measured signal

Not considered here:

## Frequency encoding ( $x$ ):

- use  $x$ -proportional magnetic field **during measurement**

## Phase encoding ( $y$ ):

- use  $y$ -proportional magnetic field **before measurement** to change **phase offset** of signal

$\leadsto$  FFT of time/phase-dependent data gives image

$\leadsto$  MRI is **controlled** imaging  $\leadsto$  optimal control

- 1 Overview
- 2 Optimal control of Bloch equation
- 3 MR pulse design
- 4 Discrete-valued pulses
- 5 Conclusion

1 Overview

2 Optimal control of Bloch equation

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# Mathematical model

## Bloch equation

$$\frac{d}{dt}M(t) = \gamma M(t) \times B(t) + R(M(t)), \quad M(0) = M_0$$

- $M(t) \in \mathbb{R}^3$  describes temporal evolution of spin ensemble
- $B(t)$  **controlled** time-dependent magnetic field
- $\gamma$  gyromagnetic ratio  $\rightsquigarrow$  resonance frequency  $\omega = \gamma B_0$
- $R(M) = \left(-M_x \frac{1}{T_2}, -M_y \frac{1}{T_2}, (-M_z - M_0) \frac{1}{T_1}\right)^T$  relaxation term  
( $T_1, T_2$  tissue parameters)



# Mathematical model

Slice selection (in rotating frame):

$$B(t) = (u_x(t)B_1, u_y(t)B_1, G_z(t)z)^T$$

$G_z(t)$  slice-selective **gradient field**,  $B_1$  static magnetic field

Bloch equation

$$\begin{cases} \frac{d}{dt}M(t; z) = A(u(t); z)M(t; z) + b(z), & t > 0, \\ M(0; z) = M^0(z), \end{cases}$$

$$A(u; z) = \begin{pmatrix} -\frac{1}{T_2} & \gamma G_z(t)z & \gamma u_y(t)B_1 \\ -\gamma G_z(t)z & -\frac{1}{T_2} & \gamma u_x(t)B_1 \\ -\gamma u_y(t)B_1 & -\gamma u_x(t)B_1 & -\frac{1}{T_1} \end{pmatrix} \quad b(z) = \begin{pmatrix} 0 \\ 0 \\ \frac{M_0}{T_1} \end{pmatrix}$$

# Optimal control problem

## Goal:

- compute control  $u(t) = (u_x(t), u_y(t))$  such that  $M(T) \approx M_d$
- $\leadsto$  control-to-state mapping  $S^{(\omega)} : u \rightarrow M(T; z)$
- $M_d(z)$  desired magnetization state  $\leadsto$  slice selection
- $(M_d = M_d^{(\omega)})$  selective to resonance frequency  $\leadsto$  spectroscopy)
- in addition: control with minimal specific absorption rate (SAR)

$$\min_{u \in L^2} \frac{1}{2} \sum_{\omega} \int_{-a}^a |S^{(\omega)}(u) - M_d^{(\omega)}|_2^2 dt + \frac{\alpha}{2} \int_0^T |u(t)|_2^2 dt$$

# Numerical solution: gradient method

## Gradient method

$$u^{k+1} = u^k - s^k g(u^k)$$

- gradient

$$g(u^k)(t) = \alpha u(t) + \gamma B_1 \begin{pmatrix} \int_{-a}^a M_z(t; z) P_y(t; z) - M_y(t; z) P_z(t; z) dz \\ \int_{-a}^a M_z(t; z) P_x(t; z) - M_x(t; z) P_z(t; z) dz \end{pmatrix}$$

- adjoint state solving (backward in time)

$$\begin{cases} -\frac{d}{dt} P(t; z) = A(u(t); z)^T P(t; z), & 0 \leq t < T, \\ P(T; z) = M(T; z) - M_d(z), \end{cases}$$

- step length  $s^k$  (Armijo, backtracking)

# Numerical solution: Newton method

## Newton method

$$H(u^k)\delta u = -g(u^k), \quad u^{k+1} = u^k + \delta u$$

### ■ Hessian

$$[H(u^k)h](t) = \alpha h(t) + \left( \int_{-a}^a \delta M(t; z) A_1 P(t; z) + M(t; z) A_1 \delta P(t; z) dz \right) \\ + \left( \int_{-a}^a \delta M(t; z) A_2 P(t; z) + M(t; z) A_2 \delta P(t; z) dz \right)$$

$$MA_1 P = \gamma B_1 (M_z P_y - M_y P_z) \quad MA_2 P = \gamma B_1 (M_z P_x - M_y P_y)$$

### ■ linearized state

$$\begin{cases} \frac{d}{dt} \delta M(t; z) = A(u^k; z) \delta M(t; z) + A'(h)M, & 0 < t \leq T, \\ \delta M(0; z) = (0, 0, 0)^T, \end{cases}$$

# Numerical solution: Newton method

## Newton method

$$H(u^k)\delta u = -g(u^k), \quad u^{k+1} = u^k + \delta u$$

### ■ Hessian

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$$MA_1 P = \gamma B_1 (M_z P_y - M_y P_z) \quad MA_2 P = \gamma B_1 (M_z P_x - M_y P_y)$$

### ■ linearized adjoint

$$\begin{cases} -\frac{d}{dt} \delta P(t; z) = A(u^k; z)^T \delta P(t; z) + A'(h)^T P, & 0 \leq t < T, \\ \delta P(T; z) = \delta M(T; z). \end{cases}$$

# Numerical solution: Newton method

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Bilinear control problem: **non-convex**

- solution of Newton step via CG method
- globalization by **trust-region** method (truncated CG [Steihaug])

Discretization:

- collocation points  $z_i$  (independent, **parallel**)
- Crank–Nicolson (state piecewise linear, controls piecewise constant)
- **adjoint-consistent**: adjoint state piecewise **constant**
- same for linearized state, adjoint
- CG method in weighted inner product (time steps)

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# MR pulse design

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**Goal:** multi-slice excitation

- initial magnetization  $M_0 = (0, 0, 1)^T$
- gradient  $G_z$  from standard Cartesian sequence (2.56 ms)
- window  $a = 0.5$  m,  $\Delta z = 0.2$  mm (5001 points)
- desired magnetization (slice width 5 mm)

$$M_d(z) = \begin{cases} (\sin(90^\circ), \cos(90^\circ), 0)^T & \text{in slice} \\ (0, 0, 1)^T & \text{out of slice} \end{cases}$$

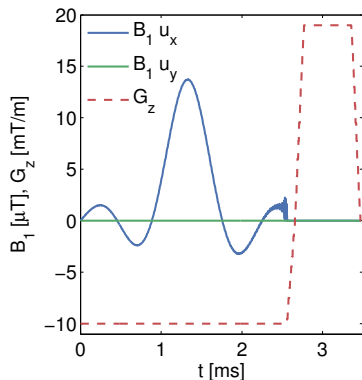
- $u_0 \equiv (0, 0)^T$ ,  $\alpha = 10^{-4}$

**Validation:**

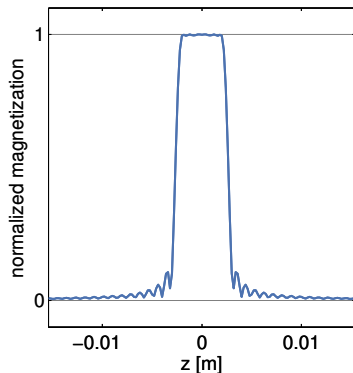
- implemented on 3T Siemens MR scanner
- phantom (slice profile homogeneity)
- healthy volunteer (image reconstruction)



# Results: slice profile

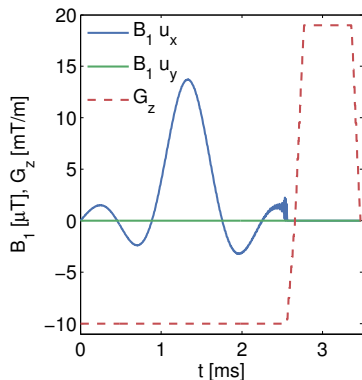


(a) optimized pulse

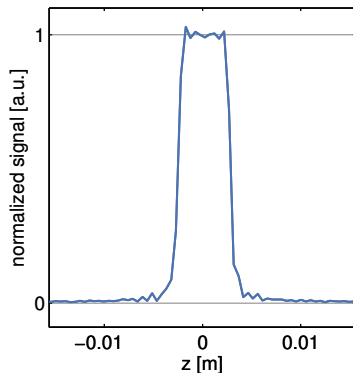


(b) optimized magnetization  $|(M_x, M_y)|_2$

# Results: slice profile

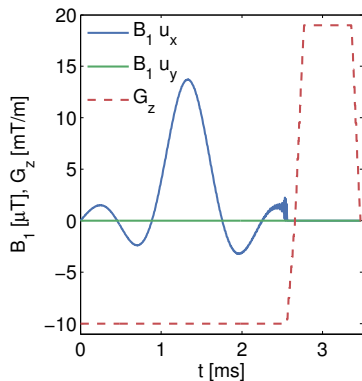


(a) optimized pulse

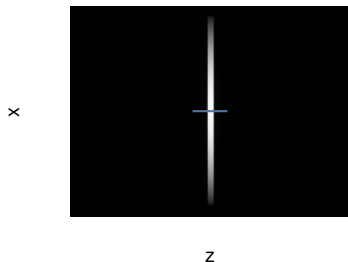


(b) measured magnetization  $|(M_x, M_y)|_2$

# Results: slice profile

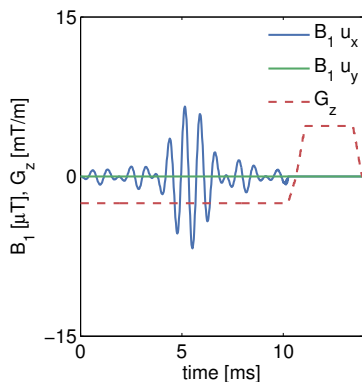


(a) optimized pulse

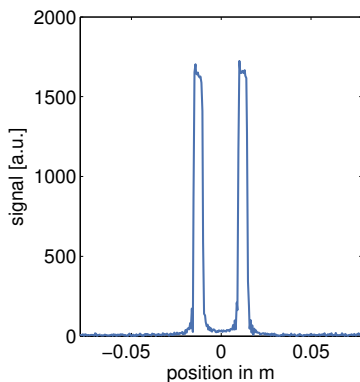


(b) reconstruction

# Results: multi-slice excitation

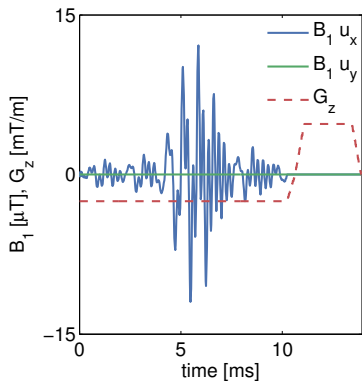


(a) optimized pulse

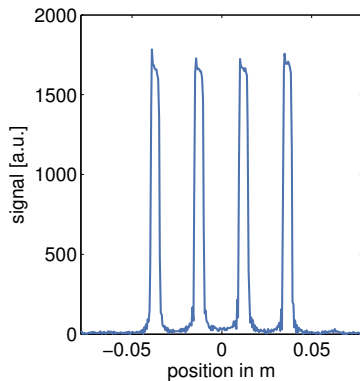


(b) measured magnetization

# Results: multi-slice excitation

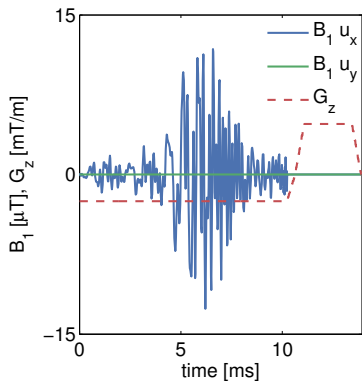


(a) optimized pulse

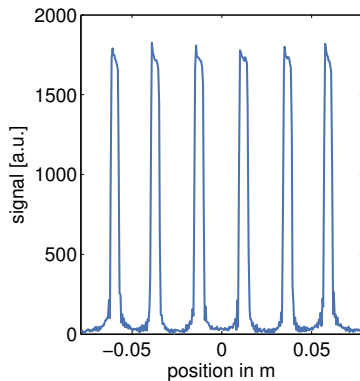


(b) measured magnetization

# Results: multi-slice excitation

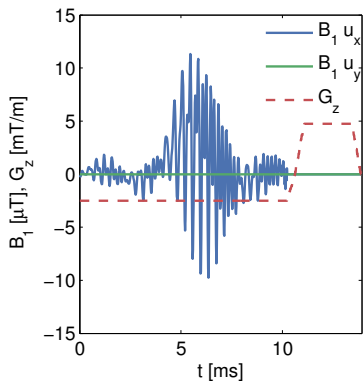


(a) optimized pulse

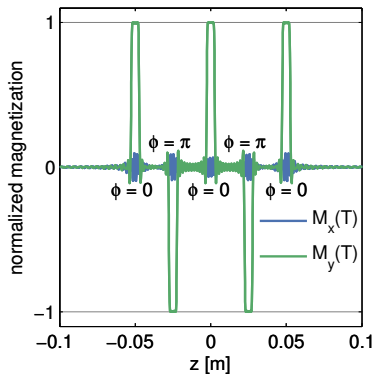


(b) measured magnetization

# Results: multi-slice reconstruction



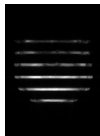
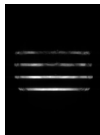
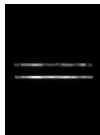
(a) optimized pulse



(b) optimized magnetization

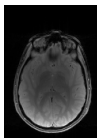
# Results: multi-slice reconstruction

z  
readout

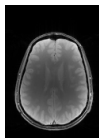


sG reconstruction

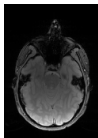
slice 3



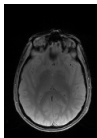
slice 4



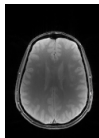
slice 2



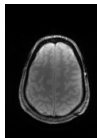
slice 3



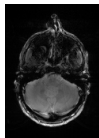
slice 4



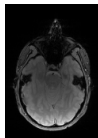
slice 5



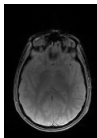
slice 1



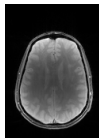
slice 2



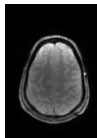
slice 3



slice 4



slice 5



slice 6





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# Discrete control

Technical limitation: device can only realize control from **discrete** set

$$U = \{u \in L^2(0, T; \mathbb{R}^2) : u(t) \in \{u_1, \dots, u_d\} \text{ a.e.}\}$$

- $u_1, \dots, u_d \in \mathbb{R}^2$  given (fixed amplitude, phases)
- **non-convex** discrete-valued control problem

$$\min_{u \in U} \frac{1}{2} \sum_{\omega} \|S^{(\omega)}(u) - M_d^{(\omega)}\|_2^2 + \frac{\alpha}{2} \int_0^T |u(t)|_2^2 dt$$

# Multi-bang penalty

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- **convex relaxation**: replace  $U$  by convex hull
- works only for  $d = 2$ , cf. bang-bang control ( $\alpha = 0$ )
- $\rightsquigarrow$  promote  $u(x) \in \{u_1, \dots, u_d\}$  by **convex pointwise penalty**

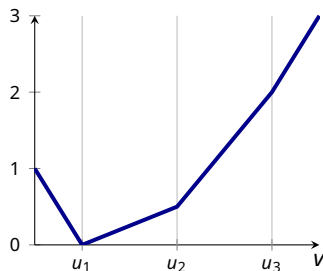
$$\mathcal{G}(u) = \int_{\Omega} g(u(x)) dx$$

- generalize  $L^1$  norm: **polyhedral epigraph** with vertices  $u_1, \dots, u_d$
- **not** exact relaxation/penalization (in general)!

# Multi-bang penalty

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- generalize  $L^1$  norm: **polyhedral epigraph** with vertices  $u_1, \dots, u_d$



- motivation: convex envelope of  $\frac{1}{2}\|u\|^2 + \delta_U$
- **multi-bang** (generalized bang-bang) control
- here: **vector-valued** control

# Vector-valued multi-bang: penalty

Here: admissible control set  $U$  of  $d$  radially distributed states, origin

$$U = \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \omega_0 \cos \theta_1 \\ \omega_0 \sin \theta_1 \end{pmatrix}, \dots, \begin{pmatrix} \omega_0 \cos \theta_d \\ \omega_0 \sin \theta_d \end{pmatrix} \right\}$$

- fixed amplitude  $\omega_0 > 0$
- phases  $0 \leq \theta_1 < \dots < \theta_d < 2\pi$

multi-bang penalty  $g = \left(\frac{1}{2}|\cdot|_2^2 + \delta_U\right)^{**}$  convex envelope

$$\begin{aligned} g^*(q) &= \left( \left( \frac{1}{2}|\cdot|_2^2 + \delta_U \right)^{**} \right)^* (q) = \left( \frac{1}{2}|\cdot|_2^2 + \delta_U \right)^* (q) \\ &= \begin{cases} 0 & \langle q, u_i \rangle \leq \frac{1}{2}\omega_0^2 \text{ for all } 1 \leq i \leq d \\ \langle q, u_i \rangle - \frac{1}{2}\omega_0^2 & \frac{\theta_{i-1} + \theta_i}{2} \leq \angle q \leq \frac{\theta_i + \theta_{i+1}}{2}, \langle q, u_i \rangle \geq \frac{1}{2}\omega_0^2 \end{cases} \end{aligned}$$

# Vector-valued multi-bang: subdifferential

Fenchel conjugate

$$g^*(q) = \begin{cases} 0 =: u_0 & q \in \bar{Q}_0 \\ \langle q, u_i \rangle - \frac{1}{2}\omega_0^2 & q \in \bar{Q}_i \end{cases}$$

Subdifferential

$$\partial g^*(q) = \begin{cases} \{u_i\} & q \in Q_i \quad 0 \leq i \leq d \\ \text{co} \{u_{i_1}, \dots, u_{i_k}\} & q \in Q_{i_1 \dots i_k} \quad 0 \leq i_1, \dots, i_k \leq d \end{cases}$$

# Vector-valued multi-bang: subdifferential

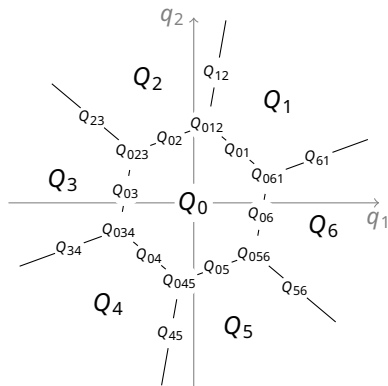
## Subdifferential

$$\partial g^*(q) = \begin{cases} \{u_i\} & q \in Q_i \quad 0 \leq i \leq d \\ \text{co} \{u_{i_1}, \dots, u_{i_k}\} & q \in Q_{i_1 \dots i_k} \quad 0 \leq i_1, \dots, i_k \leq d \end{cases}$$

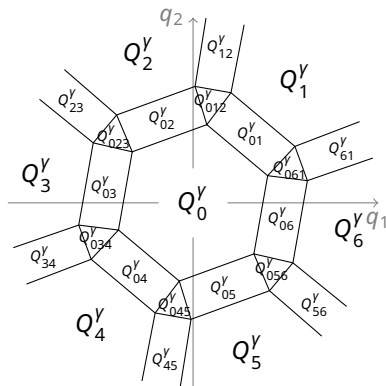
## Moreau–Yosida regularization

$$(\partial g^*)_Y(q) = \begin{cases} u_i & q \in Q_i^Y \\ \left( \frac{\langle q, u_i \rangle}{\gamma \omega_0^2} - \frac{\alpha}{2\gamma} \right) u_i & q \in Q_{0,i}^Y \\ \frac{u_i + u_{i+1}}{2} + \frac{\langle q, u_i - u_{i+1} \rangle (u_i - u_{i+1})}{\gamma |u_i - u_{i+1}|_2^2} & q \in Q_{i,i+1}^Y \\ \frac{q}{\gamma} - \frac{\alpha}{\gamma} \left( \frac{\omega_0}{|u_i + u_{i+1}|_2} \right)^2 (u_i + u_{i+1}) & q \in Q_{0,i,i+1}^Y \end{cases}$$

# Vector-valued multi-bang: subdifferential



(a) subdomains for  $\partial g^*$



(b) subdomains for  $(\partial g^*)_Y$



# Vector-valued multi-bang: Newton method

Newton derivative

$$D_N(\partial g_Y^*)(q) = \begin{cases} 0 & q \in Q_i^Y \\ \frac{u_i u_i^T \mathbf{1}}{\gamma \omega_0^2} & q \in Q_{0,i}^Y \\ \frac{(u_i - u_{i+1})(u_i - u_{i+1})^T}{\gamma |u_i - u_{i+1}|_2^2} & q \in Q_{i,i+1}^Y \\ \frac{1}{\gamma} \text{Id} & q \in Q_{0,i,i+1}^Y \end{cases}$$

Superposition operator:

$$[D_N H_Y(p)](t) := D_N(\partial g_Y^*)(p(t)) \quad \text{a.e. } t \in [0, T]$$

# Vector-valued multi-bang: Newton method

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Semismooth Newton system

$$\left( \text{Id} - D_N H_Y(\mathcal{F}'(u^k)) \mathcal{F}''(u^k) \right) \delta u = -u^k + \partial \mathcal{G}_Y^*(\mathcal{F}'(u^k))$$

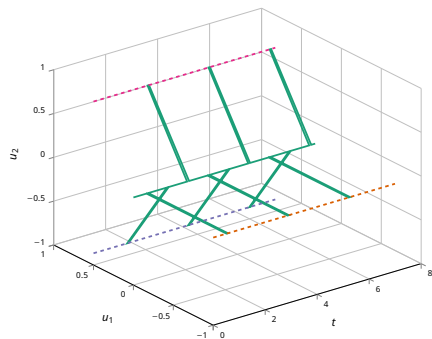
- matrix-free Krylov method for semismooth Newton step
- $\mathcal{F}'$ ,  $\mathcal{F}''$  via linearized, adjoint Bloch equation
- discretization, adjoint as before

# Numerical examples

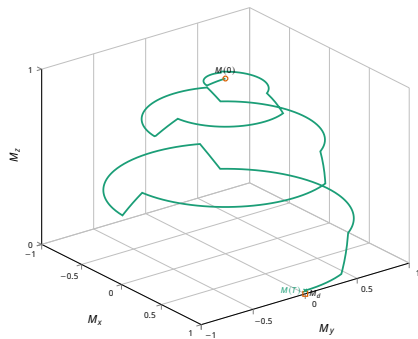
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- goal: shift magnetization from  $M_0 = (0, 0, 1)^T$  at  $t = 0$   
to  $M_d = (1, 0, 0)^T$  at  $t = T$
- $d = 3, 6$  radially distributed admissible control states
- $n = 1, 4$  isochromats with different resonance frequencies
  - 1 shift **all** isochromats
  - 2 shift **only one** isochromat
- $\alpha = 10^{-1}, \omega_0 = 1$
- example motivated by [Dridi/Lapert/Salomon/Glaser/Sugny '15]

# Numerical examples



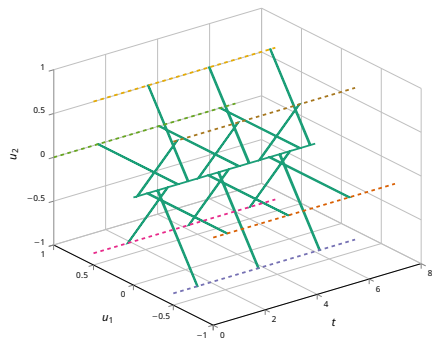
(a) control  $u(t)$



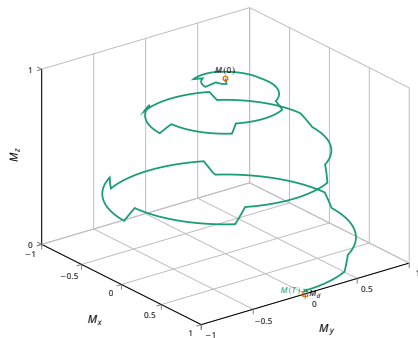
(b) state  $M(t)$

Figure:  $n = 1$  isochromat,  $d = 3$  control states

# Numerical examples



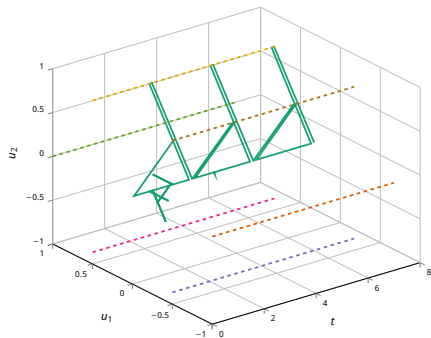
(a) control  $u(t)$



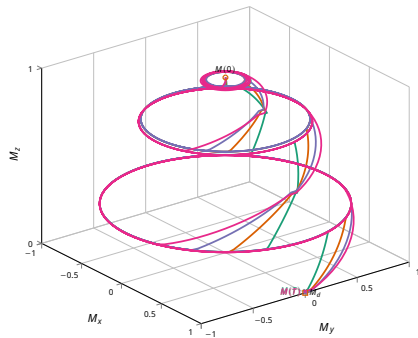
(b) state  $M(t)$

Figure:  $n = 1$  isochromat,  $d = 6$  control states

# Numerical examples



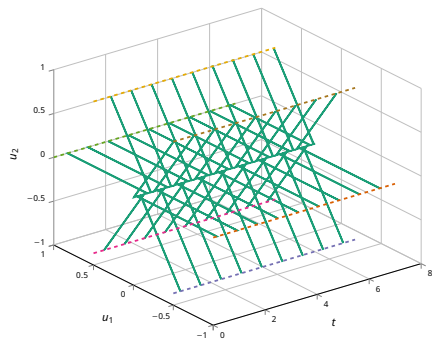
(a) control  $u(t)$



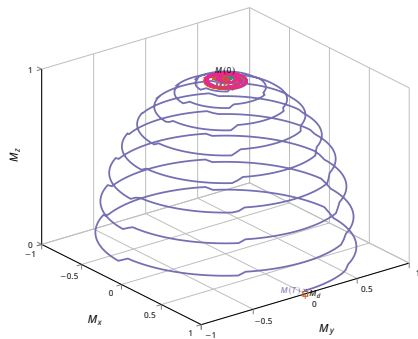
(b) state  $M(t)$

Figure:  $n = 4$  isochromats, same target

# Numerical examples



(a) control  $u(t)$



(b) state  $M(t)$

Figure:  $J = 4$  isochromats, different targets

# Conclusion

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## Optimal control for MR pulse design

- allows designing **low energy** pulses
- allows incorporating **full physical model**
- allows **accelerated imaging**
- allows **incorporating structural constraints**

## Outlook:

- joint optimization of RF pulse and gradient
- (joint) optimization of frequency, phase encoding
- joint optimization and reconstruction

## Preprints, codes:

<http://homepage.uni-graz.at/c.clason/publikationen>