

Multi-bang control of elliptic equations

Christian Clason¹ Karl Kunisch²

¹ Faculty of Mathematics, Universität Duisburg-Essen

² Institute of Mathematics and scientific Computing, Karl-Franzens-Universität Graz

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Motivation

Optimal control of elliptic PDE $Ay = u$

Bang-bang control:

- control constraints $u_1 \leq u(x) \leq u_2$, no control costs
- \rightsquigarrow control $u(x) \in \{u_1, u_2\}$ almost everywhere

Multi-bang control

- control $u(x) \in \{u_1, \dots, u_d\}$ almost everywhere
- motivation: control by discrete voltages, velocities, ...
- hybrid **discrete–continuous problem**, combinatorial
- solve using **continuous relaxation** \rightsquigarrow linear complexity in d

Formulation

$$\begin{cases} \min_{u,y} \frac{1}{2} \|y - z\|_{L^2}^2 + \frac{\alpha}{2} \|u\|_{L^2}^2 + \beta \int_{\Omega} \prod_{i=1}^d |u(x) - u_i|_0 \, dx \\ \text{s. t. } Ay = u, \quad u_1 \leq u(x) \leq u_d \end{cases}$$

- $u_1 < \dots < u_d, d \geq 2$, desired control states
- $|t|_0 := \begin{cases} 0 & \text{if } t = 0 \\ 1 & \text{if } t \neq 0 \end{cases}$ binary penalty
- \rightsquigarrow non-smooth, non-convex, not lower-semicontinuous
- $A : V \rightarrow V^*$ isomorphism for Hilbert space $V \hookrightarrow L^2(\Omega) \hookrightarrow V^*$

Approach

Consider \mathcal{F} convex, \mathcal{G} convex

$$J(\bar{u}) := \mathcal{F}(\bar{u}) + \mathcal{G}(\bar{u}) = \min_u \mathcal{F}(u) + \mathcal{G}(u)$$

Necessary optimality conditions

$$\begin{cases} -\bar{p} \in \partial \mathcal{F}(\bar{u}) \\ \bar{p} \in \partial \mathcal{G}(\bar{u}) \end{cases}$$

- Fermat, sum rule for subdifferentials (under regularity condition)

Approach

Consider \mathcal{F} convex, \mathcal{G} convex

$$J(\bar{u}) := \mathcal{F}(\bar{u}) + \mathcal{G}(\bar{u}) = \min_u \mathcal{F}(u) + \mathcal{G}(u)$$

Necessary optimality conditions

$$\begin{cases} -\bar{p} \in \partial \mathcal{F}(\bar{u}) \\ \bar{u} \in \partial \mathcal{G}^*(\bar{p}) \end{cases}$$

- $\mathcal{G}^*(p) = \sup_u \langle u, p \rangle - \mathcal{G}(u)$ Fenchel conjugate

Approach

Consider \mathcal{F} convex, \mathcal{G} non-convex

$$\min_u \mathcal{F}(u) + \mathcal{G}(u)$$

Sufficient(?) optimality conditions

$$\begin{cases} -\bar{p} \in \partial \mathcal{F}(\bar{u}) \\ \bar{u} \in \partial \mathcal{G}^*(\bar{p}) \end{cases}$$

- \mathcal{G}^* Fenchel conjugate: always convex
- \rightsquigarrow well-defined, unique solution $\bar{u} (= \arg \min \mathcal{F}(u) + \mathcal{G}^{**}(u))$
- but: \bar{u} in general not minimizer of $J \rightsquigarrow$ sub-optimal

Optimality system

Here:

$$\mathcal{F} : L^2(\Omega) \rightarrow \mathbb{R}, \quad u \mapsto \frac{1}{2} \|A^{-1}u - z\|_{L^2}^2$$

$$\mathcal{G} : L^2(\Omega) \rightarrow \overline{\mathbb{R}}, \quad u \mapsto \int_{\Omega} \left(\frac{\alpha}{2} u(x)^2 + \beta \prod_{i=1}^d |u(x) - u_i|_0 \right) dx + \delta_U(u)$$

- δ_U indicator function of

$$U := \{u \in L^2(\Omega) : u_1 \leq u(x) \leq u_d \text{ a.e.}\}$$

- \mathcal{G} defined pointwise \rightsquigarrow compute Fenchel conjugate, subdifferential pointwise

Fenchel conjugate

$$g : \mathbb{R} \rightarrow \overline{\mathbb{R}}, \quad v \mapsto \frac{\alpha}{2}v^2 + \beta \prod_{i=1}^d |v - u_i|_0 + \delta_{[u_1, u_d]}(v)$$
$$g^* : \mathbb{R} \rightarrow \overline{\mathbb{R}}, \quad q \mapsto \sup_v qv - g(v)$$

Case differentiation: sup attained at \bar{v} ,

$$g^*(q) = \begin{cases} qu_i - \frac{\alpha}{2}u_i^2 & \bar{v} = u_i, \quad 1 \leq i \leq d \\ \frac{1}{2\alpha}q^2 - \beta & \bar{v} \neq u_i, \quad 1 \leq i \leq d \end{cases}$$

Fenchel conjugate

$$g^*(q) = \begin{cases} qu_i - \frac{\alpha}{2}u_i^2 & q \in \bar{P}_i, \quad 1 \leq i \leq d \\ \frac{1}{2\alpha}q^2 - \beta & q \in \bar{P}_0 \end{cases}$$

$$P_1 := \left\{ q : q - \alpha u_1 < \sqrt{2\alpha\beta} \wedge q < \frac{\alpha}{2}(u_1 + u_2) \right\}$$

$$P_i := \left\{ q : |q - \alpha u_i| < \sqrt{2\alpha\beta} \wedge \frac{\alpha}{2}(u_{i-1} + u_i) < q < \frac{\alpha}{2}(u_i + u_{i+1}) \right\}$$

$$P_d := \left\{ q : q - \alpha u_d > \sqrt{2\alpha\beta} \wedge \frac{\alpha}{2}(u_d + u_{d-1}) < q \right\}$$

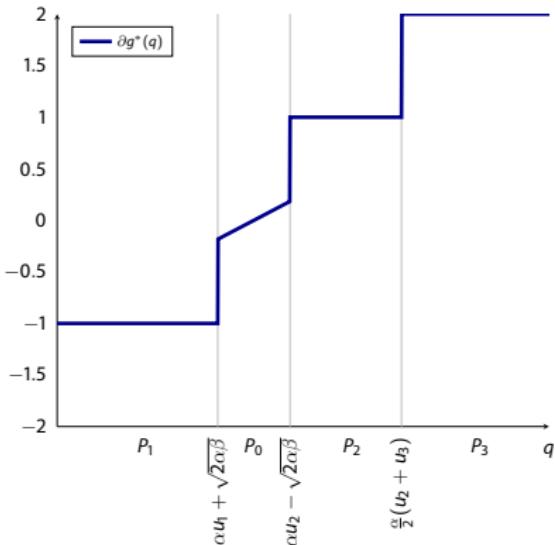
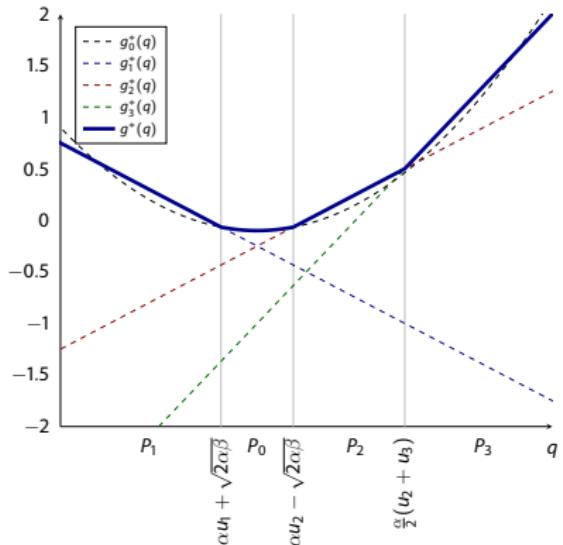
$$P_0 := \left\{ q : |q - \alpha u_j| > \sqrt{2\alpha\beta} \text{ for all } j \wedge \alpha u_1 < q < \alpha u_d \right\}$$

Fenchel conjugate

$$g^*(q) = \begin{cases} qu_i - \frac{\alpha}{2}u_i^2 & q \in \bar{P}_i, \quad 1 \leq i \leq d \\ \frac{1}{2\alpha}q^2 - \beta & q \in \bar{P}_0 \end{cases}$$

$$\partial g^*(q) = \begin{cases} \{u_i\} & q \in P_i, 1 \leq i < d \\ \{\frac{1}{\alpha}q\} & q \in P_0 \\ [u_i, u_{i+1}] & q \in \bar{P}_i \cap \bar{P}_{i+1}, 1 \leq i < d \\ [\min\{u_i, \frac{1}{\alpha}q\}, \max\{u_i, \frac{1}{\alpha}q\}] & q \in \bar{P}_i \cap \bar{P}_0, 1 \leq i \leq d \end{cases}$$

Fenchel conjugate: sketch



Optimality system

$$-\bar{p} = A^{-*}(A^{-1}\bar{u} - z)$$

$$\bar{u} \in \partial\mathcal{G}^*(\bar{p})$$

$$= \begin{cases} \{u_i\} & \bar{p}(x) \in P_i \\ \{\frac{1}{\alpha}\bar{p}(x)\} & \bar{p}(x) \in P_0 \\ [u_i, u_{i+1}] & \bar{p}(x) \in \bar{P}_i \cap \bar{P}_{i+1} \\ [\min(u_i, \frac{1}{\alpha}\bar{p}(x)), \max\{u_i, \frac{1}{\alpha}\bar{p}(x)\}] & \bar{p}(x) \in \bar{P}_i \cap \bar{P}_0 \end{cases}$$

- necessary conditions for $\min_u \mathcal{F}(u) + \mathcal{G}^{**}(u)$ (convex, l.s.c.)
- \rightsquigarrow unique solution (\bar{u}, \bar{p})

Relation to bang-bang control

- for $d = 2$ and β sufficiently large :

$$\bar{u}(x) \in \partial g^*(\bar{p}(x)) = \begin{cases} \{u_1\} & \text{if } \bar{p}(x) < \frac{\alpha}{2}(u_1 + u_d) \\ \{u_d\} & \text{if } \bar{p}(x) > \frac{\alpha}{2}(u_1 + u_d) \\ [u_1, u_d] & \text{if } \bar{p}(x) = \frac{\alpha}{2}(u_1 + u_d) \end{cases}$$

- bang-bang control

$$\bar{u}(x) \in \partial g^*(\bar{p}(x)) = \begin{cases} \{u_1\} & \text{if } \bar{p}(x) < 0 \\ \{u_d\} & \text{if } \bar{p}(x) > 0 \\ [u_1, u_d] & \text{if } \bar{p}(x) = 0 \end{cases}$$

- same for multi-bang with any $d \geq 2$ and $\alpha = 0$

$\rightsquigarrow \alpha > 0$ necessary for multi-bang control

Structure of solution

$$\Omega = \mathcal{A} \cup \mathcal{F} \cup \mathcal{S}$$

- multi-bang arc $\mathcal{A} = \bigcup_{i=1}^d \{x : \bar{u}(x) = u_i\}$
- free arc $\mathcal{F} = \{x : \bar{u}(x) = \frac{1}{\alpha} \bar{p}(x) \neq u_i\}$
- singular arc $\mathcal{S} = \{x : \bar{u}(x) \notin \{u_i, \frac{1}{\alpha} \bar{p}(x)\}\}$

Generalized multi-bang principle

- if β sufficiently large: $P_0 = \emptyset$, **free arc**

$$\mathcal{F} \subset \{\bar{p}(x) \in P_0\} = \emptyset$$

- **singular arc** corresponds to set-valued subdifferential:

$$\begin{aligned}\mathcal{S} &= \{\bar{p}(x) \in \bigcup_{i=1}^{d-1} (\bar{P}_i \cap \bar{P}_{i+1}) \cup \bigcup_{i=1}^d (\bar{P}_i \cap \bar{P}_0)\} \\ &\subset \{\bar{p}(x) \in \left\{ \frac{\alpha}{2}(u_i + u_{i+1}), \alpha u_i - \sqrt{2\alpha\beta}, \alpha u_i + \sqrt{2\alpha\beta} \right\} \}\end{aligned}$$

- for suitable A , $\bar{p}(x)$ constant implies $(A^* \bar{p})(x) = (\bar{y} - z)(x) = 0$,

$\rightsquigarrow |\{\bar{y} = z\}| = 0 \Rightarrow \bar{u} \in \{u_1, \dots, u_d\}$ a.e., **true multi-bang control**

(Sub)optimality

- duality gap for non-convex \mathcal{G} :

$$\mathcal{G}(\bar{u}) + \mathcal{G}^*(\bar{p}) - \langle \bar{p}, \bar{u} \rangle \leq \beta |\mathcal{S}|$$

(pointwise gap of β where $\partial g^*(\bar{p}(x))$ set-valued)

- \rightsquigarrow in general: \bar{u} sub-optimal:

$$J(\bar{u}) \leq J(u) + \beta |\mathcal{S}| \quad \text{for all } u$$

- but: \bar{u} true multi-bang $\rightsquigarrow |\mathcal{S}| = 0 \rightsquigarrow \bar{u}$ optimal

Numerical solution of optimality system

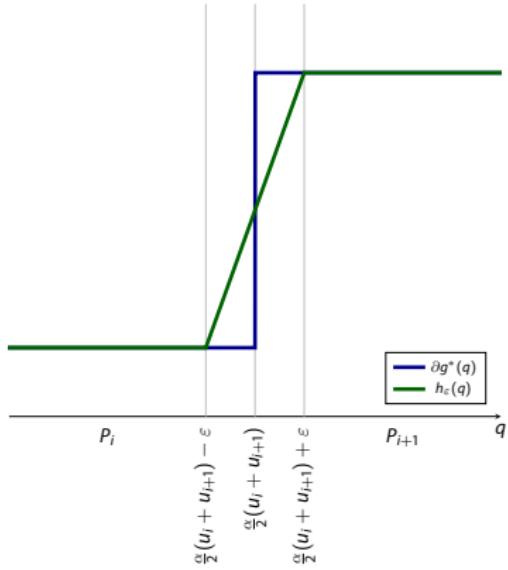
$$A\bar{y} = \bar{u}$$

$$A^*\bar{p} = z - \bar{y}$$

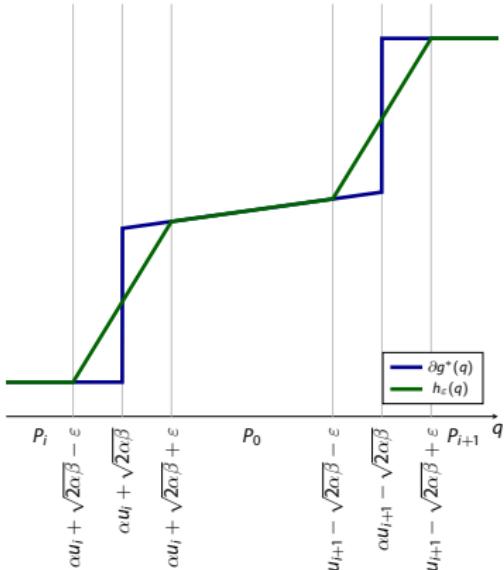
$$\bar{u} \in \begin{cases} \{u_i\} & \bar{p}(x) \in P_i \\ \{\frac{1}{\alpha}\bar{p}(x)\} & \bar{p}(x) \in P_0 \\ [u_i, u_{i+1}] & \bar{p}(x) \in \bar{P}_i \cap \bar{P}_{i+1} \\ [\min(u_i, \frac{1}{\alpha}\bar{p}(x)), \max\{u_i, \frac{1}{\alpha}\bar{p}(x)\}] & \bar{p}(x) \in \bar{P}_i \cap \bar{P}_0 \end{cases}$$

- set-valued, not differentiable
- \rightsquigarrow replace set-valued ∂g^* by piecewise linear h_ε , let $\varepsilon \rightarrow 0$

Regularization: sketch



(a) $q \in \overline{P}_i \cap \overline{P}_{i+1}$ (no free arc)



(b) $q \in \overline{P}_i \cap \overline{P}_0$ (free arc)

Regularization

Regularized system

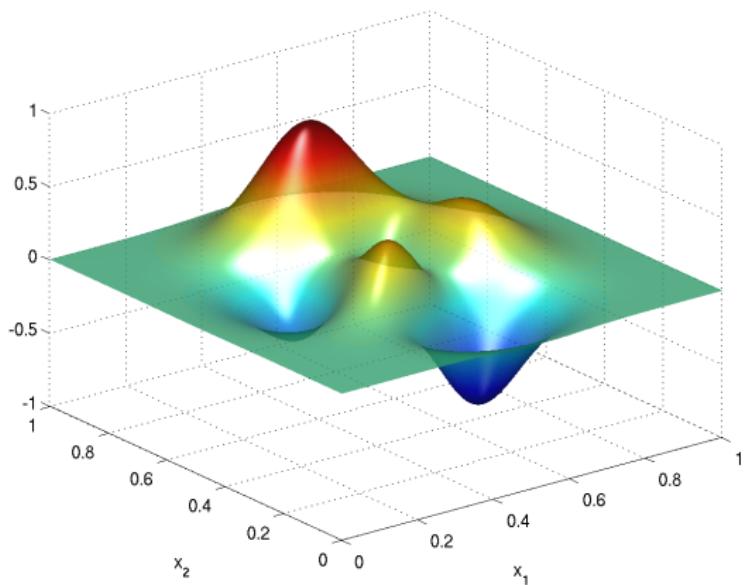
$$\begin{cases} Ay_\varepsilon = u_\varepsilon \\ A^*p_\varepsilon = z - y_\varepsilon \\ u_\varepsilon = H_\varepsilon(p_\varepsilon) \end{cases}$$

- H_ε maximal monotone \rightsquigarrow unique solution $(u_\varepsilon, p_\varepsilon, y_\varepsilon)$
- convergence $(u_\varepsilon, p_\varepsilon, y_\varepsilon) \rightharpoonup (\bar{u}, \bar{p}, \bar{y})$ as $\varepsilon \rightarrow 0$
- h_ε Lipschitz continuous, norm gap $\rightsquigarrow H_\varepsilon$ semismooth
- only number of sets P_i depends on $d \rightsquigarrow$ linear complexity

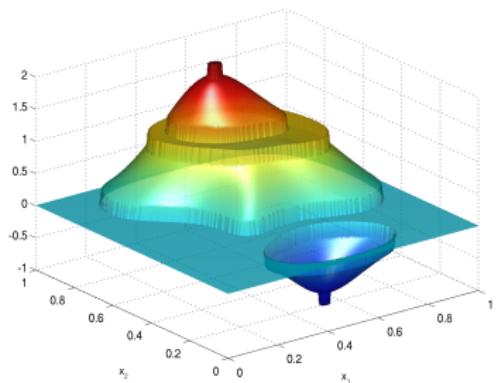
Numerical examples

- $\Omega = [0, 1]^2, A = -\Delta$
- finite element discretization: uniform grid, 256×256 nodes
- state, adjoint: piecewise linear
- control: eliminated (variational discretization)
- $d = 5, (u_1, \dots, u_5) = (-2, 1, 0, 1, 2)$
- $\varepsilon = 0$: regularized active sets empty, true multi-bang
- $\varepsilon > 0$: terminated with 2–21 nodes in regularized active sets

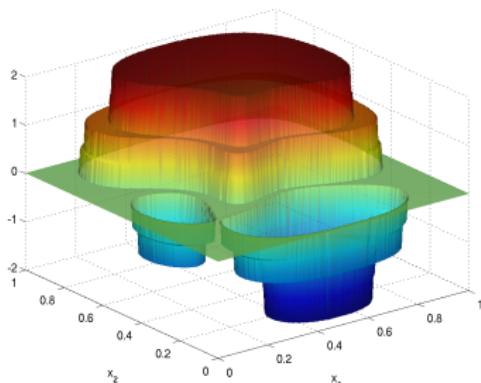
Numerical examples: target



Controls: $\beta = 10^{-4}$ (free arcs)

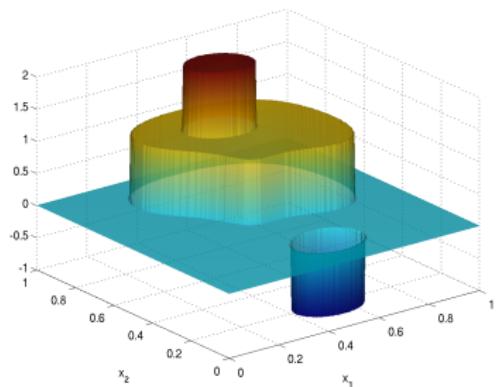


(a) $\alpha = 5 \cdot 10^{-3}$ ($\varepsilon = 0$)

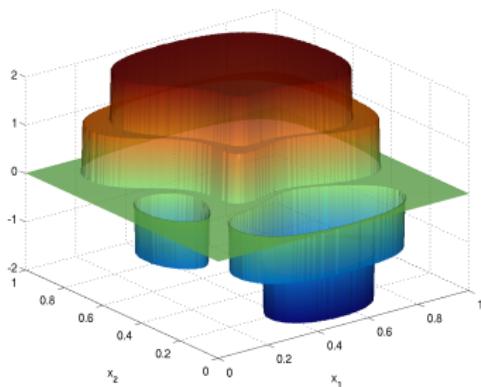


(b) $\alpha = 10^{-3}$ ($\varepsilon \approx 10^{-8}$)

Controls: $\beta = 10^{-3}$ (**no free arcs**)

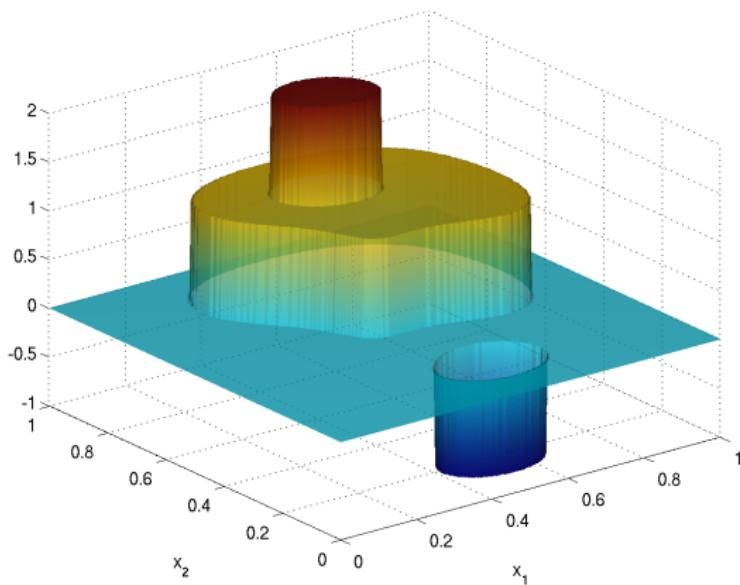


(c) $\alpha = 5 \cdot 10^{-3}$ ($\varepsilon = 0$)



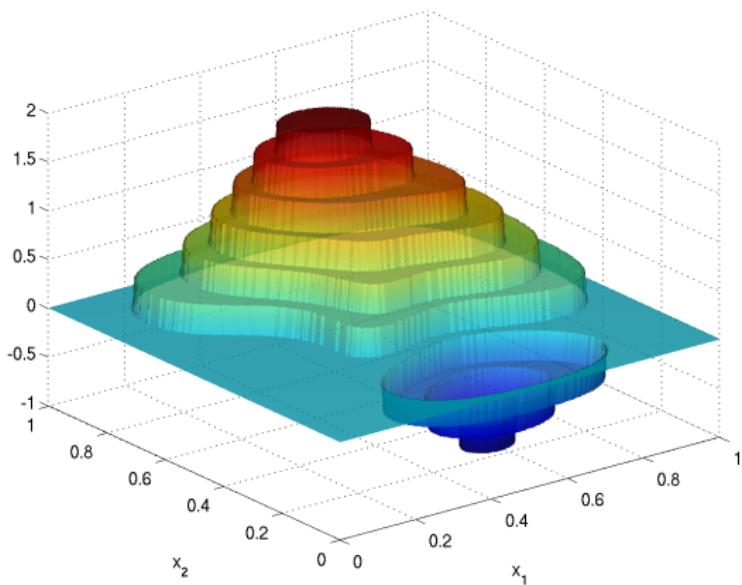
(d) $\alpha = 10^{-3}$ ($\varepsilon \approx 10^{-7}$)

Controls: effect of d



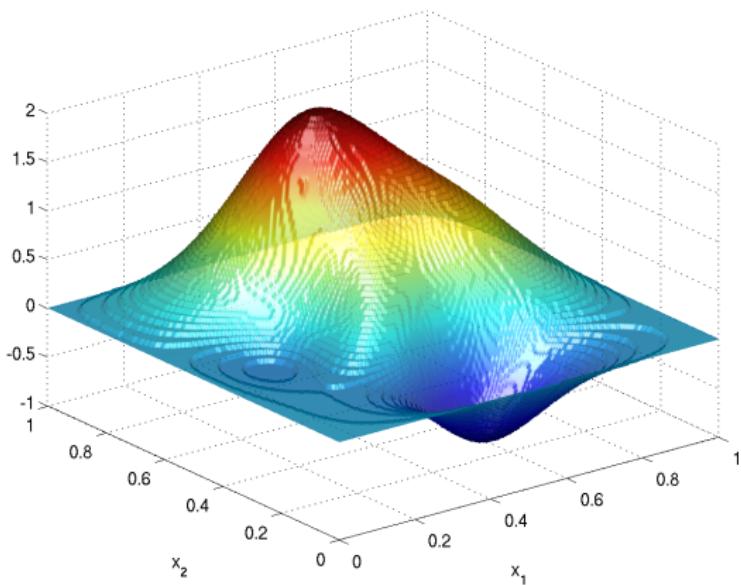
(a) $d = 5 (\varepsilon = 0)$

Controls: effect of d



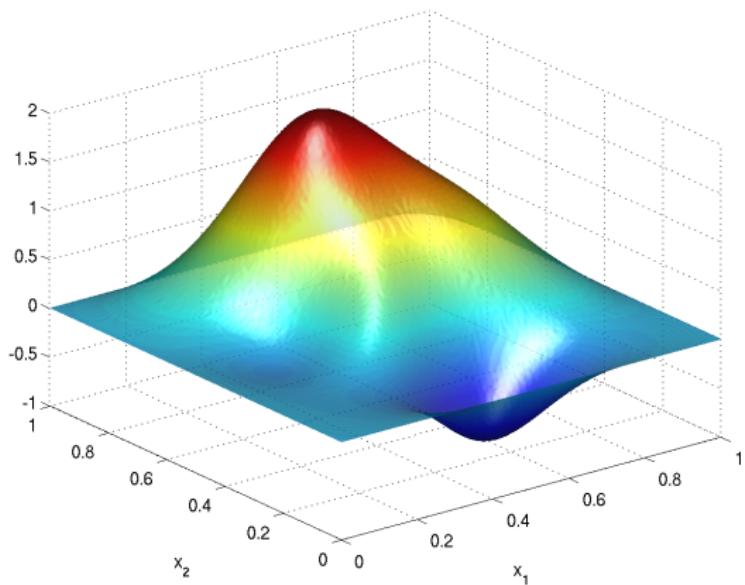
(b) $d = 15 (\varepsilon = 0)$

Controls: effect of d



(c) $d = 101 (\varepsilon \approx 10^{-9})$

Controls: effect of d



(d) $d = 1001 (\varepsilon \approx 10^{-11})$

Conclusion

(Non-)convex relaxation of discrete control problem:

- well-posed primal-dual optimality system
- controls optimal under reasonable assumptions
- linear complexity in number of desired states
- \rightsquigarrow efficient numerical solution (superlinear convergence)

Outlook:

- inverse problems (identification of known tissue types)
- nonlinear control-to-state mapping
- other hybrid discrete–continuous problems (e.g., switching)

Preprint, MATLAB/Python codes:

<http://www.uni-due.de/mathematik/agclason/publications.php>