

# Avoiding degeneracy in the Westervelt equation by state constrained optimal control

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# Motivation

## Westervelt equation

$$\left\{ \begin{array}{ll} (1 - ky)y_{tt} - c^2 \Delta y - b \Delta y_t + dy_t - k(y_t)^2 = 0 & \text{in } (0, T) \times \Omega, \\ \partial_\nu y = u & \text{on } (0, T) \times \Gamma \\ y_t + c \partial_\nu y = 0 & \text{on } (0, T) \times \hat{\Gamma} \\ y = y^0, y_t = y^1 & \text{in } \{0\} \times \Omega \end{array} \right.$$

- $y$ : acoustic sound fluctuation,  $b, c, d, k$ : material parameters
- describes propagation of high intensity focused ultrasound
- $u$ : boundary control: piezoelectric transducer

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## Westervelt equation

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- $y$ : acoustic sound fluctuation,  $b, c, d, k$ : material parameters
- describes propagation of high intensity focused ultrasound
- $u$ : boundary control: piezoelectric transducer
- nonlinear, degenerate for  $y$  large

# Motivation

## Westervelt equation

$$\begin{cases} (1 - ky)y_{tt} - c^2 \Delta y - b \Delta y_t + dy_t - k(y_t)^2 = 0 & \text{in } (0, T) \times \Omega, \\ \partial_\nu y = u & \text{on } (0, T) \times \Gamma \end{cases}$$

## Well-posedness

- requires a priori smallness bound  $\|y\|_\infty < 1/k$
- usually:  $C(0, T; H^2)$  bound, embedding  $H^2(\Omega) \hookrightarrow L^\infty(\Omega)$
- $\rightsquigarrow$  strong smoothing, requires smallness of data  $u$
- here: impose pointwise constraints  $y^- \leq y(x) \leq y^+ < 1/k$ ,  
gradient constraint  $\|y_t\|_{L^2} \leq M$
- data from solving state constrained optimal control problem

# Optimal control problem

$$\left\{ \begin{array}{l} \min_{y,u} \frac{1}{2} \|y - y^d\|_{L^2}^2 + \frac{\alpha}{2} \|u\|_U^2 \\ (1 - ky)y_{tt} - c^2 \Delta y - b \Delta y_t + dy_t - k(y_t)^2 = 0, \\ \partial_\nu y = u \\ y^- \leq y(t,x) \leq y^+, \quad \|y_t\|_{L^2} \leq M \end{array} \right.$$

- $y^d \in L^2(0, T; L^2(\Omega))$ ,  $\alpha > 0$
- some smoothness, no smallness assumption on  $u \in U$
- existence of local minimizer  $(\bar{u}, \bar{y})$  by direct method
- proof requires compact embeddings, regularity results  
(technical, not in this talk)
- characterisation of admissible data: optimality conditions

# Optimality conditions

## Abstract problem

$$\min_{u,y} J(u, y) \quad \text{s.t.} \quad G(u, y) = 0, \quad H(y) \in K$$

Classical constraint qualification (e.g., [Maurer/Zowe, Tröltzsch '10]):

- introduce control-to-state mapping  $S : u \mapsto y$  with  $G(u, y) = 0$
- consider reduced problem  $j(u) = J(u, S(u))$
- interior point condition:  $H(S(u_0)) \in K^\circ$

Then:

- $j'(\bar{u}) + S'(\bar{u})^* H'(S(\bar{u})) = 0$

**But:** requires well-posedness of  $S \rightsquigarrow$  smallness of  $u$

# Optimality conditions

## Abstract problem

$$\min_{u,y} J(u,y) \quad \text{s.t.} \quad G(u,y) = 0, \quad H(y) \in K$$

Alternative [Alibert/Raymond '98]: if there exist  $u_0, y_0$  with

- $G_u(\bar{u}, \bar{y})(u_0 - \bar{u}) + G_y(\bar{u}, \bar{y})y_0 = 0 \quad \text{with} \quad H(\bar{y}) + H'(\bar{y})y_0 \in K^o$
- $G_y(\bar{u}, \bar{y})$  surjective

Then:

- $J_y(\bar{u}, \bar{y}) + G_y(\bar{u}, \bar{y})^*p + H'(\bar{y})^*\mu = 0$
- $J_u(\bar{u}, \bar{y}) + G_u(\bar{u}, \bar{y})p = 0$
- $\langle \mu, w - H(\bar{y}) \rangle \leq 0 \text{ for all } w \in K.$

**But:**  $u$  acts only on boundary  $\rightsquigarrow$  difficult to satisfy

# Optimality conditions

## Abstract problem

$$\min_{u,y} J(u,y) \quad \text{s. t.} \quad G(u,y) = 0, \quad H(y) \in K$$

Alternative: Relaxed problem [Bonnans/Casas '89]

- 1 introduce  $z = (1 - ky)$ ,  $w = -k(y_t)^2$  in  $G$
  - 2 penalize  $z - (1 - ky)$ ,  $w + k(y_t)^2$  in  $J$
  - 3 obtain optimality conditions (easier for new  $G$ )
  - 4 pass to limit in penalization
- **but:** uses optimality of  $(\bar{u}, \bar{y})$ , only local minimizers
  - $\rightsquigarrow$  localize by penalty on  $u - \bar{u}, y - \bar{y}$  ([Casas/Tröltzsch '02])

# Relaxed problem

$$\min_{u,y,z,w} J^\varepsilon(u, y, z, w) \quad \text{s.t.} \quad G^\varepsilon(u, y, z, w) = 0, \quad H^\varepsilon(y, z) \in K$$

$$\begin{aligned} J^\varepsilon(u, y, z, w) = & \frac{1}{2} \|y - y^d\|_{L^2}^2 + \frac{\alpha}{2} \|u\|_U^2 \\ & + \frac{1}{2\varepsilon} \|z + ky - 1\|_Z^2 + \frac{1}{2\varepsilon} \|w + k(y_t)^2\|_W^2 \\ & + \frac{1}{2\delta} \|u - \bar{u}\|_U^2 + \frac{1}{2\delta} \|z + k\bar{y} - 1\|_Z^2 + \frac{1}{2\delta} \|w + k(\bar{y}_t)^2\|_W^2 \end{aligned}$$

- $U, Z, W$  suitable Hilbert spaces (needed for surjectivity)
- $\delta > 0$  sufficiently small, **fixed**

# Relaxed problem

$$\min_{u,y,z,w} J^\varepsilon(u, y, z, w) \quad \text{s.t.} \quad G^\varepsilon(u, y, z, w) = 0, \quad H^\varepsilon(y, z) \in K$$

$$G^\varepsilon(u, y, z, w) = \begin{pmatrix} zy_{tt} - c^2 \Delta y - b \nabla y_t + w \\ \partial_\nu y - u \end{pmatrix}$$

$$H_\varepsilon(y, z) = \begin{pmatrix} 1 - z - ky^+ \\ z - ky^- - 1 \\ \|y_t\|_{L^2} - M \end{pmatrix}$$

- $K$  negative cone in  $C \times C \times \mathbb{R}$

# Relaxed problem

$$\min_{u,y,z,w} J^\varepsilon(u, y, z, w) \quad \text{s.t.} \quad G^\varepsilon(u, y, z, w) = 0, \quad H^\varepsilon(y, z) \in K$$

- Existence of **global** solution  $x_\varepsilon := (u_\varepsilon, y_\varepsilon, z_\varepsilon, w_\varepsilon)$
- Localization:  $x_\varepsilon$  close to  $(\bar{u}, \bar{y})$
- (Regularity of solution)

# Regularity condition 1

There exists  $(u_0, y_0, z_0, w_0)$  with

$$G_u^\varepsilon(x_\varepsilon)(u_0 - u_\varepsilon) + G_y^\varepsilon(x_\varepsilon)y_0 + G_z^\varepsilon(x_\varepsilon)z_0 + G_w^\varepsilon(x_\varepsilon)(w_0 - w_\varepsilon) = 0$$

- $z_\varepsilon(y_0)_{tt} - c^2 \Delta y_0 - b \nabla(y_0)_t + z_0(y_\varepsilon)_{tt} + (w_0 - w_\varepsilon) = 0$
- $\partial_\nu y_0 = (u_0 - u_\varepsilon) = 0$
- $1 + ky^- < z_0 + z^\varepsilon < 1 + ky^+, \quad \|(y_0 + y_\varepsilon)_t\|_{L^2} < M$
- (necessary regularity)

Satisfied for, e.g.,

$$u_0 = u_\varepsilon, \quad y_0 = -y_\varepsilon, \quad z_0 = 1 - z_\varepsilon, \quad w_0 = -(1 - z_\varepsilon)(y_\varepsilon)_{tt} + w_\varepsilon$$

# Regularity condition 2

$G_{(y,z)}(x_\varepsilon)$  is surjective: there is solution  $(y, z)$  for given  $f$  of

$$\begin{cases} z(y_\varepsilon)_{tt} + z_\varepsilon y_{tt} - c^2 \Delta y - b \Delta y_t + dy_t = f \\ \partial_\nu y = 0 \text{ on } (0, T) \times \Gamma, \\ y_t + c \partial_\nu y = 0 \text{ on } (0, T) \times \hat{\Gamma}, \\ y = 0, y_t = 0 \text{ in } \{0\} \times \Omega \end{cases}$$

- linearized Westervelt equation
- well-posed (proof similar to [C./Kaltenbacher/Veljović '09])
- (necessary regularity)

# Relaxed optimality system

There exist  $p_\varepsilon$ , measures  $\mu_\varepsilon^+, \mu_\varepsilon^- \geq 0$ ,  $\lambda_\varepsilon \geq 0$  satisfying

Relaxed state equation (weak form)

$$\begin{aligned} & \langle z_\varepsilon(y_\varepsilon)_{tt}, v \rangle + \langle c^2 \nabla y_\varepsilon + b \nabla (y_\varepsilon)_t, \nabla v \rangle + \langle d(y_\varepsilon)_t + w, v \rangle \\ & + \langle c y_t + \frac{b}{c} y_{tt}, v \rangle_{\hat{\Gamma}} = \langle c^2 u_\varepsilon + b(u_\varepsilon)_t, v \rangle_{\Gamma} \end{aligned}$$

# Relaxed optimality system

There exist  $p_\varepsilon$ , measures  $\mu_\varepsilon^+, \mu_\varepsilon^- \geq 0$ ,  $\lambda_\varepsilon \geq 0$  satisfying

## Relaxed adjoint equation

$$\begin{aligned} & \langle z_\varepsilon p_\varepsilon, v_{tt} \rangle + \langle c^2 \nabla p_\varepsilon, \nabla v \rangle + \langle b \nabla p_\varepsilon, \nabla v \rangle + \langle dp_\varepsilon, v_t \rangle \\ & + \langle cp_\varepsilon, v_t \rangle_{\hat{\Gamma}} + \langle \frac{b}{c} p_\varepsilon, v_{tt} \rangle_{\hat{\Gamma}} = \langle y^d - y_\varepsilon, v \rangle \\ & - \frac{1}{\varepsilon} \langle z_\varepsilon + ky_\varepsilon - 1, kv \rangle_Z \\ & - \frac{1}{\varepsilon} \langle w_\varepsilon + k(y_\varepsilon)_t^2, 2ky_\varepsilon v_t \rangle_W \\ & - 2\lambda_\varepsilon \langle \| (y_\varepsilon)_t(t) \|_{L^2}^2 (y_\varepsilon)_t, v_t \rangle \end{aligned}$$

- $\langle \cdot, \cdot \rangle_X$  inner product in Hilbert space  $X$

# Relaxed optimality system

There exist  $p_\varepsilon$ , measures  $\mu_\varepsilon^+, \mu_\varepsilon^- \geq 0$ ,  $\lambda_\varepsilon \geq 0$  satisfying

## Stationarity in $z$

$$\frac{1}{\varepsilon} \langle z_\varepsilon + ky_\varepsilon - 1, v \rangle_Z + \frac{1}{\delta} \langle z_\varepsilon + k\bar{y} - 1, v \rangle_Z + \langle (y_\varepsilon)_{tt} p_\varepsilon, v \rangle = \mu_\varepsilon^+(v) - \mu_\varepsilon^-(v)$$

## Stationarity in $w$

$$\frac{1}{\varepsilon} \langle w_\varepsilon + k(y_\varepsilon)_t^2, v \rangle_W + \frac{1}{\delta} \langle w_\varepsilon + k(\bar{y}_t)^2, v \rangle_W + \langle p_\varepsilon, v \rangle = 0$$

# Relaxed optimality system

There exist  $p_\varepsilon$ , measures  $\mu_\varepsilon^+, \mu_\varepsilon^- \geq 0, \lambda_\varepsilon \geq 0$  satisfying

## Optimality

$$\langle \alpha u_\varepsilon \rangle_U + \frac{1}{\delta} \langle u_\varepsilon - \bar{u}, v \rangle_U = \langle c^2 p_\varepsilon, v \rangle_\Gamma + \langle b p_\varepsilon, v_t \rangle_\Gamma$$

## Complementarity

$$\mu_\varepsilon^+ (z_\varepsilon + k y^+ - 1) = 0, \quad \mu_\varepsilon^- (z_\varepsilon - k y^- - 1) = 0,$$

$$\lambda_\varepsilon (\| (y_\varepsilon)_t \|_{L^2}^2 - M) = 0$$

# Passing to the limit: minimizers

Consider global minimizers  $x_\varepsilon = (u_\varepsilon, y_\varepsilon, z_\varepsilon, w_\varepsilon)$  as  $\varepsilon \rightarrow 0$

1. Optimality of  $x_\varepsilon$ :

$$J^\varepsilon(u_\varepsilon, y_\varepsilon, z_\varepsilon, w_\varepsilon) \leq J^\varepsilon(\bar{u}, \bar{y}, 1 - k\bar{y}, k(\bar{y}_t)^2) = J(\bar{u}, \bar{y})$$

$\rightsquigarrow \{x_\varepsilon\}_{\varepsilon > 0}$  bounded, subsequence  $x_{\varepsilon_n} \rightharpoonup \hat{x}$

2. Boundedness of penalty terms:

$$\|z_\varepsilon + ky_\varepsilon - 1\|_Z \rightarrow 0, \quad \|w_\varepsilon + k(y_\varepsilon)_t^2\|_W \rightarrow 0$$

$$\rightsquigarrow \hat{w} + k(\hat{y}_t)^2 = 0, \quad \hat{z} + k\hat{y} - 1 = 0$$

3. Compact embeddings:  $y_\varepsilon \rightarrow \hat{y}$ ,  $z_\varepsilon \rightarrow \hat{z}$  pointwise  
(along further subsequence)

# Passing to the limit: minimizers

3. Compact embeddings:  $y_\varepsilon \rightarrow \hat{y}$ ,  $z_\varepsilon \rightarrow \hat{z}$  pointwise  
(along further subsequence)

4. Hence:  $z_\varepsilon(y_\varepsilon)_{tt} \rightarrow \hat{z}\hat{y}_{tt}$ ,

$$G(\hat{u}, \hat{y}) = G^\varepsilon(\hat{u}, \hat{y}, \hat{z}, \hat{w}) = \lim_{n \rightarrow \infty} G^\varepsilon(u_{\varepsilon_n}, y_{\varepsilon_n}, z_{\varepsilon_n}, w_{\varepsilon_n}) = 0$$

5. Also:  $H(\hat{y}) = H^\varepsilon(\hat{y}, \hat{z}) \in K$

6.  $\rightsquigarrow (\hat{u}, \hat{y})$  feasible for original problem, close to  $(\bar{u}, \bar{y})$

# Passing to the limit: minimizers

6.  $\rightsquigarrow (\hat{u}, \hat{y})$  feasible for original problem, close to  $(\bar{u}, \bar{y})$

7. Local optimality of  $(\bar{u}, \bar{y})$ , bound on  $J^\varepsilon(x_\varepsilon)$ :

$$\begin{aligned} J(\hat{u}, \hat{y}) &\geq J(\bar{u}, \bar{y}) \geq \liminf_{\varepsilon \rightarrow 0} J^\varepsilon(u_\varepsilon, y_\varepsilon, z_\varepsilon, w_\varepsilon) \\ &\geq \liminf_{\varepsilon \rightarrow 0} J(u_\varepsilon, y_\varepsilon) + \frac{1}{2\delta} \|u_\varepsilon - \bar{u}\|_U^2 \\ &\quad + \frac{1}{2\delta} \|z_\varepsilon + k\bar{y} - 1\|_Z^2 + \frac{1}{2\delta} \|w_\varepsilon + k(\bar{y}_t)^2\|_W^2 \\ &\geq J(\hat{u}, \hat{y}) + \frac{1}{2\delta} \|\hat{u} - \bar{u}\|_U^2 \\ &\quad + \frac{1}{2\delta} \|\hat{z} + k\bar{y} - 1\|_Z^2 + \frac{1}{2\delta} \|\hat{w} + k(\bar{y}_t)^2\|_W^2 \end{aligned}$$

8.  $\rightsquigarrow \hat{u} = \bar{u}, \quad k(\hat{y}_t)^2 = \hat{w} = -k(\bar{y}_t)^2, \quad 1 - k\hat{y} = \hat{z} = 1 - k\bar{y}$

# Passing to the limit: minimizers

8.  $\rightsquigarrow \hat{u} = \bar{u}, \quad k(\hat{y}_t)^2 = \hat{w} = -k(\bar{y}_t)^2, \quad 1 - k\hat{y} = \hat{z} = 1 - k\bar{y}$
9.  $\rightsquigarrow$  strong convergence of  $u_\varepsilon, w_\varepsilon, z_\varepsilon$

- $u_\varepsilon \rightarrow \bar{u}$  in  $U$
- $w_\varepsilon \rightarrow k(\bar{y}_t)^2$  in  $W$
- $z_\varepsilon \rightarrow 1 - k\bar{y}$  in  $Z$
- $y_\varepsilon \rightarrow \bar{y}$  pointwise

# Passing to the limit: optimality system

Consider optimality system for  $x_\varepsilon = (u_\varepsilon, y_\varepsilon, z_\varepsilon, w_\varepsilon)$  as  $\varepsilon \rightarrow 0$

1. Stationarity in  $z_\varepsilon, w_\varepsilon$ :

$$\begin{aligned} \frac{1}{\varepsilon} \langle z_\varepsilon + ky_\varepsilon - 1, kv \rangle_Z &= -\frac{1}{\delta} \langle z_\varepsilon + k\bar{y} - 1, kv \rangle_Z - \langle (y_\varepsilon)_{tt} p_\varepsilon, kv \rangle \\ &\quad + \mu_\varepsilon^+(kv) - \mu_\varepsilon^-(kv) \end{aligned}$$

$$\begin{aligned} \frac{1}{\varepsilon} \langle w_\varepsilon + k(y_\varepsilon)_t^2, 2k(y_\varepsilon)_t v_t \rangle_W &= -\frac{1}{\delta} \langle w_\varepsilon + k(\bar{y}_t)^2, 2k(y_\varepsilon)_t v_t \rangle_W \\ &\quad - \langle p_\varepsilon, 2k(y_\varepsilon)_t v_t \rangle \end{aligned}$$

2. Insert in relaxed adjoint equation:

# Passing to the limit: optimality system

2. Insert in relaxed adjoint equation:

$$\begin{aligned} & \langle z_\varepsilon p_\varepsilon, v_{tt} \rangle + \langle c^2 \nabla p_\varepsilon, \nabla v \rangle + \langle b \nabla p_\varepsilon, \nabla v \rangle + \langle dp_\varepsilon, v_t \rangle \\ & + \langle cp_\varepsilon, v_t \rangle_{\hat{F}} + \langle \frac{b}{c} p_\varepsilon, v_{tt} \rangle_{\hat{F}} = \langle y^d - y_\varepsilon, v \rangle \\ & + \frac{1}{\delta} \langle z_\varepsilon + k\bar{y} - 1, kv \rangle_Z + \langle (y_\varepsilon)_{tt} p_\varepsilon, kv \rangle \\ & + \mu_\varepsilon^+(kv) - \mu_\varepsilon^-(kv) \\ & + \frac{1}{\delta} \langle w_\varepsilon + k(\bar{y}_t)^2, 2k(y_\varepsilon)_t v_t \rangle_W + \langle p_\varepsilon, 2k(y_\varepsilon)_t v_t \rangle \\ & - 2\lambda_\varepsilon \langle \|(y_\varepsilon)_t(t)\|_{L^2}^2 (y_\varepsilon)_t, v_t \rangle \end{aligned}$$

# Passing to the limit: optimality system

3. First: assume  $\{p_\varepsilon, \mu_\varepsilon^+, \mu_\varepsilon^-, \lambda_\varepsilon\}_{\varepsilon>0}$  bounded  $\rightsquigarrow$  subsequence

$$p_{\varepsilon_n} \rightharpoonup \bar{p}, \quad \mu_{\varepsilon_n}^+ \rightharpoonup^\star \bar{\mu}^+, \quad \mu_{\varepsilon_n}^- \rightharpoonup^\star \bar{\mu}^-, \quad \lambda_\varepsilon \rightarrow \bar{\lambda}$$

4. Strong convergence of  $y_\varepsilon, z_\varepsilon, w_\varepsilon$  (and embeddings)

## Adjoint equation

$$\begin{aligned} & \langle (1 - k\bar{y})\bar{p}, v_{tt} \rangle + \langle c^2 \nabla \bar{p}, \nabla v \rangle + \langle b \nabla \bar{p}, \nabla v \rangle + \langle d\bar{p}, v_t \rangle \\ & + \langle c\bar{p}, v_t \rangle_{\hat{F}} + \langle \frac{b}{c}\bar{p}, v_{tt} \rangle_{\hat{F}} + \langle 2k\bar{y}_t \bar{p}, v_t \rangle + \langle k\bar{y}_{tt} \bar{p}, v_t \rangle \\ & = \langle y^d - \bar{y}, v \rangle + \bar{\mu}^+(kv) - \bar{\mu}^-(kv) \\ & - 2\lambda_\varepsilon \langle \|(\bar{y})_t(t)\|_{L^2}^2 (\bar{y})_t, v_t \rangle \end{aligned}$$

# Passing to the limit: optimality system

3. First: assume  $\{p_\varepsilon, \mu_\varepsilon^+, \mu_\varepsilon^-, \lambda_\varepsilon\}_{\varepsilon>0}$  bounded  $\rightsquigarrow$  subsequence

$$p_{\varepsilon_n} \rightharpoonup \bar{p}, \quad \mu_{\varepsilon_n}^+ \rightharpoonup^\star \bar{\mu}^+, \quad \mu_{\varepsilon_n}^- \rightharpoonup^\star \bar{\mu}^-, \quad \lambda_\varepsilon \rightarrow \bar{\lambda}$$

4. Strong convergence of  $y_\varepsilon, z_\varepsilon, w_\varepsilon$  (and embeddings)

## Optimality

$$\langle \alpha \bar{u}, v \rangle_U = \langle c^2 \bar{p}, v \rangle_\Gamma + \langle b \bar{p}, v_t \rangle_\Gamma$$

## Complementarity

$$\begin{aligned} \bar{\mu}^+(\bar{y} - \bar{y}^+) &= 0, & \bar{\mu}^-(\bar{y} + \bar{y}^-) &= 0, \\ \bar{\lambda}(\|\bar{y}_t\|_{L^2}^2 - M) &= 0 \end{aligned}$$

# Passing to the limit: optimality system

5. If  $\{p_\varepsilon, \mu_\varepsilon^+, \mu_\varepsilon^-, \lambda_\varepsilon\}_{\varepsilon>0}$  not bounded: define

$$r_\varepsilon := \|p_\varepsilon\|_P + \|\mu_\varepsilon^+\|_{\mathcal{M}} + \|\mu_\varepsilon^-\|_{\mathcal{M}} + |\lambda_\varepsilon|$$

$$\{\underline{p}_\varepsilon, \underline{\mu}_\varepsilon^+, \underline{\mu}_\varepsilon^-, \underline{\lambda}_\varepsilon\}_{\varepsilon>0} := \{p_\varepsilon/r_\varepsilon, \mu_\varepsilon^+/r_\varepsilon, \mu_\varepsilon^-/r_\varepsilon, \lambda_\varepsilon/r_\varepsilon\}_{\varepsilon>0}$$

6.  $\rightsquigarrow$  bounded; subsequence converges to  $(\bar{p}, \bar{\mu}^+, \bar{\mu}^-, \bar{\lambda})$
7. Insert in relaxed adjoint equation

# Passing to the limit: optimality system

6.  $\rightsquigarrow$  bounded; subsequence converges to  $(\bar{p}, \bar{\mu}^+, \bar{\mu}^-, \bar{\lambda})$

7. Insert in relaxed adjoint equation

$$\begin{aligned} & \langle z_\varepsilon p_\varepsilon, v_{tt} \rangle + \langle c^2 \nabla p_\varepsilon, \nabla v \rangle + \langle b \nabla p_\varepsilon, \nabla v \rangle + \langle d p_\varepsilon, v_t \rangle \\ & + \langle c p_\varepsilon, v_t \rangle_{\hat{\Gamma}} + \langle \frac{b}{c} p_\varepsilon, v_{tt} \rangle_{\hat{\Gamma}} = \frac{1}{r_\varepsilon} \langle y^d - y_\varepsilon, v \rangle \\ & + \frac{1}{r_\varepsilon \delta} \langle z_\varepsilon + k \bar{y} - 1, k v \rangle_Z + \langle (y_\varepsilon)_{tt} p_\varepsilon k, v \rangle \\ & + \underline{\mu}_\varepsilon^+(kv) - \underline{\mu}_\varepsilon^-(kv) \\ & + \frac{1}{r_\varepsilon \delta} \langle w_\varepsilon + k(\bar{y}_t)^2, 2k(y_\varepsilon)_t v_t \rangle_W + \langle p_\varepsilon, 2k(y_\varepsilon)_t v_t \rangle \\ & - 2\underline{\lambda}_\varepsilon \langle \|(y_\varepsilon)_t(t)\|_{L^2}^2 (y_\varepsilon)_t, v_t \rangle \end{aligned}$$

# Passing to the limit: optimality system

6.  $\rightsquigarrow$  bounded; subsequence converges to  $(\bar{p}, \bar{\mu}^+, \bar{\mu}^-, \bar{\lambda})$
7. Insert in relaxed adjoint equation

## Adjoint equation

$$\begin{aligned}\langle (1 - k\bar{y})\bar{p}, v_{tt} \rangle + \langle c^2 \nabla \bar{p}, \nabla v \rangle + \langle b \nabla \bar{p}, \nabla v \rangle + \langle d\bar{p}, v_t \rangle \\ + \langle c\bar{p}, v_t \rangle_{\hat{F}} + \langle \frac{b}{c}\bar{p}, v_{tt} \rangle_{\hat{F}} + \langle 2k\bar{y}_t \bar{p}, v_t \rangle + \langle k\bar{y}_{tt} \bar{p}, v_t \rangle \\ = \bar{\mu}^+(kv) - \bar{\mu}^-(kv) \\ - 2\lambda_\varepsilon \langle \|(\bar{y})_t(t)\|_{L^2}^2 (\bar{y})_t, v_t \rangle\end{aligned}$$

## 8. Insert into relaxed stationarity condition

$$\frac{1}{r_\varepsilon} \langle \alpha u_\varepsilon \rangle_U + \frac{1}{r_\varepsilon \delta} \langle u_\varepsilon - \bar{u}, v \rangle_U = \langle c^2 p_\varepsilon, v \rangle_\Gamma + \langle b p_\varepsilon, v_t \rangle_\Gamma$$

## 8. Insert into relaxed stationarity condition

### Optimality

$$\langle c^2 \bar{p}, v \rangle_{\Gamma} + \langle b \bar{p}, v_t \rangle_{\Gamma} = 0$$

### Complementarity

$$\begin{aligned}\bar{\mu}^+ (\bar{y} - \bar{y}^+) &= 0, & \bar{\mu}^- (\bar{y} + \bar{y}^-) &= 0, \\ \bar{\lambda} (\|\bar{y}_t\|_{L^2}^2 - M) &= 0\end{aligned}$$

Optimal control of singular equation with **state constraints**

- yields **large solution** to Westervelt equation
- requires no smallness assumption on data
- is of **practical interest** (lithotripsy)
- is applicable to other problems in nonlinear acoustics

**Preprints:**

[http://www.uni-due.de/agclason/clason\\_pubs.php](http://www.uni-due.de/agclason/clason_pubs.php)