

Global exponential stability of primal-dual gradient flow dynamics based on the proximal augmented Lagrangian: A Lyapunov-based approach

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Nonsmooth composite minimization

$$\begin{array}{ccc} \text{minimize} & f(x) & + & g(Tx) \\ x & & & \\ & \downarrow & & \downarrow \\ & \text{performance} & & \text{structure} \end{array}$$

T – select coordinates to impose structure

f – strongly convex; Lipschitz cts gradient

g – non-differentiable; convex

Examples

Optimization problem	$g(z)$
minimize $f(x)$ subject to $Tx = b$	$g(z) = \begin{cases} 0, & z = b \\ \infty, & \text{otherwise} \end{cases}$
minimize $f(x)$ subject to $Tx \leq b$	$g(z) = \begin{cases} 0, & z \leq b \\ \infty, & \text{otherwise} \end{cases}$
minimize $f(x) + \gamma \ Tx\ _1$	$g(z) = \gamma \ z\ _1$

Proximal operator and Moreau envelope

Proximal operator

$$\mathbf{prox}_{\mu g}(v) := \underset{z}{\operatorname{argmin}} g(z) + \frac{1}{2\mu} \|z - v\|^2$$

Moreau envelope

$$M_{\mu g}(v) := g(\mathbf{prox}_{\mu g}(v)) + \frac{1}{2\mu} \|\mathbf{prox}_{\mu g}(v) - v\|^2$$

continuously differentiable in v

$$\mu \nabla M_{\mu g}(v) = v - \mathbf{prox}_{\mu g}(v)$$

Augmented Lagrangian

$$\underset{x}{\text{minimize}} \quad f(x) + g(Tx)$$

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$$\underset{x,z}{\text{minimize}} \quad f(x) + g(z)$$

$$\text{subject to} \quad Tx - z = 0$$

Augmented Lagrangian

$$\mathcal{L}_\mu(x, z; y) = f(x) + g(z) + \underbrace{y^T(Tx - z) + \frac{1}{2\mu}\|Tx - z\|^2}_{\text{penalty terms}}$$

$$\mathcal{L}_\mu(x, z; y) = f(x) + g(z) + \underbrace{\frac{1}{2\mu} \|z - (Tx + \mu y)\|^2 - \frac{\mu}{2} \|y\|^2}_{\text{penalty terms}}$$

$$\mathcal{L}_\mu(x, z; y) = f(x) + g(z) + \underbrace{\frac{1}{2\mu} \|z - (Tx + \mu y)\|^2 - \frac{\mu}{2} \|y\|^2}_{\text{penalty terms}}$$

Proximal augmented Lagrangian

$$\mathcal{L}_\mu(x, z; y) = f(x) + \underbrace{g(z) + \frac{1}{2\mu} \|z - (Tx + \mu y)\|^2 - \frac{\mu}{2} \|y\|^2}_{\text{penalty terms}}$$

Minimizer of $\mathcal{L}_\mu(x, z; y)$ over z

$$z_\mu^*(x, y) = \mathbf{prox}_{\mu g}(Tx + \mu y)$$

Evaluate $\mathcal{L}_\mu(x, z; y)$ at z_μ^*

$$\begin{aligned}\mathcal{L}_\mu(x; y) &:= \mathcal{L}_\mu(x, z_\mu^*; y) \\ &= f(x) + M_{\mu g}(Tx + \mu y) - \frac{\mu}{2} \|y\|^2\end{aligned}$$

continuously differentiable in x and y

Primal-dual gradient flow dynamics

Primal-descent dual-ascent

$$\begin{aligned} \begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix} &= \begin{bmatrix} -\nabla_x \mathcal{L}_\mu(x; y) \\ \nabla_y \mathcal{L}_\mu(x; y) \end{bmatrix} \\ &= \begin{bmatrix} -(\nabla f(x) + T^T \nabla M_{\mu g}(Tx + \mu y)) \\ \mu(\nabla M_{\mu g}(Tx + \mu y) - y) \end{bmatrix} \\ &\qquad \qquad \qquad \mu \nabla M_{\mu g}(v) = v - \mathbf{prox}_{\mu g}(v) \end{aligned}$$

- Lipschitz cts RHS
- $\bar{x} = x^*$, $\bar{y} = y^*$ – optimal solution

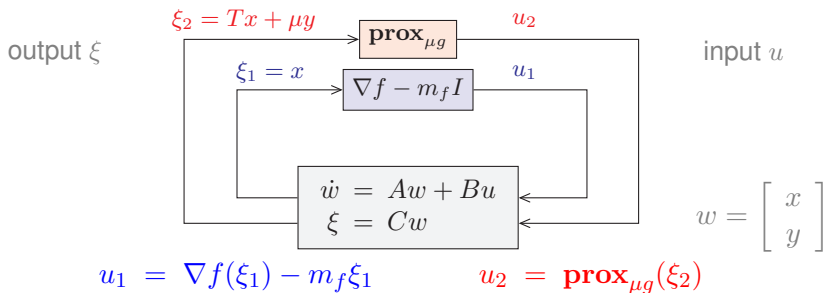
Primal-dual gradient flow dynamics

$$\begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix} = \begin{bmatrix} -(\nabla f(x) + T^T \nabla M_{\mu g}(Tx + \mu y)) \\ \mu(\nabla M_{\mu g}(Tx + \mu y) - y) \end{bmatrix}$$

$$\downarrow \quad \mu \nabla M_{\mu g}(v) = v - \mathbf{prox}_{\mu g}(v)$$

$$\begin{aligned} \begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix} &= \begin{bmatrix} -(m_f I + \frac{1}{\mu} T^T T) & -T^T \\ T & 0 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \\ &\quad - \begin{bmatrix} I \\ 0 \end{bmatrix} (\nabla f(x) - m_f x) \\ &\quad + \begin{bmatrix} \frac{1}{\mu} T^T \\ -I \end{bmatrix} \mathbf{prox}_{\mu g}(Tx + \mu y) \end{aligned}$$

Nonlinear feedback model



LTI system

$$A = \begin{bmatrix} -(m_f I + \frac{1}{\mu} T^T T) & -T^T \\ T & 0 \end{bmatrix}$$

$$B = \begin{bmatrix} -I & \frac{1}{\mu} T^T \\ 0 & -I \end{bmatrix}, \quad C = \begin{bmatrix} I & 0 \\ T & \mu I \end{bmatrix}$$

Quadratic Lyapunov function

$$V(\tilde{w}) = \tilde{w}^T P \tilde{w}$$

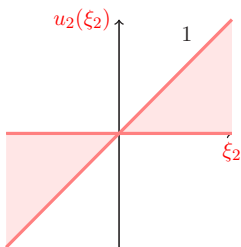
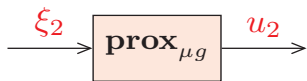
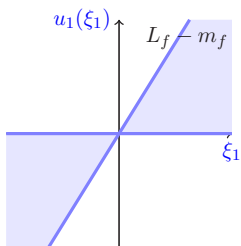
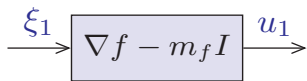
$$P = \alpha \begin{bmatrix} I & \frac{1}{\mu} T^T \\ \frac{1}{\mu} T & (1 + \frac{m_f}{\mu}) I + \frac{1}{\mu^2} T T^T \end{bmatrix} \succ 0$$

A – Hurwitz

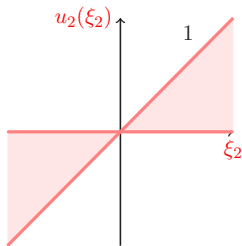
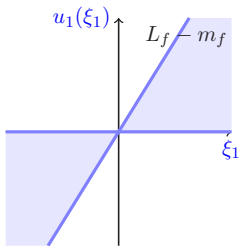
$$A^T P + P A = -2\alpha \begin{bmatrix} m_f I & 0 \\ 0 & (1/\mu) T T^T \end{bmatrix} \prec 0.$$

$$\tilde{w} := w - w^* = \begin{bmatrix} x \\ y \end{bmatrix} - \begin{bmatrix} x^* \\ y^* \end{bmatrix}$$

Sector nonlinearities



Sector nonlinearities



Pointwise quadratic constraints

$$\begin{bmatrix} \xi_i - \xi_i^* \\ u_i - u_i^* \end{bmatrix}^T \underbrace{\begin{bmatrix} 0 & L_i I \\ L_i I & -2I \end{bmatrix}}_{\Pi_i} \begin{bmatrix} \xi_i - \xi_i^* \\ u_i - u_i^* \end{bmatrix} \geq 0$$

Global exponential stability

$$\dot{V} = \begin{bmatrix} \tilde{w} \\ \tilde{u} \end{bmatrix}^T \begin{bmatrix} A^T P + PA & PB \\ B^T P & 0 \end{bmatrix} \begin{bmatrix} \tilde{w} \\ \tilde{u} \end{bmatrix}$$

- Quadratic constraint

$$\begin{bmatrix} \tilde{w} \\ \tilde{u} \end{bmatrix}^T \begin{bmatrix} 0 & C^T \Pi_0 \\ \Pi_0 C & -2\Lambda \end{bmatrix} \begin{bmatrix} \tilde{w} \\ \tilde{u} \end{bmatrix} \geq 0$$

Exponential stability condition

$$\begin{bmatrix} -(A^T P + PA + 2\rho P) & -(PB + C^T \Pi_0) \\ -(PB + C^T \Pi_0)^T & 2\Lambda \end{bmatrix} \succcurlyeq 0$$

Exponential convergence rate

$$\begin{bmatrix} -(A^T P + PA + 2\rho P) & -(PB + C^T \Pi_0) \\ -(PB + C^T \Pi_0)^T & 2\Lambda \end{bmatrix} \succeq 0$$
$$\begin{bmatrix} \tilde{w} \\ \tilde{u} \end{bmatrix}^T \quad \Downarrow \quad \begin{bmatrix} \tilde{w} \\ \tilde{u} \end{bmatrix}$$
$$\dot{V} \leq -2\rho V$$

Exponential decay

$$\|w(t) - w^*\| \leq \sqrt{\kappa_P} e^{-\rho t} \|w(0) - w^*\|$$

Main result

Global exponential stability with rate $\rho > 0$

$$\|w(t) - w^*\| \leq \sqrt{\kappa_P} e^{-\rho t} \|w(0) - w^*\|$$

$$\rho \geq \rho_0(\mu) := \frac{1}{2} \frac{\sigma_{\min}(T)}{\mu + m_f + \frac{\sigma_{\max}(T)}{\mu}}$$

- $\mu \geq \max(L_f - m_f, \hat{\mu})$

- ▶ $\hat{\mu} \geq \sigma_{\max}(T)$

- ▶ $2m_f \geq \frac{\sigma_{\max}^2(T)}{2\hat{\mu}} \left(1 + \frac{m_f}{\hat{\mu}}\right) + \frac{8\rho_0(\hat{\mu})^2}{\hat{\mu}} + 2\rho_0(\hat{\mu})$

Example

$$\begin{aligned} & \underset{x}{\text{minimize}} && \frac{1}{2}x^T Qx + q^T x \\ & \text{subject to} && Tx \leq b \end{aligned}$$

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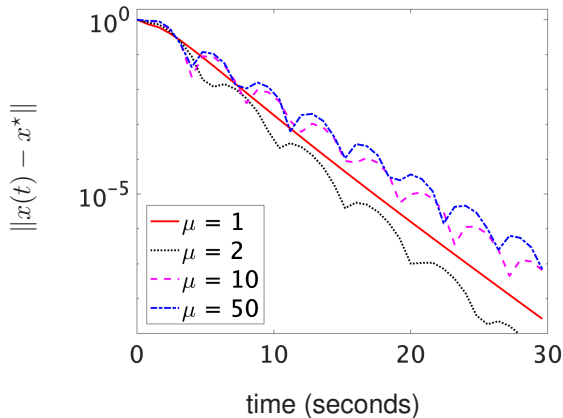
$$\begin{aligned} & \underset{x, z}{\text{minimize}} && f(x) + g(z) \\ & \text{subject to} && Tx - z = 0 \end{aligned}$$

$$f(x) = \frac{1}{2}x^T Qx + q^T x$$

$$g(z) = \{0, z \leq b; \infty, \text{otherwise}\}$$

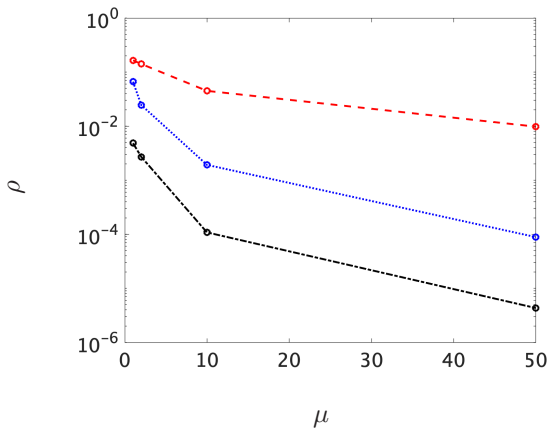
Exponential convergence

$$\kappa_Q \approx 1.2$$



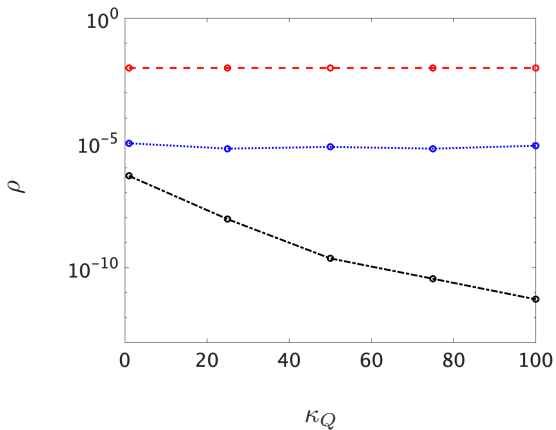
Convergence rate (I)

$$\kappa_Q \approx 1.2$$



--- Our estimation (Ding, Jovanović, 19) -.-.- (Qu, Li, 19)

Convergence rate (II)



--- Our estimation (Ding, Jovanović, 19) - - - - (Qu, Li, 19)

Summary

Primal-dual gradient flow dynamics

- Lyapunov-based convergence analysis
- Less conservative rates

Future work

- Optimal convergence rate
- Other optimization problems

THANK YOU!