Accelerated Primal-Dual Methods for Convex-Strongly-Concave Saddle Point Problems

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Problem Definition and Important Measures

- Saddle Point Problem

$$\mathcal{L}(x, y) := \min_{x \in X} \max_{y \in Y} f(x) + \phi(x, y) - g(y). \tag{1}$$

- Gap function at $\bar{z} = (\bar{x}, \bar{y})$

$$Gap(\bar{z}) = \max_{z \in X \times Y} \{Q(\bar{z}, z) := \mathcal{L}(\bar{x}, y) - \mathcal{L}(x, \bar{y})\}.$$

Assumptions

$\phi(\cdot, y)$ is L_{xx}-smooth, $\phi(x, \cdot)$ is L_{yy}-smooth and ϕ is L_{xy}-smooth, if the followings hold for all $x, x' \in X,\ y, y' \in Y$ respectively:

$$\begin{aligned}
\|\nabla_x \phi(x', y) - \nabla_x \phi(x, y)\| &\leq L_{xx}\|x' - x\|, \\
\|\nabla_y \phi(x, y') - \nabla_y \phi(x, y)\| &\leq L_{yy}\|y' - y\|, \\
\|\nabla_y \phi(x', y) - \nabla_y \phi(x, y)\| &\leq L_{xy}\|x' - x\|.
\end{aligned}$$

Motivation of Study

In many problems, the following function is a nonsmooth function which is hard to optimize.

$$P(x) : f(x) + \max_{y \in Y} \phi(x, y). \tag{2}$$

1. One way to smoothen this function is to use Nesterov's smoothing technique. This technique involves subtracting a strongly convex regularizing function, resulting in a convex-strongly-concave SPP.
2. We assume that $f(x)$ is an easy function to evaluate. This might not be true in many cases. Hence, linearization of f might be a good approach to handle this problem.
3. A popular approach is using a linearized primal-dual method (LPD).

Linearized Primal-Dual method

Algorithm Linearized PD (LPD) method

1: **Initialize** $\tilde{x}_1 = x_1 \in X,\ \ y_1 \in Y$
2: **for** $t = 1, \ldots, K$ **do**
3: $\quad y_{t+1} \leftarrow \arg\min_{y \in Y} \langle -A\tilde{x}_t, y \rangle + g(y) + \frac{1}{2\tau_t}\|y - y_t\|^2$
4: $\quad x_{t+1} \leftarrow \arg\min_{x \in X} \langle \nabla f(x_t) + A^\top y_{t+1}, x \rangle + \frac{1}{2\eta_t}\|x - x_t\|^2$
5: $\quad \tilde{x}_{t+1} \leftarrow x_{t+1} + \theta_t(x_{t+1} - x_t)$
6: **end for**
7: **return** $\bar{x}_{K+1} = \frac{\sum_{t=1}^K \gamma_{t+1} x_{t+1}}{\sum_{t=1}^K \gamma_{t+1}}, \bar{y}_{K+1} = \frac{\sum_{t=1}^K \gamma_{t+1} y_{t+1}}{\sum_{t=1}^K \gamma_{t+1}}$

Convergence analysis of LPD

Theorem

For a μ_f-strongly-convex-concave bilinear SPP, LPD has the optimal convergence rate of $\mathcal{O}(\frac{L_f+\|A\|^2}{K^2})$, and for a μ_g-strongly-concave-convex bilinear SPP, it has convergence rate of $\mathcal{O}(\frac{L_f}{K}+\frac{\|A\|^2}{K^2})$ where f is L_f-smooth.

- **Observation**: Strong concavity can not handle the errors caused by the linearization of f.

Accelerated LPD (ALPD)

Algorithm Accelerated Linearized PD (ALPD) method

1: **Initialize** $\bar{x}_1 = x_0 = x_1 \in X, \bar{y}_1 = y_0 = y_1 \in Y$
2: **for** $t = 1, \ldots, K$ **do**
3: $\quad \underline{x}_t \leftarrow (1 - \beta_t^{-1})\bar{x}_t + \beta_t^{-1} x_t$
4: $\quad v_t \leftarrow (1 + \theta_t)\nabla_y \phi(x_t, y_t) - \theta_t \nabla_y \phi(x_{t-1}, y_{t-1})$
5: $\quad y_{t+1} \leftarrow \arg\min_{y \in Y} \langle -v_t + \nabla g(y_t), y \rangle + \frac{1}{2\tau_t}\|y - y_t\|^2$
6: $\quad x_{t+1} \leftarrow \arg\min_{x \in X} \langle \nabla f(\underline{x}_t) + \nabla_x \phi(x_t, y_{t+1}), x \rangle + \frac{1}{2\eta_t}\|x - x_t\|^2$
7: $\quad \bar{x}_{t+1} = (1 - \beta_t^{-1})\bar{x}_t + \beta_t^{-1} x_{t+1}$
8: $\quad \bar{y}_{t+1} = (1 - \beta_t^{-1})\bar{y}_t + \beta_t^{-1} y_{t+1}$
9: **end for**
10: **return** $\bar{x}_{K+1}, \bar{y}_{K+1}$

Convergence rates of ALPD for semi-linear and nonlinear coupling

Theorem

- *Case 1: Semi-linear ϕ with $L_{xx} = 0$:*

$$\max_{z \in X \times Y} \{Q(\bar{z}_{K+1})\} = \mathcal{O}\left(\frac{L_f + L_{yy}}{K^2} + \frac{L_{xy}^2}{\mu_g K^2}\right)$$

- *Case 2: nonlinear ϕ with $L_{xx} > 0$:*

$$\max_{z \in X \times Y} \{Q(\bar{z}_{K+1})\} = \mathcal{O}\left(\frac{L_f + L_{yy}}{K^2} + \frac{L_{xy}^2}{\mu_g K^2} + \frac{L_{xx}}{K}\right)$$

- ALPD is not optimal at full nonlinearity.

Inexact ALPD

Algorithm Inexact ALPD Method

Initialize $\bar{x}_1 = x_0 = x_1 \in X, \bar{y}_1 = y_0 = y_1 \in Y$
for $t = 1, \ldots, K$ **do**
  $\underline{x}_t \leftarrow (1 - \beta_t^{-1})\bar{x}_t + \beta_t^{-1} x_t$
  $v_t \leftarrow (1 + \theta_t)\nabla_y \phi(x_t, y_t) - \theta_t \nabla_y \phi(x_{t-1}, y_{t-1})$
  $y_{t+1} \leftarrow \arg\min_{y \in Y} \langle -v_t + \nabla g(y_t), y \rangle + \frac{1}{2\tau_t}\|y - y_t\|^2$
  x_{t+1} is a δ_t-approximate solution of the problem:

$$\min_{x \in X} \langle \nabla f(\underline{x}_t), x \rangle + \phi(x, y_{t+1}) + \frac{1}{2\eta_t}\|x - x_t\|^2$$

  $\bar{x}_{t+1} \leftarrow (1 - \beta_t^{-1})\bar{x}_t + \beta_t^{-1} x_{t+1}$
  $\bar{y}_{t+1} \leftarrow (1 - \beta_t^{-1})\bar{y}_t + \beta_t^{-1} y_{t+1}$
end for
return $\bar{x}_{K+1}, \bar{y}_{K+1}$

Complexity analysis of inexact ALPD

Theorem

Inexact ALPD requires $\mathcal{O}(\sqrt{\frac{L_f+L_{yy}}{\epsilon}})$ gradient evaluation of ∇f and $\nabla_y \phi$, and requires $\mathcal{O}(\frac{\sqrt{L_{xx}}}{\epsilon^{3/4}}\log(\frac{1}{\epsilon})) = \tilde{\mathcal{O}}(\frac{\sqrt{L_{xx}}}{\epsilon^{3/4}})$ gradient evaluation of $\nabla_x \phi$. Hence, the gradient complexity of $\nabla_x \phi$ improves significantly (c.f. $\mathcal{O}(\frac{L_{xx}}{\epsilon})$ gradient complexity in ALPD).

Numerical Experiment: ALPD vs. LPD

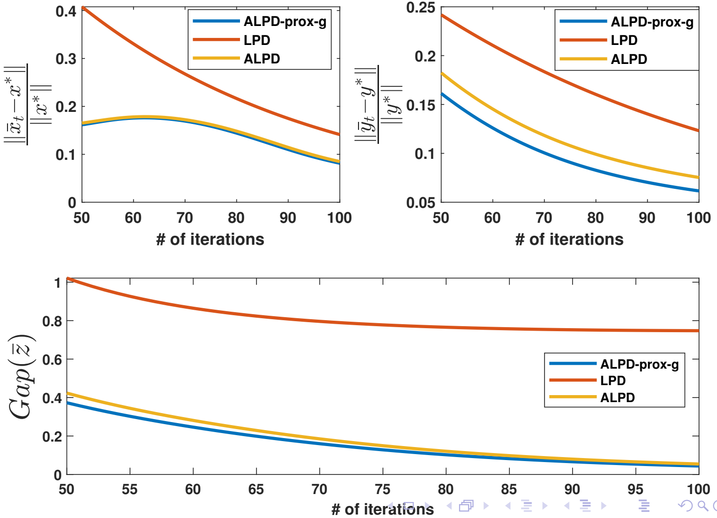
The ℓ_q-norm penalty problem with linear constraints is

$$\min_{x \in X} f(x) + \rho \|Ax - b\|_q \equiv \min_{x \in X} \max_{\|y\|_p \le 1} f(x) + \rho \langle y, Ax - b \rangle,$$

Smooth approximation of the nonsmooth penalty term using Nesterov's smoothing technique:

$$\min_{x \in X} \max_{\|y\|_p \le 1} \{ f(x) + \rho \langle y, Ax - b \rangle - \tfrac{\mu_g}{2} \|y\|^2 \}, \tag{3}$$

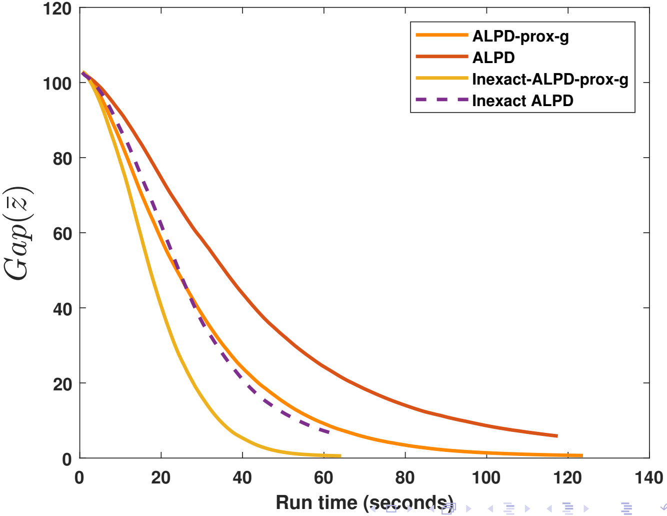
Numerical Experiment: ALPD vs. LPD



Numerical Experiment: ALPD vs. Inexact ALPD

- Consider a penalty problem with non-linear constraints.
- The corresponding coupling function in SPP becomes nonlinear ($L_{xx} > 0$)

Numerical Experiment: ALPD vs. Inexact ALPD



Conclusion

Table 1: Comparison of our work. Gradient complexity is for obtaining an ϵ error in gap function.

	Coupling	Linearizing f	Gradient Complexity	
			$\mu_f > 0$	$\mu_g > 0$
(Chambolle & Pock, 2011)	bilinear	No	$\mathcal{O}(\frac{1}{\sqrt{\epsilon}})$	NA
(Chambolle & Pock, 2016)	bilinear	Yes	$\mathcal{O}(\frac{1}{\sqrt{\epsilon}})$	NA
(Hamedani & Aybat, 2021)	semi-linear	No	$\mathcal{O}(\frac{1}{\sqrt{\epsilon}})$	NA
(Thekumparampil et al., 2022)	bilinear	Yes	NA	$\mathcal{O}(\sqrt{\frac{L_f}{\epsilon}} + \frac{\\|A\\|}{\sqrt{\mu_g \epsilon}})$
LPD (Algorithm 1)	bilinear	Yes	$\mathcal{O}(\frac{1}{\sqrt{\epsilon}})$	$\mathcal{O}(\frac{L_f}{\epsilon} + \frac{\\|A\\|}{\sqrt{\mu_g \epsilon}})$
ALPD (Algorithm 2)	semi-linear	Yes	NA	$\mathcal{O}(\sqrt{\frac{L_f+L_{yy}}{\epsilon}} + \frac{L_{xy}}{\sqrt{\mu_g \epsilon}})$
	general			$\mathcal{O}(\sqrt{\frac{L_f+L_{yy}}{\epsilon}} + \frac{L_{xy}}{\sqrt{\mu_g \epsilon}} + \frac{L_{xx}}{\epsilon})$
Inexact ALPD (Algorithm 3)	general	Yes	NA	For $\nabla f, \nabla_y \phi:\ \mathcal{O}(\sqrt{\frac{L_f+L_{yy}}{\epsilon}} + \frac{L_{xy}}{\sqrt{\mu_g \epsilon}})$ For $\nabla_x \phi:\ \mathcal{O}(\frac{\sqrt{L_{xx}\sqrt{L_f+L_{xy}^2/\mu_g}}}{\epsilon^{3/4}} \log(\frac{1}{\epsilon}))$

- Thanks!
- Question?