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Stochastic Primal Dual Hybrid Gradient Algorithm with Adaptive Step-Sizes

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Abstract

In this work we propose a new primal-dual algorithm with adaptive step-sizes. The stochastic primal-dual hybrid gradient (SPDHG) algorithm with constant step-sizes has become widely applied in large-scale convex optimization across many scientific fields due to its scalability. While the product of the primal and dual step-sizes is subject to an upper-bound in order to ensure convergence, the selection of the ratio of the step-sizes is critical in applications. Up-to-now there is no systematic and successful way of selecting the primal and dual step-sizes for SPDHG. In this work, we propose a general class of adaptive SPDHG (A-SPDHG) algorithms, and prove their convergence under weak assumptions. We also propose concrete parameters-updating strategies which satisfy the assumptions of our theory and thereby lead to convergent algorithms. Numerical examples on computed tomography demonstrate the effectiveness of the proposed schemes.

1 Introduction

The stochastic primal-dual hybrid gradient (SPDHG) algorithm introduced in [8] is a stochastic version of the primal-dual hybrid gradient (PDHG) algorithm, also known as Chambolle–Pock algorithm [9]. SPDHG has proved efficient in the framework of large-scale convex optimisation, in particular in the field of inverse problems [13, 21, 23, 26]. Like PDHG, SPDHG is convergent if the product of the primal and dual step-sizes is not too large. The ratio of the step-sizes is a free parameter and can be interpreted as a control on the balance between convergence of the primal and dual variable. Empirical observations have shown that the ratio has a strong impact on the convergence speed [12], however it is not clear how to choose said ratio in practice.

In this work we propose a variant of SPDHG with adaptive step-sizes, allowing online tuning of the ratio of the step-size parameters. We prove that a very broad class of strategies to adaptively

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choose the step-size parameters leads to a convergent algorithm. Moreover, we propose concrete strategies to adapt the ratio which satisfy to our theoretical conditions on convergence.

Similar work has been undertaken for the deterministic PDHG [14, 20], and empirically tested for SPDHG applied to Magnetic Particle Imaging [26], albeit without convergence proof. Because SPDHG is stochastic, new concepts are required for the convergence proof. We build on almost-sure convergence proofs [1, 16] by introducing the concept of C -stability, which generalises the notion of Féjer-monotonicity [2, 10, 11], and investigating its properties for random sequences in a variable metric framework.

More broadly, the idea of adaptive step-sizes inducing variable metrics has proved very fruitful to improve convergence speed and bypass the need for explicit model constants, like Lipschitz constants or operator norms in a variety of algorithms, namely gradient methods in [19], subgradient methods in [3] and splitting methods in [4, 5, 6, 7, 18].

Notice that the adaptiveness of the primal-dual balance parameter is different to backtracking procedures, where the goal is to avoid explicit computation of the upper-bound required for convergence. Such a backtracking procedure has been developed for PDHG [14, 20] but not for SPDHG. For PDHG, variable step-sizes have also been proposed in order to adapt to local smoothness [24].

In Section 2, we introduce SPDHG with adaptive step-sizes, state the convergence theorem, and carry the proof. In Section 3, we propose concrete schemes to implement the adaptiveness, followed by numeric tests on CT data in Section 4. We conclude in Section 5. Finally, Section 6 collects some useful lemmas and proofs.

2 Theory

2.1 Convergence theorem

The variational problem to solve takes the form:

$$\min_{x \in X} \sum_{i=1}^n f_i(A_i x) + g(x),$$

where X and $(Y_i)_{i \in \{1, \dots, n\}}$ are Hilbert spaces, $A_i : X \rightarrow Y_i$ are bounded linear operators, $f_i : Y_i \rightarrow \mathbb{R} \cup \{+\infty\}$ and $g : X \rightarrow \mathbb{R} \cup \{+\infty\}$ are convex functions. We define $Y = Y_1 \times \dots \times Y_n$ with elements $y = (y_1, \dots, y_n)$ and $A : X \rightarrow Y$ such that $Ax = (A_1 x, \dots, A_n x)$. Each iteration of SPDHG involves the selection of a random subset of $\llbracket 1, n \rrbracket := \{1, \dots, n\}$. In this article, we are interested in the serial sampling case, where the random subset is a singleton.

SPDHG with constant step-sizes is described in Algorithm 2.1. Under the condition

$$\tau \sigma_i < \frac{p_i}{\|A_i\|^2}, \quad i \in \llbracket 1, n \rrbracket, \quad (2.1)$$

SPDHG iterates converge almost surely to a solution of the saddle-point problem ([1, 16]):

$$\min_{x \in X} \sup_{y \in Y} \sum_{i=1}^n \langle A_i x, y_i \rangle - f_i^*(y_i) + g(x). \quad (2.2)$$

The set of solution to (2.2) is denoted by \mathcal{C} . Elements (x^*, y^*) of \mathcal{C} are called saddle-points and characterized by

$$A_i \tilde{x} \in \partial f_i^*(\tilde{y}_i), \quad -A_i^* \tilde{y} \in \partial g(\tilde{x}), \quad i \in \llbracket 1, n \rrbracket. \quad (2.3)$$

Algorithm 2.1: SPDHG (constant step-sizes, serial sampling)

Input: dual step-sizes $(\sigma_i)_{i \in \llbracket 1, n \rrbracket}$, primal step-size τ ; probabilities $(p_i)_{i \in \llbracket 1, n \rrbracket}$; primal variable x^0 , dual variable y^0
Initialize $\bar{y}^0 = y^0$
for $k \in \llbracket 0, K - 1 \rrbracket$ **do**
 $x^{k+1} = \text{prox}_{\tau g}(x^k - \tau A^* \bar{y}^k)$
 Randomly pick $i \in \llbracket 1, n \rrbracket$ with probability p_i
 $y_j^{k+1} = \begin{cases} \text{prox}_{\sigma_i f_i^*}(y_i^k + \sigma_i A_i x^{k+1}) & \text{if } j = i \\ y_j^k & \text{if } j \neq i \end{cases}$
 $\bar{y}_j^{k+1} = \begin{cases} y_j^{k+1} + \frac{1}{p_i} (y_j^{k+1} - y_j^k) & \text{if } j = i \\ y_j^k & \text{if } j \neq i \end{cases}$
end for
return x^K

Algorithm 2.2: A-SPDHG (variable step-sizes, serial sampling)

Input: dual step-sizes $(\sigma_i^0)_{i \in \llbracket 1, n \rrbracket}$, primal step-size τ^0 , update rule; probabilities $(p_i)_{i \in \llbracket 1, n \rrbracket}$; primal variable x^0 , dual variable y^0
Initialize $\bar{y}^0 = y^0$
for $k \in \llbracket 0, K - 1 \rrbracket$ **do**
 Determine $(\sigma_i^{k+1})_{i \in \llbracket 1, n \rrbracket}$, τ^{k+1} according to the update rule
 $x^{k+1} = \text{prox}_{\tau^{k+1} g}(x^k - \tau^{k+1} A^* \bar{y}^k)$
 Randomly pick $i \in \llbracket 1, n \rrbracket$ with probability p_i
 $y_j^{k+1} = \begin{cases} \text{prox}_{\sigma_i^{k+1} f_i^*}(y_i^k + \sigma_i^{k+1} A_i x^{k+1}) & \text{if } j = i \\ y_j^k & \text{if } j \neq i \end{cases}$
 $\bar{y}_j^{k+1} = \begin{cases} y_j^{k+1} + \frac{1}{p_j} (y_j^{k+1} - y_j^k) & \text{if } j = i \\ y_j^k & \text{if } j \neq i \end{cases}$
end for
return x^K

We introduce the adaptive stochastic primal-dual hybrid gradient (A-SPDHG) algorithm in Algorithm 2.2. The main theorem, Theorem 2.1 below, gives conditions on the update rule under which A-SPDHG is provably convergent. Plainly speaking, these conditions are threefold:

- (i) the step-sizes for step $k + 1$, $(\sigma_i^{k+1})_{i \in \llbracket 1, n \rrbracket}$ and τ^{k+1} , depend only of the iterates up to step k ,
- (ii) the step-sizes satisfy to a uniform version of condition (2.1),
- (iii) the step-sizes sequences $(\tau^k)_{k \geq 0}$ and $(\sigma_i^k)_{k \geq 0}$ for $i \in \llbracket 1, n \rrbracket$ do not decrease too fast. More precisely, they are uniformly almost surely quasi-increasing in the sense defined below.

In order to state the theorem rigorously, let us introduce some useful notation and definitions. The set of non-negative integers is denoted by \mathbb{N} . For all $k \in \mathbb{N}$, the σ -algebra generated by the iterates up to point k , $\mathcal{F}((x^l, y^l), l \in \llbracket 0, k \rrbracket)$, is denoted by \mathcal{F}^k . We say that a sequence $(u^k)_{k \in \mathbb{N}}$ is $(\mathcal{F}^k)_{k \in \mathbb{N}}$ -adapted if for all $k \in \mathbb{N}$, u^k is measurable with respect to \mathcal{F}^k .

A positive real sequence $(u^k)_{k \in \mathbb{N}}$ is said to be *quasi-increasing* if there exists a sequence $(\eta^k)_{k \in \mathbb{N}}$ with values in $[0, 1)$, called the control on $(u^k)_{k \in \mathbb{N}}$, such that $\sum_{k=1}^{\infty} \eta_k < \infty$ and :

$$u^{k+1} \geq (1 - \eta^k)u^k, \quad k \in \mathbb{N}. \quad (2.4)$$

By extension, we call a random positive real sequence $(u^k)_{k \in \mathbb{N}}$ *uniformly almost surely quasi-increasing* if there exists a deterministic sequence $(\eta^k)_{k \in \mathbb{N}}$ with values in $[0, 1)$ such that $\sum_{k=1}^{\infty} \eta_k < \infty$ and equation (2.4) above holds almost surely (a.s.).

Theorem 2.1 (Convergence of A-SPDHG). *Let X and Y be separable Hilbert spaces, $A_i : X \rightarrow Y_i$ bounded linear operators, $f_i : Y_i \rightarrow \mathbb{R} \cup \{+\infty\}$ and $g : X \rightarrow \mathbb{R} \cup \{+\infty\}$ proper, convex and lower semi-continuous functions for all $i \in \llbracket 1, n \rrbracket$. Assume that the set of saddle-points \mathcal{C} is non-empty and the sampling is proper, that is to say $p_i > 0$ for all $i \in \llbracket 1, n \rrbracket$. If the following conditions are met:*

- (i) *the step-size sequences $(\tau^{k+1})_{k \in \mathbb{N}}$, $(\sigma_i^{k+1})_{k \in \mathbb{N}}$, $i \in \llbracket 1, n \rrbracket$ are $(\mathcal{F}^k)_{k \in \mathbb{N}}$ -adapted,*
- (ii) *there exists $\beta \in (0, 1)$ such that for all index $i \in \llbracket 1, n \rrbracket$ and iterate $k \in \mathbb{N}$,*

$$\tau^k \sigma_i^k \frac{\|A_i\|^2}{p_i} \leq \beta < 1, \quad (2.5)$$

- (iii) *the initial step-sizes τ^0 and σ_i^0 for all index $i \in \llbracket 1, n \rrbracket$ are positive and the step-sizes sequences $(\tau^k)_{k \in \mathbb{N}}$ and $(\sigma_i^k)_{k \in \mathbb{N}}$ for all index $i \in \llbracket 1, n \rrbracket$ are uniformly almost surely quasi-increasing,*

then the sequence of iterates $(x^k, y^k)_{k \in \mathbb{N}}$ converges almost surely to an element of \mathcal{C} .

While the conditions (i)-(iii) are general enough to cover a large range of step-sizes update rules, we will focus in practice on the primal-dual balancing strategy, which consists in scaling the primal and the dual step-sizes by an inverse factor at each iteration. In that case, the update rule depends on a random positive sequence $(\gamma^k)_{k \in \mathbb{N}}$ and reads as:

$$\tau^{k+1} = \frac{\tau^k}{\gamma^k}, \quad \sigma_i^{k+1} = \gamma^k \sigma_i^k, \quad i \in \llbracket 1, n \rrbracket. \quad (2.6)$$

Lemma 2.2 (Primal-dual balancing). *Let the step-sizes sequences satisfy to equation (2.6) and assume in addition that $(\gamma^k)_{k \in \mathbb{N}}$ is $(\mathcal{F}^k)_{k \in \mathbb{N}}$ -adapted, that the initial step-sizes satisfy to*

$$\tau^0 \sigma_i^0 \frac{\|A_i\|^2}{p_i} < 1, \quad i \in \llbracket 1, n \rrbracket,$$

and are positive, that there exists a deterministic sequence $(\epsilon^k)_{k \in \mathbb{N}}$ with values in $[0, 1)$ such that $\sum \epsilon^k < \infty$ and for all $k \in \mathbb{N}$ and $i \in \llbracket 1, n \rrbracket$,

$$\min \{ \gamma^k, (\gamma^k)^{-1} \} \geq 1 - \epsilon^k. \quad (2.7)$$

Then, the step-sizes sequences satisfy to assumptions (i)-(iii) of Theorem 2.1.

Lemma 2.2 is proved in Section 6.

Connection with the literature:

- The primal-dual balancing strategy has been introduced in [14] for PDHG and indeed for $n = 1$ we recover with Lemma 2.2 the non-backtracking algorithm presented in [14]. As a consequence, our theorem also implies the pointwise convergence of this algorithm, whose convergence was established in the sense of vanishing residuals in [14].
- Still for PDHG, [20] proposes without proof an update rule where the ratio of the step-sizes is either quasi non-increasing or quasi non-decreasing. This requirement is similar to but not directly connected with ours, where we ask the step-sizes themselves to be quasi non-increasing.
- For SPDHG, the angular constraint step-size rule proposed without convergence proof in [26] satisfies to assumptions (i)-(iii).

Proof strategy: Theorem 2.1 is proved in the following sub-sections. We first define in Section 2.2 metrics related to the algorithm step-sizes on the primal-dual product space. As the step-sizes are adaptive, we obtain a sequence of metrics. The proof of Theorem 2.1 is then similar in strategy to those of [1] and [16] but requires novel elements to deal with the metrics variability. In Theorem 2.5, we state convergence conditions for an abstract random sequence in a Hilbert space equipped with random variable metrics. In Section 2.4 and Section 2.5 we show that A-SPDHG falls within the scope of Theorem 2.5. We collect all elements and conclude the proof in Section 2.6.

2.2 Variable metrics

For a Hilbert space H , we call $\mathbb{S}(H)$ the set of bounded self-adjoint linear operators from H to H , and for all $M \in \mathbb{S}(H)$ we introduce the notation:

$$\|u\|_M^2 = \langle Mu, u \rangle, \quad u \in H.$$

By an abuse of notation we write $\|\cdot\|_\alpha^2 = \|\cdot\|_{\alpha \text{Id}}^2$ for a scalar $\alpha \in \mathbb{R}$. Notice that $\|\cdot\|_M$ is a norm on H if M is positive definite. Furthermore, we introduce the partial order \preceq on $\mathbb{S}(H)$ such that for $M, N \in \mathbb{S}(H)$,

$$N \preceq M \quad \text{if} \quad \forall u \in H, \|u\|_N \leq \|u\|_M.$$

We call $\mathbb{S}_\alpha(H)$ the subset of $\mathbb{S}(H)$ comprised of M such that $\alpha \text{Id} \preceq M$. Furthermore a random sequence $(M^k)_{k \in \mathbb{N}}$ in $\mathbb{S}(H)$ is said to be *uniformly almost surely quasi-decreasing* if there exists a non-negative sequence $(\eta^k)_{k \in \mathbb{N}}$ such that $\sum_{k=1}^{\infty} \eta_k < \infty$ and a.s.

$$M^{k+1} \preceq (1 + \eta^k)M^k, \quad k \in \mathbb{N}.$$

Coming back to A-SPDHG, let us define for every iteration $k \in \mathbb{N}$ and every index $i \in \llbracket 1, n \rrbracket$ two block operators of $\mathbb{S}(X \times Y_i)$ as:

$$M_i^k = \begin{pmatrix} \frac{1}{\tau^k} \text{Id} & -\frac{1}{p_i} A_i \\ -\frac{1}{p_i} A_i^* & \frac{1}{p_i \sigma_i^k} \text{Id} \end{pmatrix}, \quad N_i^k = \begin{pmatrix} \frac{1}{\tau^k} \text{Id} & 0 \\ 0 & \frac{1}{p_i \sigma_i^k} \text{Id} \end{pmatrix},$$

and a block operator of $\mathbb{S}(X \times Y)$ as:

$$N^k = \begin{pmatrix} \frac{1}{\tau^k} \text{Id} & & & 0 \\ & \ddots & & \\ & & \frac{1}{p_i \sigma_i^k} \text{Id} & \\ 0 & & & \ddots \end{pmatrix}. \quad (2.8)$$

The following lemma translates assumptions (i)-(iii) of Theorem 2.1 on properties on the variable metric sequences.

Lemma 2.3 (Variable metric properties). *(a) Assumption (i) of Theorem 2.1 implies that $(M_i^k)_{k \in \mathbb{N}}, (N_i^k)_{k \in \mathbb{N}}, i \in \llbracket 1, n \rrbracket$ and $(N^k)_{k \in \mathbb{N}}$ are $(\mathcal{F}^k)_{k \in \mathbb{N}}$ -adapted.*

(b) Assumption (ii) of Theorem 2.1 is equivalent to the the existence of $\beta \in (0, 1)$ such that for all index $i \in \llbracket 1, n \rrbracket$ and iterate $k \in \mathbb{N}$,

$$(1 - \beta)N_i^k \preceq M_i^k.$$

(c) Assumption (ii) and (iii) of Theorem 2.1 implies that $(M_i^k)_{k \in \mathbb{N}}, (N_i^k)_{k \in \mathbb{N}}, i \in \llbracket 1, n \rrbracket$ and $(N^k)_{k \in \mathbb{N}}$ are uniformly a.s. quasi-decreasing.

(d) Assumption (ii) and (iii) of Theorem 2.1 imply that there exists $\alpha > 0$ such that for all index $i \in \llbracket 1, n \rrbracket$ and iterate $k \in \mathbb{N}$, $\tau^k > \alpha^{-1}$ and $\sigma_i^k > \alpha^{-1}$, or equivalently that $N_i^k \in \mathbb{S}_\alpha(X \times Y_i)$ for all $i \in \llbracket 1, n \rrbracket$ and $k \in \mathbb{N}$, or equivalently that $N^k \in \mathbb{S}_\alpha(X \times Y)$ for all $k \in \mathbb{N}$.

Remark 2.4 (Step-sizes induced metrics on the primal-dual product space). *The lemma implies that M_i^k, N_i^k and N^k are positive definite, hence induce a metric on the corresponding spaces. If $n = 1$ and for constant step-sizes, M_i^k corresponds to the metric used in [17], where PDHG is reformulated as a proximal point algorithm for a non-trivial metric on the primal-dual product space.*

Proof of Lemma 2.3. Assertion (a) of the lemma follows from the fact that for all iterate $k \in \mathbb{N}$, the operators M_i^k, N_i^k and N^k are in the σ -algebra generated by $\{\tau^k, \sigma_i^k, i \in \llbracket 1, n \rrbracket\}$. Assertion (b) follows from equation (6.2) of Lemma 6.1 to be found in the complementary material. The proof of assertion (c) is a bit more involved. Let us assume that assumption (iii) of Theorem 2.1 holds

and let $(\eta_0^k)_{k \in \mathbb{N}}$ and $(\eta_i^k)_{k \in \mathbb{N}}$ be the controls of $(\tau^k)_{k \in \mathbb{N}}$ and $(\sigma_i^k)_{k \in \mathbb{N}}$ for $i \in \llbracket 1, n \rrbracket$ respectively. We define a common control $(\eta^k)_{k \in \mathbb{N}}$ by:

$$\eta^k = \max \{ \eta_i^k, i \in \llbracket 0, n \rrbracket \}, \quad k \in \mathbb{N}. \quad (2.9)$$

Let us fix $k \in \mathbb{N}$ and $i \in \llbracket 1, n \rrbracket$. It holds almost surely that for all $(x, y_i) \in X \times Y_i$,

$$\begin{aligned} \|x, y_i\|_{N_i^{k+1}}^2 &= \frac{1}{\tau^{k+1}} \|x\|^2 + \frac{1}{\sigma_i^{k+1}} \|y_i\|^2 \\ &\leq \frac{1}{1 - \eta^k} \left(\frac{1}{\tau^k} \|x\|^2 + \frac{1}{\sigma_i^k} \|y_i\|^2 \right) \\ &= \frac{1}{1 - \eta^k} \|x, y_i\|_{N_i^k}^2. \end{aligned}$$

Hence the sequence $(N_i^k)_{k \in \mathbb{N}}$ is uniformly quasi-decreasing with control $((1 - \eta^k)^{-1})_{k \in \mathbb{N}}$, which is indeed a positive sequence with bounded sum. One can see by a similar proof that $(N^k)_{k \in \mathbb{N}}$ is uniformly quasi-decreasing with the same control. To follow with the case of $(M_i^k)_{k \in \mathbb{N}}$, let us first reformulate the desired conclusion. By equation (6.2) of Lemma 6.1, $(M_i^k)_{k \in \mathbb{N}}$ is uniformly quasi-decreasing with control $(\epsilon^k)_{k \in \mathbb{N}}$ if and only if a.s. for all $k \in \mathbb{N}$

$$\begin{aligned} &\begin{pmatrix} \frac{1}{\tau^{k+1}} \text{Id} & -\frac{1}{p_i} A_i \\ -\frac{1}{p_i} A_i^* & \frac{1}{p_i \sigma_i^{k+1}} \text{Id} \end{pmatrix} \preceq (1 + \epsilon^k) \begin{pmatrix} \frac{1}{\tau^k} \text{Id} & -\frac{1}{p_i} A_i \\ -\frac{1}{p_i} A_i^* & \frac{1}{p_i \sigma_i^k} \text{Id} \end{pmatrix} \\ \Leftrightarrow 0 &\preceq \begin{pmatrix} \left(\frac{1+\epsilon^k}{\tau^k} - \frac{1}{\tau^{k+1}} \right) \text{Id} & -\frac{\epsilon^k}{p_i} A_i \\ -\frac{\epsilon^k}{p_i} A_i^* & \left(\frac{1+\epsilon^k}{p_i \sigma_i^k} - \frac{1}{p_i \sigma_i^{k+1}} \right) \text{Id} \end{pmatrix} \\ \Leftrightarrow \tau^k \sigma_i^k \frac{\|A_i\|^2}{p_i} &\frac{(\epsilon^k)^2}{\left(1 + \epsilon^k - \frac{\tau^k}{\tau^{k+1}}\right) \left(1 + \epsilon^k - \frac{\sigma_i^k}{\sigma_i^{k+1}}\right)} \leq 1. \end{aligned} \quad (2.10)$$

Now, by assumption (ii), there exists $\beta \in (0, 1)$ such that $\tau^k \sigma_i^k \|A_i\|^2 p_i^{-1} \leq \beta$ for all $k \in \mathbb{N}$. Let us define

$$\epsilon^k = \lambda^{-1} \left(\frac{1}{1 - \eta^k} - 1 \right), \quad k \in \mathbb{N},$$

with λ a real number such that $0 < \lambda \leq 1 - \sqrt{\beta}$. Then, $(\epsilon^k)_{k \in \mathbb{N}}$ is a positive sequence with bounded sum and it holds that for all $k \in \mathbb{N}$

$$\frac{\tau^k}{\tau^{k+1}} \leq \frac{1}{1 - \eta^{k+1}}, \quad \frac{\sigma_i^k}{\sigma_i^{k+1}} \leq \frac{1}{1 - \eta^{k+1}}, \quad \frac{1}{1 - \eta^{k+1}} = \lambda \epsilon^k + 1.$$

As a consequence, the left-hand side of (2.10) is bounded by above by

$$\beta \frac{(\epsilon^k)^2}{(1 + \epsilon^k - (1 + \lambda \epsilon^k))^2} = \frac{\beta}{(1 - \lambda)^2} \leq 1,$$

hence (2.10) holds and $(M_i^k)_{k \in \mathbb{N}}$ is uniformly quasi-decreasing with control $(\epsilon^k)_{k \in \mathbb{N}}$.

To conclude with the proof of assertion (c), observe that by assumption (ii), the product of the sequences $(\tau^k)_{k \in \mathbb{N}}$ and $(\sigma_i^k)_{k \in \mathbb{N}}$ is almost surely bounded by above. Furthermore, each sequence $(\tau^k)_{k \in \mathbb{N}}$ and $(\sigma_i^k)_{k \in \mathbb{N}}$ is uniformly a.s. quasi-increasing, hence is a.s. bounded by below by the deterministic constant $C = \min \{ \tau^0, \sigma_i^0, i \in \llbracket 1, n \rrbracket \} \prod_{j=1}^{\infty} (1 - \eta^j)$ which is positive as the initial step-sizes are positive and $(\eta^k)_{k \in \mathbb{N}}$ takes values in $[0, 1)$ and has finite sum. As a consequence, each sequence $(\tau^k)_{k \in \mathbb{N}}$ and $(\sigma_i^k)_{k \in \mathbb{N}}$ is a.s. bounded by above by a deterministic constant $\alpha^{-1} > 0$. The equivalence with $N_i^k \in \mathbb{S}_\alpha(X \times Y_i)$ for all $i \in \llbracket 1, n \rrbracket$, and with $N^k \in \mathbb{S}_\alpha(X \times Y)$, is straightforward. \square

2.3 Convergence of random C -stable sequences in random variable metrics

Let H be a Hilbert space and $C \subset H$ a subset of H . Let $(\Omega, \sigma(\Omega), \mathbb{P})$ be a probability space. All random variables in the following are assumed to be defined on Ω and measurable with respect to $\sigma(\Omega)$ unless stated otherwise. Let $(Q^k)_{k \in \mathbb{N}}$ be a random sequence of $\mathbb{S}(H)$.

A random sequence $(u^k)_{k \in \mathbb{N}}$ with values in H is said to be *stable with respect to the target C relative to $(Q^k)_{k \in \mathbb{N}}$* if for all $u \in C$, the sequence $(\|u^k - u\|_{Q^k})_{k \in \mathbb{N}}$ converges almost surely. The following theorem then states sufficient conditions for the convergence of such sequences.

Theorem 2.5 (Convergence of C -stable sequences). *Let H be a separable Hilbert space, C a closed non-empty subset of H , $(Q^k)_{k \in \mathbb{N}}$ a random sequence of $\mathbb{S}(H)$, and $(u^k)_{k \in \mathbb{N}}$ a random sequence of H . If the following conditions are met:*

- (i) $(Q^k)_{k \in \mathbb{N}}$ takes values in $\mathbb{S}_\alpha(H)$ for a given $\alpha > 0$ and is uniformly a.s. quasi-decreasing,
- (ii) $(u^k)_{k \in \mathbb{N}}$ is stable with respect to the target C relative to $(Q^k)_{k \in \mathbb{N}}$,
- (iii) every weak sequential cluster point of $(u^k)_{k \in \mathbb{N}}$ is almost surely in C ,

then $(u^k)_{k \in \mathbb{N}}$ converges almost surely weakly to a random variable in C .

Stability with respect to a target set C is implied by Féjer and quasi-Féjer monotonicity with respect to C , which have been studied either for random sequences ([10]) or in the framework of variable metrics ([11]), but to the best of our knowledge not both at the same time. The proof of Theorem 2.5 follows the same lines than [10, Proposition 2.3 (iii)] and uses two results from [11].

Proof. The set C is a closed subset of the separable Hilbert space H , hence is separable. Let $\{c^n, n \in \mathbb{N}\}$ be a countable set whose closure is equal to C . Thanks to assumption (ii), there exists for all $n \in \mathbb{N}$ a measurable subset $\Omega_{(ii)}^n$ of Ω with probability one such that the sequence $(\|u^k(\omega) - c^n\|_{W^k(\omega)})_{k \in \mathbb{N}}$ converges for all $\omega \in \Omega_{(ii)}^n$. Furthermore, let $\Omega_{(i)}$ and $\Omega_{(iii)}$ be measurable subsets of Ω of probability one corresponding to the almost sure property for assumptions (i) and (iii) respectively. Let

$$\tilde{\Omega} = \left(\bigcap_{n \geq 0} \Omega_{(ii)}^n \right) \cap \Omega_{(i)} \cap \Omega_{(iii)}.$$

As the intersection of a countable number of measurable subsets of probability one, $\tilde{\Omega}$ is itself a measurable set of Ω with $\mathbb{P}(\tilde{\Omega}) = 1$. Fix $\omega \in \tilde{\Omega}$ for the rest of the proof.

The sequence $(Q^k(\omega))_{k \in \mathbb{N}}$ takes values in $\mathbb{S}_\alpha(H)$ for $\alpha > 0$ and is quasi-decreasing with control $(\eta^k(\omega))_{k \in \mathbb{N}}$. Furthermore, for all $k \in \mathbb{N}$,

$$\|Q^k(\omega)\| \leq \left(\prod_{j=0}^{k-1} (1 + \eta^j) \right) \|Q^0(\omega)\| \leq \left(\prod_{j=0}^{\infty} (1 + \eta^j) \right) \|Q^0(\omega)\|,$$

where the product $\prod_{j=0}^{\infty} (1 + \eta^j)$ is finite because $(\eta^k)_{k \in \mathbb{N}}$ is positive and summable. By [11, Lemma 2.3], $(Q^k(\omega))_{k \in \mathbb{N}}$ converges pointwise strongly to some $Q(\omega) \in \mathbb{S}_\alpha(H)$.

Furthermore, for all $x \in C$, there exists a sequence $(x^n)_{n \in \mathbb{N}}$ with values in $\{c^n, n \in \mathbb{N}\}$ converging strongly to x . By assumption, for all $n \in \mathbb{N}$, the sequence $(\|u^k(\omega) - x^n\|_{Q^k(\omega)})_{k \in \mathbb{N}}$ converges to a limit which shall be called $l^n(\omega)$. For all $n \in \mathbb{N}$ and $k \in \mathbb{N}$, we can write thanks to the triangular inequality:

$$-\|x^n - x\|_{Q^k(\omega)} \leq \|u^k(\omega) - x\|_{Q^k(\omega)} - \|u^k(\omega) - x^n\|_{Q^k(\omega)} \leq \|x^n - x\|_{Q^k(\omega)}.$$

By taking the limit $k \rightarrow +\infty$, it follows that:

$$\begin{aligned} -\|x^n - x\|_{Q(\omega)} &\leq \liminf_{k \rightarrow \infty} \|u^k(\omega) - x\|_{Q^k(\omega)} - l^n(\omega) \\ &\leq \limsup_{k \rightarrow \infty} \|u^k(\omega) - x\|_{Q^k(\omega)} - l^n(\omega) \leq \|x^n - x\|_{Q(\omega)}. \end{aligned}$$

Taking now the limit $n \rightarrow +\infty$ shows that the sequence $(\|u^k(\omega) - x\|_{Q^k(\omega)})_{k \in \mathbb{N}}$ converges for all $x \in C$. On the other hand, because $\omega \in \Omega_{(iii)}$, the weak cluster points of $(u^k(\omega))_{k \in \mathbb{N}}$ lie in C . Hence, by [11, Theorem 3.3], the sequence $(u^k(\omega))_{k \in \mathbb{N}}$ converges almost surely to a point $u(\omega) \in C$. \square

We are now equipped to prove Theorem 2.1. We show in Section 2.4 and Section 2.5 that A-SPDHG satisfies to points (ii) and (iii) of Theorem 2.5 respectively and conclude the proof in Section 2.6. Interestingly, the proofs of point (ii) and of point (iii) rely on two different ways of apprehending A-SPDHG. Point (ii) relies on a convex optimisation argument: by taking advantage of the measurability of the primal variable at step $k + 1$ with respect to \mathcal{F}^k , one can write a contraction-type inequality relating the conditional expectation of the iterates' norm at step $k + 1$ to the iterates' norm at step k . Point (iii) relies on monotone operator theory: we use the fact that the update from the half-shifted iterations (y^k, x^{k+1}) to (y^{k+1}, x^{k+2}) can be interpreted as a step of a proximal-point algorithm on $X \times Y_i$ conditionally to i being the index randomly selected at step k .

2.4 A-SPDHG is stable with respect to the set of saddle-points

In this section, we show that $(x^k, y^k)_{k \in \mathbb{N}}$ is stable with respect to \mathcal{C} relative to the variable metrics sequence $(N^k)_{k \in \mathbb{N}}$ defined in equation (2.8) above. We introduce the operators $P \in \mathbb{S}(Y)$ and $\Sigma^k \in \mathbb{S}(Y)$ defined respectively by

$$(Py)_i = p_i y_i, \quad (\Sigma^k y)_i = \sigma_i^k y_i, \quad i \in \llbracket 1, n \rrbracket,$$

and the functionals $(U^k)_{k \in \mathbb{N}}$, $(V^k)_{k \in \mathbb{N}}$ defined for all $(x, y) \in X \times Y$ as:

$$\begin{aligned} U^k(y) &= \|y\|_{(P\Sigma^k)^{-1}}^2, \\ V^k(x, y) &= \|x\|_{(\tau^k)^{-1}}^2 - 2\langle P^{-1}Ax, y \rangle + \|y\|_{(P\Sigma^k)^{-1}}^2. \end{aligned}$$

We begin by recalling the cornerstone inequality satisfied by the iterates of SPDHG stated first in [8] and reformulated in [1].

Lemma 2.6 ([1], Lemma 4.1). *For every saddle-point (x^*, y^*) , it a.s. stands that for all $k \in \mathbb{N} \setminus \{0\}$,*

$$\begin{aligned} &\mathbb{E} [V^{k+1}(x^{k+1} - x^*, y^{k+1} - y^k) + U^{k+1}(y^{k+1} - y^*) | \mathcal{F}^k] \\ &\leq V^{k+1}(x^k - x^*, y^k - y^{k-1}) + U^{k+1}(y^k - y^*) \\ &\quad - V^{k+1}(x^{k+1} - x^k, y^k - y^{k-1}). \end{aligned} \tag{2.11}$$

The second step is to relate the assumptions of Theorem 2.1 to properties of the functionals appearing in (2.11). Let us introduce $Y_{\text{sparse}} \subset Y$ the set of elements (y_1, \dots, y_n) having at most one non-vanishing component.

Lemma 2.7 (Properties of functionals of interest). *Under the assumptions of Theorem 2.1, there exists a non-negative, summable sequence $(\eta^k)_{k \in \mathbb{N}}$ such that a.s. for every iterate $k \in \mathbb{N}$ and $x \in X$, $y \in Y$, $z \in Y_{\text{sparse}}$:*

$$U^{k+1}(y) \leq (1 + \eta^k)U^k(y), \tag{2.12a}$$

$$V^{k+1}(x, z) \leq (1 + \eta^k)V^k(x, z), \tag{2.12b}$$

$$\|(x, z)\|_{N^k}^2 \geq \alpha \|(x, z)\|^2, \tag{2.12c}$$

$$V^k(x, z) \geq (1 - \beta) \|(x, z)\|_{N^k}^2, \tag{2.12d}$$

$$|\langle P^{-1}Ax, z \rangle| \leq \beta \|x\|_{(\tau^k)^{-1}} \|z\|_{(P\Sigma^k)^{-1}}. \tag{2.12e}$$

Proof. Let $(\eta_i^k)_{k \in \mathbb{N}}$ and $(\tilde{\eta}_i^k)_{k \in \mathbb{N}}$ be the controls of $(M_i^k)_{k \in \mathbb{N}}$ and $(N_i^k)_{k \in \mathbb{N}}$ respectively for all $i \in \llbracket 1, n \rrbracket$. We define a common control $(\eta^k)_{k \in \mathbb{N}}$ by:

$$\eta^k = \max \{ \max \{ \eta_i^k, \tilde{\eta}_i^k \}, i \in \llbracket 1, n \rrbracket \}, \quad k \in \mathbb{N}. \tag{2.13}$$

For all $y \in Y$, we can write

$$U^{k+1}(y) = \sum_{i=1}^n \|(0, y_i)\|_{N_i^{k+1}}^2 \leq (1 + \eta^k) \sum_{i=1}^n \|(0, y_i)\|_{N_i^k}^2 = (1 + \eta^k)U^k(y),$$

which proves (2.12a). Let us now fix $x \in X$, $z \in Y_{\text{sparse}}$ and $k \in \mathbb{N}$. By definition, there exists $i \in \llbracket 1, n \rrbracket$ such that $z_j = 0$ for all $j \neq i$. We obtain the inequalities (2.12b)-(2.12d) by writing:

$$V^{k+1}(x, z) = \|(x, z_i)\|_{M_i^{k+1}}^2 \leq (1 + \eta^k) \|(x, z_i)\|_{M_i^k}^2 = (1 + \eta^k)V^k(x, z),$$

$$\|(x, z)\|_{N^k}^2 = \|(x, z_i)\|_{N_i^k}^2 \geq \alpha \|(x, z_i)\|^2 = \|(x, z)\|^2,$$

$$V^k(x, z) = \|(x, z_i)\|_{M_i^k}^2 \geq (1 - \beta) \|(x, z_i)\|_{N_i^k}^2 = (1 - \beta) \|(x, z)\|_{N^k}^2.$$

Finally, let us introduce

$$\widetilde{M}_i^k = \begin{pmatrix} \frac{1}{\tau^k} \text{Id} & \frac{1}{p_i} A_i \\ \frac{1}{p_i} A_i^* & \frac{1}{p_i \sigma_i^k} \text{Id} \end{pmatrix} \in \mathbb{S}(X \times Y_i), \quad i \in \llbracket 1, n \rrbracket.$$

Thanks to Lemma 6.1, we can write that for all $i \in \llbracket 1, n \rrbracket$ and $k \in \mathbb{N}$,

$$M_i^k \succcurlyeq (1 - \beta) N_i^k \Leftrightarrow \tau^k \sigma_i^k \frac{\|A_i\|^2}{p_i} \leq \beta \Leftrightarrow \widetilde{M}_i^k \succcurlyeq (1 - \beta) N_i^k.$$

By the same reasoning as above,

$$\|(x, z_i)\|_{\widetilde{M}_i^k}^2 \geq (1 - \beta) \|(x, z_i)\|_{N_i^k}^2 = (1 - \beta) \|(x, z)\|_{N^k}^2.$$

We observe that

$$\begin{aligned} \langle P^{-1}Ax, z \rangle &= \|(x, z_i)\|_{N_i^k}^2 - \|(x, z_i)\|_{M_i^k}^2 \leq \beta \|(x, z)\|_{N^k}^2, \\ \langle P^{-1}Ax, z \rangle &= \|(x, z_i)\|_{M_i^k}^2 - \|(x, z_i)\|_{N_i^k}^2 \geq -\beta \|(x, z)\|_{N^k}^2, \end{aligned}$$

which proves (2.12e). \square

Lemma 2.8 (A-SPDHG is \mathcal{C} -stable). *Under the assumptions of Theorem 2.1, the sequence $(x^k, y^k)_{k \in \mathbb{N}}$ of Algorithm 2.2 is stable with respect to \mathcal{C} relative to $(N^k)_{k \in \mathbb{N}}$.*

Proof. By definition of A-SPDHG with serial sampling, the difference between two consecutive dual iterates is almost surely sparse:

$$y^k - y^{k-1} \in Y_{\text{sparse}}, \quad k \in \mathbb{N} \setminus \{0\}.$$

Let us define the sequences

$$A^k = V^k(x^k - x^*, y^k - y^{k-1}) + U^k(y^k - y^*), \quad B^k = V^{k+1}(x^{k+1} - x^k, y^k - y^{k-1}),$$

which are a.s. non-negative thanks to (2.12c) and (2.12d). Furthermore, inequalities (2.11), (2.12a) and (2.12b) imply that almost surely for all $k \in \mathbb{N} \setminus \{0\}$,

$$\mathbb{E}[A^{k+1} | \mathcal{F}^k] \leq (1 + \eta^k) A^k - B^k.$$

By Robbins-Siegmund lemma ([22]), (A^k) converges almost surely, $\sup_k \mathbb{E}[A^k] < \infty$ and $\sum_k \mathbb{E}[B^k] < \infty$. From the last point in particular, we can write thanks to (2.12d) and the monotone convergence theorem:

$$\begin{aligned} \mathbb{E} \left[\sum_k \|y^k - y^{k-1}\|_{(P\Sigma^{k+1})^{-1}}^2 \right] &\leq \mathbb{E} \left[\sum_k \|(x^{k+1} - x^k, y^k - y^{k-1})\|_{N^{k+1}}^2 \right] \\ &\leq \mathbb{E} \left[\sum_k B^k \right] = \sum_k \mathbb{E}[B^k] < \infty, \end{aligned}$$

hence $\sum_k \|y^k - y^{k-1}\|_{(P\Sigma^{k+1})^{-1}}^2$ is almost surely finite, thus $\left(\|y^k - y^{k-1}\|_{(P\Sigma^{k+1})^{-1}}^2\right)$ converges almost surely to 0. Furthermore, $\sup_k \mathbb{E}[A^k] < \infty$ hence $\sup_k \|x^k - x^*\|_{(\tau^k)^{-1}}^2$ is finite, and by (2.12e), one can write that for $k \in \mathbb{N} \setminus \{0\}$,

$$\begin{aligned} |\langle P^{-1}A(x^k - x^*), y^k - y^{k-1} \rangle| &\leq \beta \|x^k - x^*\|_{(\tau^{k+1})^{-1}}^2 \|y^k - y^{k-1}\|_{(P\Sigma^{k+1})^{-1}}^2 \\ &\leq \beta(1 + \eta^k) \|x^k - x^*\|_{(\tau^k)^{-1}}^2 \|y^k - y^{k-1}\|_{(P\Sigma^{k+1})^{-1}}^2. \end{aligned}$$

We know that $(\eta^k)^{k \in \mathbb{N}}$ is summable hence converges to 0. As a consequence,

$$|\langle P^{-1}A(x^k - x^*), y^k - y^{k-1} \rangle| \rightarrow 0 \quad \text{almost surely.}$$

To conclude with, thanks to the identity

$$A^k = \|(x^k - x^*, y^k - y^*)\|_{N^k}^2 + \langle P^{-1}A(x^k - x^*), y^k - y^{k-1} \rangle, \quad k \in \mathbb{N} \setminus \{0\},$$

the almost sure convergence of $(A^k)_{k \in \mathbb{N}}$ implies in turn that of $(\|(x^k - x^*, y^k - y^*)\|_{N^k}^2)_{k \in \mathbb{N}}$. \square

As a by-product of the proof, one also obtains the following useful lemma.

Lemma 2.9. *Under the assumptions of Theorem 2.1,*

$$\mathbb{E} \left[\sum_k \|(x^{k+1} - x^k, y^k - y^{k-1})\|^2 \right] < \infty \quad \text{and a.s.} \quad \|x^{k+1} - x^k\| \rightarrow 0.$$

Proof. The first assertion is a straightforward consequence of

$$\mathbb{E} \left[\sum_k B^k \right] = \sum_k \mathbb{E}[B^k] < \infty$$

and bounds (2.12c) and (2.12d). Furthermore, it implies that $\sum_k \|(x^{k+1} - x^k, y^k - y^{k-1})\|^2$ is a.s. finite, hence $(\|(x^{k+1} - x^k, y^k - y^{k-1})\|)$ a.s. converges to 0, and so does $(\|x^{k+1} - x^k\|)$. \square

2.5 Weak cluster points of A-SPDHG are saddle-points

The goal of this section is to prove that A-SPDHG satisfies to point (ii) of Theorem 2.5. For all $i \in \llbracket 1, n \rrbracket$ and positive scalars σ_i and τ , define

$$F_i = \begin{pmatrix} \partial g & A_i^* \\ -A_i & \partial f_i^* \end{pmatrix}, \quad O_i^{\sigma_i, \tau} = \begin{pmatrix} \frac{1}{\tau} \text{Id} & -\frac{1}{\sigma_i} A_i^* \\ -A_i & \frac{1}{\sigma_i} \text{Id} \end{pmatrix}.$$

Lemma 2.10. *Under the assumptions of Theorem 2.1,*

(i) *The operator F_i is maximally monotone for all $i \in \llbracket 1, n \rrbracket$.*

(ii) Let us call $(I^k)_{k \in \mathbb{N}}$ the random index with value in $\llbracket 1, n \rrbracket$ selected at iteration k . For all $i \in \llbracket 1, n \rrbracket$ and $\sigma_i, \tau > 0$, there exists an operator $T_i^{\sigma_i, \tau} : X \times Y_i \rightarrow X \times Y_i$ such that on the event $\{I^k = i\}$,

$$(x^{k+2}, y_i^{k+1}) = T_i^{\sigma_i^{k+1}, \tau^{k+2}}(x^{k+1}, y_i^k). \quad (2.14)$$

(iii) For all $i \in \llbracket 1, n \rrbracket$, scalars $\sigma_i, \tau > 0$ and $(x, y_i) \in X \times Y_i$, the following identity is satisfied:

$$O_i^{\sigma_i, \tau}(T_i^{\sigma_i, \tau}(x, y_i) - (x, y_i)) \in F_i(T_i^{\sigma_i, \tau}(x, y_i)). \quad (2.15)$$

Remark 2.11 (A-SPDHG as a random asymmetric proximal point algorithm). A sequence $(u^k)_{k \in \mathbb{N}}$ of a Hilbert space H satisfying to the variational inequality

$$\langle u - u^{k+1}, F(u^{k+1}) + O(u^{k+1} - u^k) \rangle \geq 0, \quad u \in H, \quad k \in \mathbb{N}, \quad (2.16)$$

can be interpreted as a proximal point algorithm in H equipped with the norm induced by O if F is a strongly monotone operator and O a positive definite self-adjoint linear operator. PDHG satisfies to an identity of the type (2.16) as shown in [17]. For SPDHG, equation (2.15) implies that conditionally on the random index selection, the iterate $u^k = (x^{k+1}, y_i^k)$ satisfies to the variational inequality (2.16) with $F = F^i$ and $O = O_i^{\sigma_i^{k+1}, \tau^{k+2}}$. However the operator $O_i^{\sigma_i, \tau}$ is not self-adjoint, because the extrapolation parameter is $p_i^{-1} \neq 1$. SPDHG can thus be seen as a random asymmetric proximal point algorithm.

Proof of Lemma 2.10. For point (i), observe that F_i is the sum of the two operators

$$\begin{pmatrix} \partial g & 0 \\ 0 & \partial f_i^* \end{pmatrix}, \quad \begin{pmatrix} 0 & A_i^* \\ -A_i & 0 \end{pmatrix}.$$

As by assumption the functionals g and f_i^* are convex, lower semi-continuous and proper, ∂g and ∂f_i^* are strongly monotone and so is the operator on the left. The skew-symmetric bounded linear operator on the right is strongly monotone as shown in [2, example 20.35]. Hence F_i is strongly monotone as the sum of strongly monotone operators.

Let us now prove point (ii). On the event $\{I^k = i\}$, A-SPDHG update procedure can be rewritten as

$$\begin{aligned} y_i^{k+1} &= \text{prox}_{\sigma_i^{k+1} f_i^*}(y_i^k + \sigma_i^{k+1} A_i x^{k+1}), \quad \bar{y}_i^{k+1} = y_i^{k+1} + \frac{1}{p_i}(y_i^{k+1} - y_i^k), \\ x^{k+2} &= \text{prox}_{\tau^{k+2} g}(x^{k+1} - \tau^{k+2} A_i^* \bar{y}_i^{k+1}). \end{aligned}$$

Hence identity (2.14) stands with $T_i^{\sigma_i, \tau}(x, y_i) = (\hat{x}, \hat{y}_i)$ and

$$\hat{x} = \text{prox}_{\tau g} \left(x - \tau A_i^* \left(\hat{y}_i + \frac{1}{p_i}(\hat{y}_i - y_i) \right) \right), \quad \hat{y}_i = \text{prox}_{\sigma_i f_i^*}(y_i + \sigma_i A_i x).$$

Finally for point (iii), observe that the equations above can be rewritten as

$$\begin{aligned} & \begin{cases} x - \tau A^* \left(\hat{y}_i + \frac{1}{p_i} (\hat{y}_i - y_i) \right) - \hat{x} & \in \tau \partial g(\hat{x}) \\ y_i + \sigma_i A_i x - \hat{y}_i & \in \sigma_i \partial f_i^*(\hat{y}_i) \end{cases} \Leftrightarrow \begin{cases} 0 & \in \partial g(\hat{x}) - \frac{1}{\tau} (x - \hat{x}) + A^* \left(\hat{y}_i + \frac{1}{p_i} (\hat{y}_i - y_i) \right) \\ 0 & \in \partial f_i^*(\hat{y}_i) - \frac{1}{\sigma_i} (y_i - \hat{y}_i) - A_i x \end{cases} \\ \Leftrightarrow & \begin{cases} 0 & \in \partial g(\hat{x}) - \frac{1}{\tau} (x - \hat{x}) + \frac{1}{p_i} A^* (\hat{y}_i - y_i) + A^* \hat{y}_i \\ 0 & \in \partial f_i^*(\hat{y}_i) - \frac{1}{\sigma_i} (y_i - \hat{y}_i) - A_i (x - \hat{x}) - A_i \hat{x} \end{cases} \Leftrightarrow \begin{pmatrix} 0 \\ 0 \end{pmatrix} \in F_i \begin{pmatrix} \hat{x} \\ \hat{y}_i \end{pmatrix} - O_i^{\tau, \sigma^i} \begin{pmatrix} \hat{x} - x \\ \hat{y}_i - y_i \end{pmatrix}. \end{aligned}$$

□

Even though the operator $O_i^{\sigma^i, \tau}$ is not auto-adjoint, we can leverage identities (2.14) and (2.15) to obtain the desired result.

Lemma 2.12 (Cluster points of A-SPDHG are saddle points). *Let (\tilde{x}, \tilde{y}) be a random variable almost surely taking its values in the set of weak cluster points of $(x^k, y^k)_{k \in \mathbb{N}}$, and assume that the assumptions of Theorem 2.1 hold. Then (\tilde{x}, \tilde{y}) is a.s. in \mathcal{C} .*

Proof. Thanks to Lemma 2.9, Lemma 2.10 and the monotone convergence theorem,

$$\begin{aligned} \mathbb{E} \left[\sum_k \|(x^{k+1} - x^k, y^k - y^{k-1})\|^2 \right] &= \sum_k \mathbb{E} \left[\|(x^{k+1} - x^k, y^k - y^{k-1})\|^2 \right] \\ &= \sum_k \mathbb{E} \left[\mathbb{E} [\|(x^{k+1} - x^k, y^k - y^{k-1})\|^2 | I^k] \right] \\ &= \sum_k \sum_{i=1}^n \mathbb{P}(I^{k-1} = i) \mathbb{E} \left[\left\| T_i^{\sigma_i^k, \tau^{k+1}}(x^{k+1}, y_i^k) - (x^k, y_i^{k-1}) \right\|^2 \right] \\ &= \sum_{i=1}^n p_i \mathbb{E} \left[\sum_k \left\| T_i^{\sigma_i^k, \tau^{k+1}}(x^{k+1}, y_i^k) - (x^k, y_i^{k-1}) \right\|^2 \right] \\ &< \infty. \end{aligned}$$

Let us fix an index $i \in \llbracket 1, n \rrbracket$. By assumption, p_i is positive, hence the quantity

$$\mathbb{E} \left[\sum_{k \in \mathbb{N}} \left\| T_i^{\sigma_i^k, \tau^{k+1}}(x^{k+1}, y_i^k) - (x^k, y_i^{k-1}) \right\|^2 \right]$$

is finite, hence the series inside the expectation is a.s. finite, and in turn the summand converges almost surely to 0:

$$\left\| T_i^{\sigma_i^k, \tau^{k+1}}(x^{k+1}, y_i^k) - (x^k, y_i^{k-1}) \right\| \rightarrow 0 \quad \text{almost surely.}$$

Let us define

$$\delta_i^k = O_i^k \left(T_i^{\sigma_i^k, \tau^{k+1}}(x^{k+1}, y_i^k) - (x^k, y_i^{k-1}) \right), \quad k \in \mathbb{N} \setminus \{0\}.$$

For all $k \in \mathbb{N}$, one can see that

$$\left\| O_i^{\sigma_i^k, \tau^{k+1}} \right\|^2 \leq 2 \left(\max \left\{ \frac{1}{(\tau^{k+1})^2}, \frac{1}{(\sigma_i^k)^2} \right\} + \frac{\|A_i\|^2}{p_i^2} \right) \leq 2 \left(\alpha^2 + \frac{\|A_i\|^2}{p_i^2} \right) = M^2,$$

where the second bound comes from assumption (ii) of Theorem 2.1. As a consequence,

$$\|\delta_i^k\| \leq M \left\| \left(T_i^{\sigma_i^k, \tau^k} (x^{k+1}, y_i^k) - (x^k, y_i^{k-1}) \right) \right\| \rightarrow 0 \quad \text{almost surely.}$$

Let us now consider a sub-sequence $(x^{k_m}, y^{k_m})_{m \in \mathbb{N}}$ which converges weakly a.s. to (\tilde{x}, \tilde{y}) . By Lemma 2.9, the sequence $(\|x^{k+1} - x^k\|)$ converges a.s. to 0, hence (x^{k_m+1}) converges weakly a.s. to \tilde{x} and $(x^{k_m+1}, y^{k_m})_{m \in \mathbb{N}}$ converges weakly a.s. to (\tilde{x}, \tilde{y}) . By Lemma 2.10, $\delta_i^{k_m} \in F^i(x^{k_m+1}, y^{k_m})$ for every $k_m \in \mathbb{N} \setminus \{0\}$ and F^i is maximally monotone. This implies that a.s. $0 \in F^i(\tilde{x}, \tilde{y})$ [2, Proposition 20.38], that is to say a.s.

$$A_i \tilde{x} \in \partial f_i^*(\tilde{y}_i), \quad -A_i^* \tilde{y} \in \partial g(\tilde{x}).$$

This being true for all $i \in \llbracket 1, n \rrbracket$, (\tilde{x}, \tilde{y}) a.s. satisfies to (2.3) hence is a.s. in \mathcal{C} . \square

2.6 Proof of Theorem 2.1

Under the assumptions of Theorem 2.1, the set \mathcal{C} of saddle-points is closed and non-empty and $X \times Y$ is a separable Hilbert space. By Lemma 2.3, the variable metrics sequence $(N^k)_{k \in \mathbb{N}}$ defined in (2.8) satisfies to condition (i) of Theorem 2.5. Furthermore, the iterates of Algorithm 2.2 comply with condition (ii) and (iii) of Theorem 2.5 by Lemma 2.8 and Lemma 2.12 respectively, hence converge almost surely to a point in \mathcal{C} .

3 Algorithmic Design and Practical Implementations

In this section we present practical instances of our A-SPDHG algorithm, where we specify a step-size adjustment rule which satisfies our assumptions in convergence proof. We extend the adaptive step-size balancing rule for deterministic PDHG, which is proposed by [14], into our stochastic setting, with minibatch approximation to minimize the computational overhead.

We present our first practical implementation in Algorithm 3.1 as our rule-(a), where we estimate the progress of primal and dual via the two sequences p_k and d_k evaluated in each iteration, utilizing the fact that:

$$\mathbb{E}[(x^k - x^{k+1})/\tau_k - \frac{1}{p_i} A_i^*(y_i^k - y_i^{k+1})] \in \partial g(x^{k+1}) + A^* y^{k+1}, \quad (3.1)$$

meanwhile:

$$(y_i^k - y_i^{k+1})/\sigma_k - A_i(x^k - x^{k+1}) \in \partial f_i^*(y_i^{k+1}) - A_i x^{k+1}. \quad (3.2)$$

Hence our v_k and d_k estimate the lengths of the subgradients of the saddle-point objective $g(x) + \sum_i \langle A_i x, y_i \rangle - f_i^*(y_i)$ w.r.t. the primal and dual updates at each iteration. By making them balanced on the fly, we can enforce the algorithm to achieve similar progress in both primal and dual steps, hence improve the convergence. Note that here we adopt the choice of ℓ_1 -norm as the length measure for v_k and d_k as done by Goldstein et al [14, 15], since we also observe numerically the benefit over the more intuitive choice of ℓ_2 -norm.

For full-batch case ($n = 1$), it reduces to the adaptive PDHG proposed by [14, 15]. We adjust the ratio between primal and dual step sizes according to the ratio between p_k and d_k , and whenever the step-sizes changed, we shrink α (which controls the amplitude of the changes) by a factor $\eta \in (0, 1)$

Algorithm 3.1: A-SPDHG, rule (a)

Input: dual step-size σ^0 , primal step-size τ^0 , $s > 0$ (default choice: $s = \|A\|$), $\alpha^0 \in (0, 1)$, $\eta \in (0, 1)$, $\delta > 1$, probabilities $(p_i)_{1 \leq i \leq n}$; primal variable x^0 , dual variable y^0
Initialize $\bar{y}^0 = y^0$, $v^0 = d^0 = 0$
for $k \in \llbracket 0, K - 1 \rrbracket$ **do**
 If $v^k > sd^k \delta$ **then** $\tau^{k+1} = \frac{\tau^k}{1 - \alpha^k}$, $\sigma^{k+1} = \sigma^k(1 - \alpha^k)$, $\alpha^{k+1} = \alpha^k \eta$
 If $v^k < sd^k / \delta$ **then** $\tau^{k+1} = \tau^k(1 - \alpha^k)$, $\sigma^{k+1} = \frac{\sigma^k}{1 - \alpha^k}$, $\alpha^{k+1} = \alpha^k \eta$
 If $sd^k / \delta \leq v^k \leq sd^k \delta$ **then** $\tau^{k+1} = \tau^k$, $\sigma^{k+1} = \sigma^k$, $\alpha^{k+1} = \alpha^k$
 $x^{k+1} = \text{prox}_{\tau^{k+1}g}(x^k - \tau^{k+1}A^*y^k)$
 Randomly pick $i \in \llbracket 1, n \rrbracket$ with probability p_i
 $y_j^{k+1} = \begin{cases} \text{prox}_{\sigma^{k+1}f_i^*}(y_i^k + \sigma^{k+1}A_i x^{k+1}) & \text{if } j = i \\ y_j^k & \text{if } j \neq i \end{cases}$
 $\bar{y}_j^{k+1} = \begin{cases} y_j^{k+1} + \frac{1}{p_i}(y_j^{k+1} - y_j^k) & \text{if } j = i \\ y_j^k & \text{if } j \neq i \end{cases}$
 $v^{k+1} = \|(x^k - x^{k+1})/\tau^{k+1} - \frac{1}{p_i}A_i^*(y_i^k - y_i^{k+1})\|_1$
 $d^{k+1} = \frac{1}{p_i}\|(y_i^k - y_i^{k+1})/\sigma^{k+1} - A_i(x^k - x^{k+1})\|_1$ – or approximate this step by (3.3)
end for
return x^K

– we typically choose $\eta = 0.995$ in our experiments. For the choice of s , we choose $s = \|A\|$ as our default.¹

Noting that unlike the deterministic case which does not have the need of extra matrix-vector multiplication since A^*y^k and Ax^k can be memorized, our stochastic extension will require the computation of $A_i x^k$ since we will sample different subsets between back-to-back iterations with high probability. Assuming that the evaluations of these matrix-vector products dominate the computational cost, we will have a maximum 50% overhead in terms of FLOPs count which is acceptable. Moreover, we found numerically that very often we can further reduce this overhead significantly by approximation tricks such as subsampling:

$$d^{k+1} \approx \frac{\rho}{p_i} \|S^k(y_i^k - y_i^{k+1})/\sigma^{k+1} - (S^k A_i)(x^k - x^{k+1})\|_1 \quad (3.3)$$

with S^k being a random subsampling operator satisfying $\mathbb{E}[(S^k)^T S^k] = \frac{1}{\rho} \text{Id}$. In our experiments we choose 10% subsampling for this approximation hence the overhead is reduced from 50% to only 5% which is negligible.

More recently, Yokota and Hontani [25] propose a variant of adaptive step-size balancing scheme for PDHG, utilizing the angles between the subgradients $\partial g(x^{k+1}) + A^*y^{k+1}$ and the difference of the updates $x^k - x^{k+1}$.

If these two directions are highly aligned, then the primal step size can be increased for bigger step. If these two directions have a large angle, then the primal step-size should be shrunken.

¹The choice of s is crucial for the convergence behavior of rule (a), and we found numerically that it is better to scale with the operator norm $\|A\|$ instead of depending on the range of pixel values suggested in [15].

Algorithm 3.2: A-SPDHG, rule (b)

Input: dual step-size σ^0 , primal step-size τ^0 , $s > 0$ (default choice: $s = \|A\|$), $\alpha^0 \in (0, 1)$, $\eta \in (0, 1)$, $\delta > 1$, probabilities $(p_i)_{1 \leq i \leq n}$; primal variable x^0 , dual variable y^0
Initialize $\bar{y}^0 = y^0$, $w^0 = 0$
for $k \in \llbracket 0, K - 1 \rrbracket$ **do**
 If $w^k \geq c$ **then** $\tau^{k+1} = \frac{\tau^k}{1 - \alpha^k}$, $\sigma^{k+1} = \sigma^k(1 - \alpha^k)$, $\alpha^{k+1} = \alpha^k \eta$
 If $w^k < 0$ **then** $\tau^{k+1} = \tau^k(1 - \alpha^k)$, $\sigma^{k+1} = \frac{\sigma^k}{1 - \alpha^k}$, $\alpha^{k+1} = \alpha^k \eta$
 If $0 \leq w^k < c$ **then** $\tau^{k+1} = \tau^k$, $\sigma^{k+1} = \sigma^k$, $\alpha^{k+1} = \alpha^k$
 $x^{k+1} = \text{prox}_{\tau^{k+1}g}(x^k - \tau^{k+1}A^*y^k)$
 Randomly pick $i \in \llbracket 1, n \rrbracket$ with probability p_i
 $y_j^{k+1} = \begin{cases} \text{prox}_{\sigma^{k+1}f_i^*}(y_i^k + \sigma^{k+1}A_i x^{k+1}) & \text{if } j = i \\ y_j^k & \text{if } j \neq i \end{cases}$
 $\bar{y}_j^{k+1} = \begin{cases} y_j^{k+1} + \frac{1}{p_i}(y_j^{k+1} - y_j^k) & \text{if } j = i \\ y_j^k & \text{if } j \neq i \end{cases}$
 $q^{k+1} = (x^k - x^{k+1})/\tau^{k+1} - \frac{1}{p_i}A_i^*(y_i^k - y_i^{k+1})$
 $w^{k+1} = \langle x^k - x^{k+1}, q^{k+1} \rangle / (\|x^k - x^{k+1}\|_2 \|q^{k+1}\|_2)$
end for
return x^K

By extending this scheme to stochastic setting we obtain another choice of adaptive scheme for SPDHG.

We present this scheme in Algorithm 3.2 as our rule (b). At iteration k , compute:

$$q^{k+1} = (x^k - x^{k+1})/\tau^{k+1} - \frac{1}{p_i}A_i^*(y_i^k - y_i^{k+1}), \quad (3.4)$$

as an unbiased estimate of $\partial g(x^{k+1}) + A^*y^{k+1}$, then measure the cosine of the angle between this and $x^k - x^{k+1}$:

$$w^{k+1} = \frac{\langle x^k - x^{k+1}, q^{k+1} \rangle}{(\|x^k - x^{k+1}\|_2 \|q^{k+1}\|_2)}. \quad (3.5)$$

The threshold c for the cosine value (which triggers the increase of the primal step-size) typically need to be very close to 1 (we recommend $c = 0.999$).

Recently Zdun et al [26] proposed a heuristic similar to our rule (b), but they choose q^{k+1} to be the approximation for an element of $\partial g(x^{k+1})$ instead of $\partial g(x^{k+1}) + A^*y^{k+1}$. Our choice follows more closely to the original scheme of Yokota and Hontani [25]. We numerically found that their scheme is not competitive in our settings and we hence do not recommend it.

4 Numerical Experiments

In this section we present our numerical studies of our proposed scheme in solving one of the most typical imaging inverse problems, the X-ray computed tomography. We compare our A-SPDHG algorithm with the original SPDHG, on different choices of starting ratio of the primal and dual step-sizes.

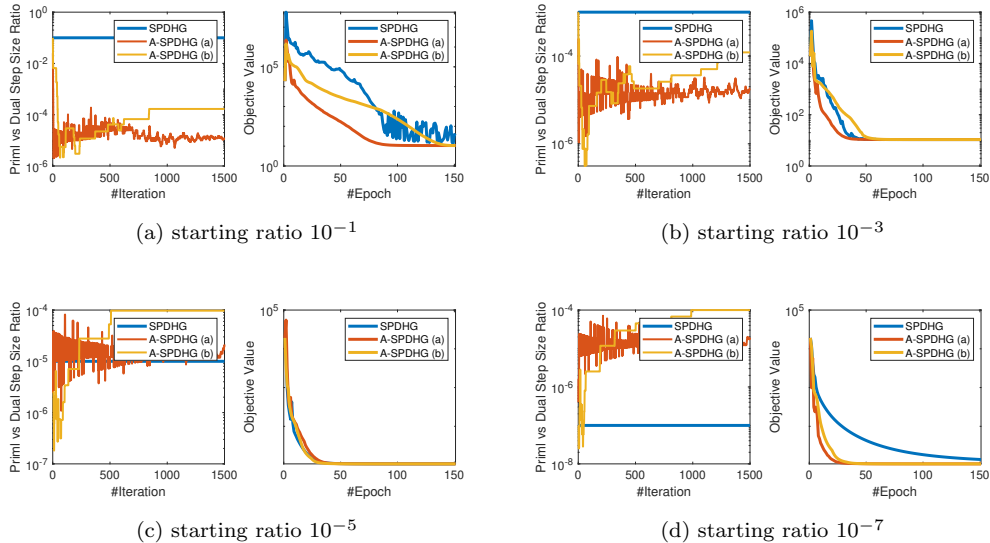


Figure 1: Comparison between SPDHG and our A-SPDHG on X-ray CT (Example 1), with a variety of starting primal-dual step-size ratios.

In our X-ray CT imaging example, we seek to reconstruct the tomography images from fan-beam X-ray measurement data, by solving the following TV-regularized objective:

$$x^* \in \arg \min_{x \in [0,1]^d} \frac{1}{2} \|Ax - b\|_2^2 + \lambda \|Dx\|_1 \quad (4.1)$$

where D denotes the 2D differential operator, $d = 65536$, $m = 92160$ (with 360 views from equally-spaced angles, and 256 observations per view), $A \in \mathbb{R}^{m \times d}$ and $x \in \mathbb{R}^d$. We test the A-SPDHG and SPDHG on two images (Example 1 on real CT image from the Mayo dataset, and Example 2 being a phantom image), on 4 different starting ratios (10^{-1} , 10^{-3} , 10^{-5} and 10^{-7}). We split the measurement data and operator into $n = 10$ minibatches for both algorithms. For A-SPDHG we choose to use the approximation step for d^k presented in (3.3) with 10% subsampling hence the computational overhead is negligible in this experiment.

We present our numerical results in Figures 1 and 3, where we can observe that no matter how we initialize the primal-dual step-size ratio, our A-SPDHG can automatically and consistently adjust the step size ratio to the optimal choice which is around 10^{-5} , and significantly outperform the original SPDHG for the cases where the starting ratio is away from 10^{-5} .

In Figures 5 and 6, we present some numerical studies on the choices of parameters of rule (a) and rule (b) of A-SPDHG algorithm. We choose the fixed starting ratio of 10^{-3} for primal-dual step-sizes in these experiments. For rule (a), we found that it is robust to the choice of the starting shrinking rate α_0 and the gap δ . For the shrinking rate exponential η , our result suggests that a smaller η would harm the ability of the algorithm in adjusting the ratio at later iterations hence we recommend larger choices. The choice of s can significantly influence the convergence of the rule (a) – note here that in our rule (a), we propose the default choice to be $s = \|A\|$, and in this

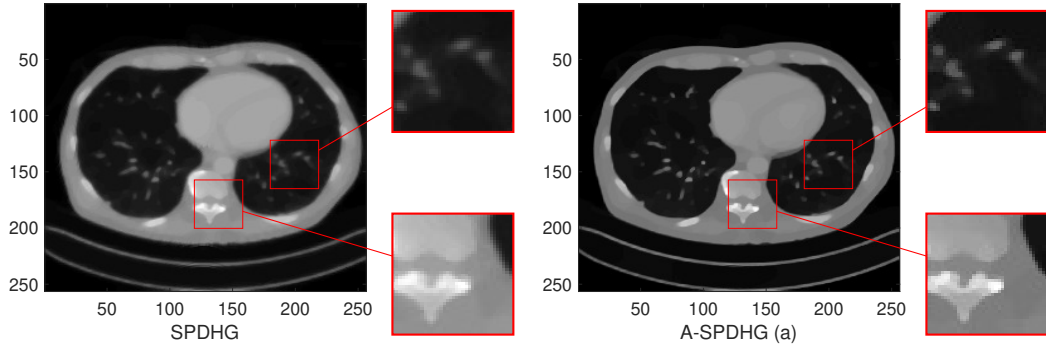


Figure 2: Illustration of SPDHG and A-SPDHG on X-ray CT reconstruction at 150th epoch (Example 1, starting step-size ratio 10^{-7})

CT example it happens to be very near to 255. For rule (b), we found that the final choice of the step-size ratio is quite sensitive to the choice of parameter c and η . Our numerical studies suggest that rule (a) is a better-performing choice than rule (b), but each of them have certain weaknesses, which require further studies and improvements.

5 Conclusion

In this work we propose a new framework (A-SPDHG) for adaptive step-size balancing in stochastic primal-dual hybrid gradient methods. We first derive theoretically sufficient conditions on the adaptive primal and dual step-sizes for ensuring convergence in the stochastic setting. We then propose a number of practical schemes which satisfy the condition for convergence, and our numerical results on imaging inverse problems supports the effectiveness of our approach.

To our knowledge, this work constitutes the first theoretical analysis of adaptive step-sizes for a stochastic primal-dual algorithm. Our on-going work includes the theoretical analysis and algorithmic design of further accelerated stochastic primal-dual methods with line-search schemes for even faster convergence rates.

6 Complementary material for Section 2

We begin by a useful lemma.

Lemma 6.1. *Let a, b be positive scalars, $\beta \in (0, 1)$, and P a bounded linear operator from a Hilbert space X to a Hilbert space Y . Then,*

$$(ab)^{-1/2}\|P\| \leq 1 \Leftrightarrow \begin{pmatrix} a Id & P \\ P^* & b Id \end{pmatrix} \succcurlyeq 0. \quad (6.1)$$

$$(ab)^{-1/2}\|P\| \leq \beta \Leftrightarrow \begin{pmatrix} a Id & P \\ P^* & b Id \end{pmatrix} \succcurlyeq (1 - \beta) \begin{pmatrix} a Id & 0 \\ 0 & b Id \end{pmatrix}. \quad (6.2)$$

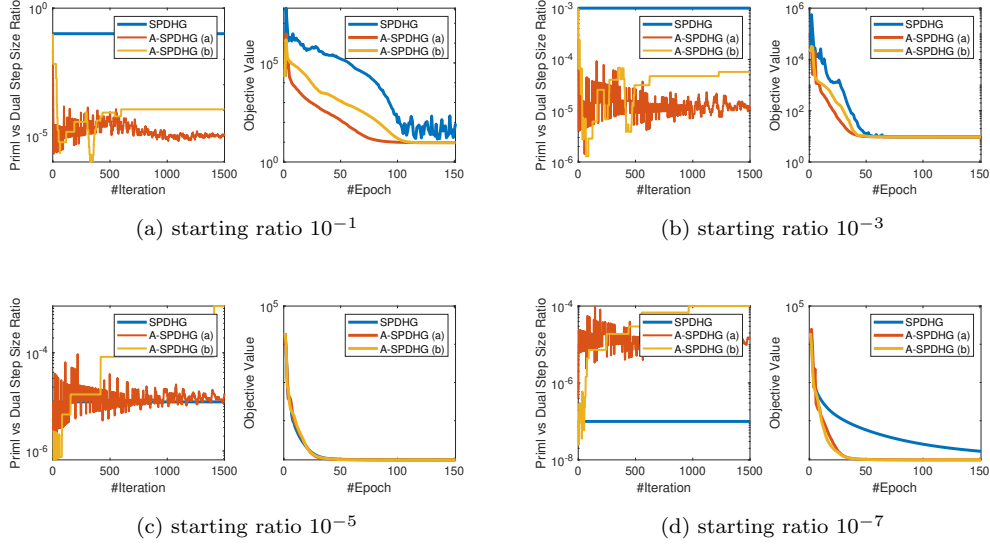


Figure 3: Comparison between SPDHG and our A-SPDHG on X-ray CT (Example 2), with a variety of starting primal-dual step-size ratios.

Proof. Let us call

$$M = \begin{pmatrix} a\text{Id} & P \\ P^* & b\text{Id} \end{pmatrix}.$$

For all $(x, y) \in X \times Y$,

$$\|(x, y)\|_M^2 \geq a\|x\|^2 + b\|y\|^2 - 2\|P\|\|x\|\|y\| = \|x\|_a^2 + \|y\|_b^2 - 2(ab)^{-1/2}\|P\|\|x\|_a\|y\|_b,$$

which proves the direct implication of (6.1). For the converse implication, consider $x \in X$ such that $\|Px\| = \|P\|\|x\|$ and $y = -\lambda Px$ for a scalar λ . Then, the non-negativity of the polynomial

$$\|(x, y)\|_M^2 = b\|P\|^2\lambda^2 - 2\|P\|^2\lambda + a$$

for all $\lambda \in \mathbb{R}$ implies that $\|P\|^4 - ab\|P\|^2 \geq 0$, which is equivalent to the desired conclusion $(ab)^{-1/2}\|P\| \leq 1$.

Equivalence (6.2) is straightforward by noticing that

$$\begin{pmatrix} a\text{Id} & P \\ P^* & b\text{Id} \end{pmatrix} \succcurlyeq (1 - \beta) \begin{pmatrix} a\text{Id} & 0 \\ 0 & b\text{Id} \end{pmatrix} \Leftrightarrow \begin{pmatrix} \beta a\text{Id} & P \\ P^* & \beta b\text{Id} \end{pmatrix} \succcurlyeq 0.$$

□

Let us now turn to the proof of Lemma 2.2.

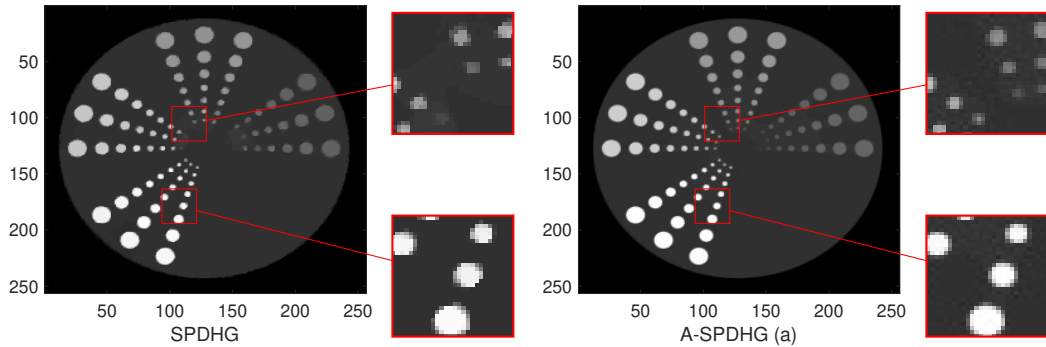


Figure 4: Illustration of SPDHG and A-SPDHG on X-ray CT reconstruction at 150th epoch (Example 2, starting step-size ratio 10^{-1})

Proof of Lemma 2.2. Let us assume that the step-sizes satisfy to the assumptions of the lemma. Then, Assumption (i) of Theorem 2.1 is straightforwardly satisfied. Moreover, for $i \in \llbracket 1, n \rrbracket$, the product sequence $(\tau^k \sigma_i^k)_{k \in \mathbb{N}}$ is constant along the iterations by equation (2.6) and satisfies to equation (2.5) for iterate $k = 0$, thus satisfies to (2.5) for all $k \in \mathbb{N}$, which proves Assumption (ii). Finally, equation (2.7) implies that Assumption (iii) is satisfied. \square

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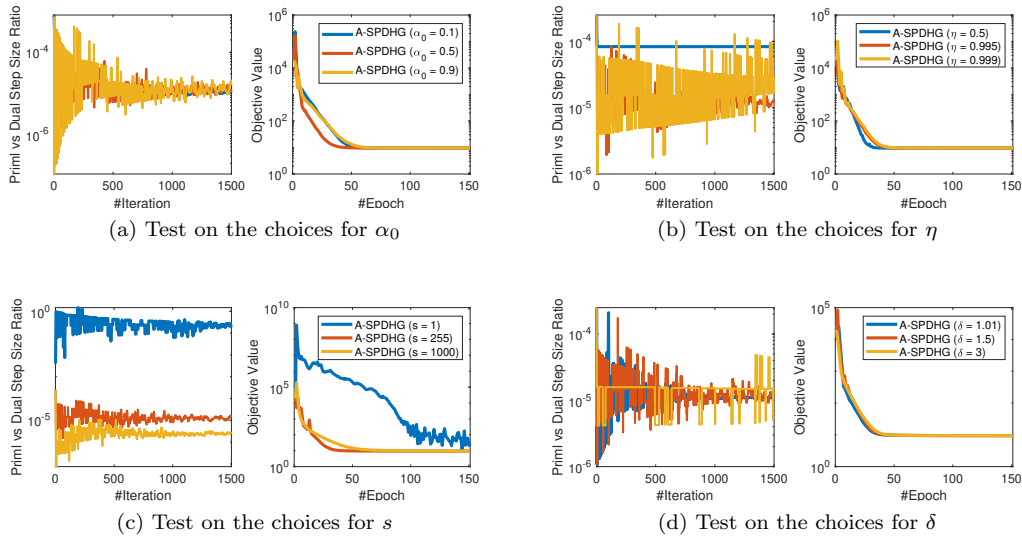


Figure 5: Test on different choices of parameters of A-SPDHG (rule-a) on X-ray fanbeam CT example, starting ratio of primal-dual step-sizes: 10^{-3} .

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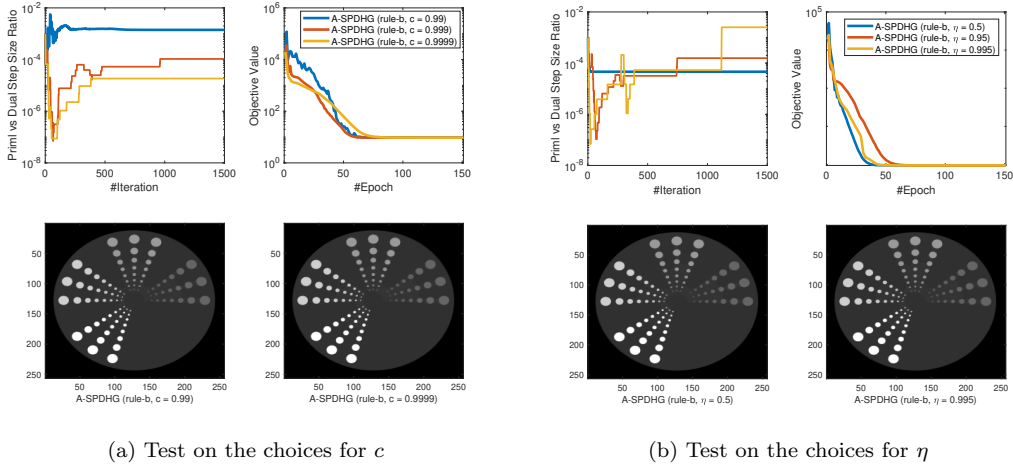


Figure 6: Test on different choices of parameters of A-SPDHG (rule-b) on X-ray fanbeam CT example, starting ratio of primal-dual step-sizes: 10^{-3} .

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