

# COMPLEXITY OF PROJECTED GRADIENT METHODS FOR STRONGLY CONVEX OPTIMIZATION WITH HÖLDER CONTINUOUS GRADIENT TERMS\*

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**Abstract.** This paper studies the complexity of projected gradient descent methods for a class of strongly convex constrained optimization problems where the objective function is expressed as a summation of  $m$  component functions, each possessing a gradient that is Hölder continuous with an exponent  $\alpha_i \in (0, 1]$ . Under this formulation, the gradient of the objective function may fail to be globally Hölder continuous, thereby rendering existing complexity results inapplicable to this class of problems. Our theoretical analysis reveals that, in this setting, the complexity of projected gradient methods is determined by  $\hat{\alpha} = \min_{i \in \{1, \dots, m\}} \alpha_i$ . We first prove that, with an appropriately fixed stepsize, the complexity bound for finding an approximate minimizer with a distance to the true minimizer less than  $\varepsilon$  is  $O(\log(\varepsilon^{-1})^{2(\hat{\alpha}-1)/(1+\hat{\alpha})})$ , which extends the well-known complexity result for  $\hat{\alpha} = 1$ . Next we show that the complexity bound can be improved to  $O(\log(\varepsilon^{-1})^{2(\hat{\alpha}-1)/(1+3\hat{\alpha})})$  if the stepsize is updated by the universal scheme. We illustrate our complexity results by numerical examples arising from elliptic equations with a non-Lipschitz term.

**Key words.** projected gradient descent, complexity, Hölder continuity

**MSC codes.** 90C25, 65L05, 65Y20

**1. Introduction.** Given a closed and convex set  $\Omega \subseteq \mathbb{R}^n$ , this paper considers the following optimization problem,

$$21 \quad (1.1) \qquad \min_{\mathbf{u} \in \Omega} f(\mathbf{u}) := \frac{1}{m} \sum_{i=1}^m f_i(\mathbf{u}),$$

where the objective function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  satisfies the following blanket assumption.

### ASSUMPTION 1.1.

24 (i) The function  $f$  is  $\mu$ -strongly convex with a parameter  $\mu > 0$  on  $\Omega$ , that is,

$$f(\mathbf{u}) \geq f(\mathbf{v}) + \langle \nabla f(\mathbf{v}), \mathbf{u} - \mathbf{v} \rangle + \frac{\mu}{2} \|\mathbf{u} - \mathbf{v}\|^2,$$

26 for all  $\mathbf{u}, \mathbf{v} \in \Omega$ .

(ii) For each  $i \in [m] := \{1, 2, \dots, m\}$ , the function  $f_i : \mathbb{R}^n \rightarrow \mathbb{R}$  is continuously differentiable and the gradient  $\nabla f_i$  is (globally) Hölder continuous with an exponent  $\alpha_i \in (0, 1]$  on  $\Omega$ , namely, there exists a constant  $L_i > 0$  such that

$$30 \quad (1.2) \quad \|\nabla f_i(\mathbf{u}) - \nabla f_i(\mathbf{v})\| \leq L_i \|\mathbf{u} - \mathbf{v}\|^{\alpha_i},$$

31 for all  $\mathbf{u}, \mathbf{v} \in \Omega$ .

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32 Here,  $\|\cdot\|$  is the  $\ell_2$  norm and  $\langle \cdot, \cdot \rangle$  is the inner product on  $\mathbb{R}^n$ . We also denote by  
 33  $\mathbf{u}^* \in \Omega$  and  $f^* = f(\mathbf{u}^*)$  the global minimizer and the optimal value of problem (1.1),  
 34 respectively.

35 Suppose that each  $\nabla f_i$  is Lipschitz continuous, which corresponds to condition  
 36 (1.2) with  $\alpha_i = 1$  for all  $\mathbf{u}, \mathbf{v} \in \Omega$ . Then  $\nabla f$  is also Lipschitz continuous and  
 37 the associated Lipschitz constant is  $L = \sum_{i=1}^m L_i/m$ . Let  $\Pi_\Omega(\cdot)$  be the projection  
 38 operator onto the set  $\Omega$ . It is well known that the classical projected gradient descent  
 39 method

40 (1.3) 
$$\mathbf{u}_{k+1} = \Pi_\Omega(\mathbf{u}_k - \tau \nabla f(\mathbf{u}_k)),$$

41 with any initial point  $\mathbf{u}_0 \in \mathbb{R}^n$  and the stepsize  $\tau \in (0, 2/(\mu + L)]$ , achieves a linear  
 42 rate of convergence [11, Theorem 2.2.14] as follows,

43 
$$\|\mathbf{u}_k - \mathbf{u}^*\| \leq (1 - \mu\tau)^k \|\mathbf{u}_0 - \mathbf{u}^*\|.$$

44 Therefore, for a given  $\varepsilon > 0$ , method (1.3) is guaranteed to find a point  $\mathbf{u}_k \in \Omega$   
 45 satisfying  $\|\mathbf{u}_k - \mathbf{u}^*\| \leq \varepsilon$  after at most  $O(\log(\varepsilon^{-1}))$  iterations. Unfortunately, this  
 46 analysis fails if there exists at least one index  $i \in [m]$  such that  $\alpha_i < 1$ . We explain  
 47 the failure of the convergence of method (1.3) to  $\mathbf{u}^*$  by the following example.

48 *Example 1.2.* [6, Example 1] Consider the following univariate optimization prob-  
 49 lem on  $\Omega = \mathbb{R}$ ,

50 (1.4) 
$$\min_{x \in \mathbb{R}} f(x) = \frac{1}{2}x^2 + \frac{2}{3}|x|^{3/2},$$

51 which is a special instance of problem (1.1) with  $f_1(x) = x^2/2$  and  $f_2(x) = 2|x|^{3/2}/3$ .  
 52 It is easy to see that the global minimizer is  $x^* = 0$ . Method (1.3) with the fixed  
 53 stepsize  $\tau > 0$  starting from  $x_0 \neq 0$  proceeds as follows,

54 
$$x_{k+1} = x_k - \tau \nabla f(x_k) = (1 - \tau)x_k - \tau \text{sign}(x_k)|x_k|^{1/2},$$

55 where  $\text{sign}(x) = 1$  if  $x > 0$ ,  $0$  if  $x = 0$ , and  $-1$  otherwise. A straightforward verification  
 56 reveals that

57 
$$|x_{k+1}|^2 - |x_k|^2 = -\tau(2 - \tau)|x_k|^2 - 2\tau(1 - \tau)|x_k|^{3/2} + \tau^2|x_k|.$$

58 It is evident that, when  $|x_k|$  is sufficiently small, the last term in the right-hand side  
 59 becomes dominant, resulting in that  $|x_{k+1}|^2 - |x_k|^2 \geq 0$ . Therefore, the distance to  
 60 the global minimizer ceases to decrease once it achieves a certain level.

61 Moreover, in [6] we show that  $\nabla f$  is locally, but not globally, Hölder continuous.  
 62 In fact, from

63 
$$|\nabla f(|h|) - \nabla f(0)| = |h| + |h|^{1/2} = \left(|h|^{1-\alpha} + |h|^{1/2-\alpha}\right)|h|^\alpha,$$

64 we can obtain that,  $|h|^{1-\alpha} \rightarrow \infty$  when  $\alpha \in (0, 1)$  and  $|h| \rightarrow \infty$ , while  $|h|^{1/2-\alpha} \rightarrow \infty$   
 65 when  $\alpha = 1$  and  $|h| \rightarrow 0$ . Therefore,  $\nabla f$  cannot be globally Hölder continuous for all  
 66  $\alpha \in (0, 1]$ .

67 On the other hand, problem (1.4) satisfies all the conditions in Assumption 1.1.  
 68 It is clear that  $f$  is strongly convex. In addition, we have

69 
$$|\nabla f_1(x) - \nabla f_1(y)| = |x - y|,$$

70 and

$$71 \quad |\nabla f_2(x) - \nabla f_2(y)| = \left| \text{sign}(x) |x|^{1/2} - \text{sign}(y) |y|^{1/2} \right| \leq \sqrt{2} |x - y|^{1/2},$$

72 for all  $x, y \in \mathbb{R}$ .

73 This simple example demonstrates that, in problem (1.1), a function  $f$  expressed  
 74 as a sum of component functions  $f_i$ , each endowed with a Hölder continuous gradient,  
 75 may itself fail to possess a Hölder continuous gradient. This phenomenon, initially  
 76 observed in our previous work [6], was later revisited and further highlighted by  
 77 Nesterov (see [12, Example 1]).

78 Since  $\nabla f$  may not be globally Hölder continuous, most existing complexity results  
 79 are inapplicable to problem (1.1). For the special case where  $m = 1$ , namely,  $\nabla f$  is  
 80 globally Hölder continuous with an exponent  $\alpha \in (0, 1]$ , Devolder et al. [7] presented  
 81 the following bound for method (1.3),

$$82 \quad f(\hat{\mathbf{u}}_N) - f(\mathbf{u}^*) \leq K(N) := \frac{L_\alpha \|\mathbf{u}_0 - \mathbf{u}^*\|^{1+\alpha}}{1 + \alpha} \left( \frac{2}{N} \right)^{\frac{1+\alpha}{2}},$$

83 where  $L_\alpha$  is the Hölder constant and  $\hat{\mathbf{u}}_N = \sum_{k=1}^N \mathbf{u}_k / N$ . In the strongly convex case,  
 84 (51) in [7] comes to

$$85 \quad \|\hat{\mathbf{u}}_N - \mathbf{u}^*\|^2 \leq \frac{2}{\mu} K(N),$$

86 which implies that finding an  $N$  average of iterations  $\hat{\mathbf{u}}_N$  satisfying  $\|\hat{\mathbf{u}}_N - \mathbf{u}^*\| \leq \varepsilon$   
 87 requires  $O(\varepsilon^{-4/(1+\alpha)})$  iterations.

88 The contribution of this paper is to provide new complexity results for the pro-  
 89 jected gradient descent methods to solve problem (1.1), which are dictated by the  
 90 parameter  $\hat{\alpha} = \min_{i \in [m]} \alpha_i \in (0, 1]$ . We first show that, with an appropriately fixed  
 91 stepsize, the complexity bound for finding an iterate with a distance to the global  
 92 minimizer less than  $\varepsilon$  is  $O(\log(\varepsilon^{-1})\varepsilon^{2(\hat{\alpha}-1)/(1+\hat{\alpha})})$ , which extends the well-known com-  
 93 plexity result for  $\hat{\alpha} = 1$ . Next, we demonstrate that this complexity bound can be  
 94 improved to  $O(\log(\varepsilon^{-1})\varepsilon^{2(\hat{\alpha}-1)/(1+3\hat{\alpha})})$  if the stepsize is updated at each iteration us-  
 95 ing the universal scheme. Even in the special case where  $m = 1$ , our complexity bound  
 96 is at least  $O(\varepsilon^{-1})$  lower than (51) in [7]. For example, when  $\hat{\alpha} = 1/2$ , our bound is  
 97  $O(\log(\varepsilon^{-1})\varepsilon^{-2/5})$  but (51) in [7] is  $O(\varepsilon^{-8/3})$ .

98 Our study is motivated by elliptic equations with a non-Lipschitz term [3, 14],  
 99 complementarity problems [1, 13], and optimization problems with an  $\ell_p$ -norm ( $1 <$   
 100  $p < 2$ ) regularization term [2, 5]. We illustrate our complexity results by two numerical  
 101 examples arising from elliptic equations with a non-Lipschitz term in section 5, after  
 102 we present complexity of projected gradient methods with fixed stepsizes and updated  
 103 stepsizes in sections 2 to 4, respectively.

## 104 2. Vanilla Projected Gradient Descent Method with a Fixed Stepsize.

105 In this section, we attempt to employ the vanilla projected gradient descent method  
 106 (1.3) with a fixed stepsize to solve problem (1.1), whose complexity bound is also  
 107 provided. Example 1.2 illustrates that the projected gradient descent method (1.3)  
 108 with a fixed stepsize will experience stagnation before reaching the global minimizer.

109 To obtain an approximate solution to problem (1.1), it is necessary to choose  
 110 a sufficiently small stepsize  $\tau$  in the projected gradient descent method (1.3), the

111 magnitude of which depends on the desired level of accuracy. Let  $M > 0$  be a  
 112 constant defined as

$$113 \quad (2.1) \quad M = \max_{i \in [m]} \left\{ \left[ \frac{2(1 - \alpha_i)}{\mu(1 + \alpha_i)} \right]^{(1 - \alpha_i)/(1 + \alpha_i)} L_i^{2/(1 + \alpha_i)} \right\},$$

114 with the convention  $0^0 = 1$ . We select a specific stepsize  $\tau = \varepsilon^{2(1 - \hat{\alpha})/(1 + \hat{\alpha})}/M$  in  
 115 the projected gradient descent method, whose complete framework is presented in  
 116 Algorithm 1. Two sequences  $\{\mathbf{v}_k\}$  and  $\{\mathbf{u}_k\}$  are maintained in Algorithm 1, where  
 117  $\mathbf{v}_k$  is generated by the projected gradient descent method and  $\mathbf{u}_k$  corresponds to the  
 118 iterate achieving the smallest objective function value among the first  $k$  iterations.

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**Algorithm 1:** Projected Gradient Descent Method (PGDM).

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**Input:**  $\varepsilon > 0$ .

Initialize  $\mathbf{u}_0 = \mathbf{v}_0 \in \Omega$ .

Choose the stepsize  $\tau = \varepsilon^{2(1 - \hat{\alpha})/(1 + \hat{\alpha})}/M$ .

**for**  $k = 0, 1, 2, \dots$  **do**

  Compute



$$\mathbf{v}_{k+1} = \Pi_{\Omega} (\mathbf{v}_k - \tau \nabla f(\mathbf{v}_k)).$$

  Set

$$\mathbf{u}_{k+1} = \begin{cases} \mathbf{v}_{k+1}, & \text{if } f(\mathbf{v}_{k+1}) \leq f(\mathbf{u}_k), \\ \mathbf{u}_k, & \text{otherwise.} \end{cases}$$

**Output:**  $\mathbf{u}_{k+1}$ .

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119 Our subsequent analysis is based on the inexact oracle [7] derived from the Hölder  
 120 continuity condition of gradients, which is generalized to problem (1.1) and demon-  
 121 strated in the following proposition.

122 **PROPOSITION 2.1.** *Let  $\delta > 0$  and*

$$123 \quad \rho \geq \max_{i \in [m]} \left\{ \left[ \frac{1 - \alpha_i}{(1 + \alpha_i)\delta} \right]^{(1 - \alpha_i)/(1 + \alpha_i)} L_i^{2/(1 + \alpha_i)} \right\}.$$

124 *Then for all  $\mathbf{u}, \mathbf{v} \in \Omega$ , we have*

$$125 \quad f(\mathbf{v}) \leq f(\mathbf{u}) + \langle \nabla f(\mathbf{u}), \mathbf{v} - \mathbf{u} \rangle + \frac{\rho}{2} \|\mathbf{v} - \mathbf{u}\|^2 + \frac{\delta}{2}.$$

126 *Proof.* Since  $\nabla f_i$  is Hölder continuous with an exponent  $\alpha_i$ , we can obtain from  
 127 [15, Lemma 1] that

$$128 \quad f_i(\mathbf{v}) \leq f_i(\mathbf{u}) + \langle \nabla f_i(\mathbf{u}), \mathbf{v} - \mathbf{u} \rangle + \frac{L_i}{1 + \alpha_i} \|\mathbf{v} - \mathbf{u}\|^{1 + \alpha_i},$$

129 for all  $\mathbf{u}, \mathbf{v} \in \Omega$ . Then, for each  $i$ , it follows from [10, Lemma 2] that

$$130 \quad f_i(\mathbf{v}) \leq f_i(\mathbf{u}) + \langle \nabla f_i(\mathbf{u}), \mathbf{v} - \mathbf{u} \rangle + \frac{\rho}{2} \|\mathbf{v} - \mathbf{u}\|^2 + \frac{\delta}{2}.$$

131 Summing the above relationship over  $i \in [m]$ , we immediately arrive at the assertion  
 132 of this proposition. The proof is completed.  $\square$

133 Now, we are able to derive the complexity bound of Algorithm 1 in the following  
 134 theorem.

135 THEOREM 2.2. *Let  $\varepsilon \in (0, 1)$  be a sufficiently small constant. Then after at most*

$$136 \quad O\left(\log\left(\frac{M^{(1+\hat{\alpha})/4}}{\varepsilon}\right) \frac{M}{\varepsilon^{2(1-\hat{\alpha})/(1+\hat{\alpha})}}\right)$$

137 iterations, Algorithm 1 will find an iterate  $\mathbf{u}_k \in \Omega$  satisfying  $\|\mathbf{u}_k - \mathbf{u}^*\| \leq \varepsilon$ .

138 *Proof.* In view of Proposition 2.1, we take

$$139 \quad \rho = \frac{1}{\tau} = \frac{M}{\varepsilon^{2(1-\hat{\alpha})/(1+\hat{\alpha})}} \geq \max_{i \in [m]} \left\{ \left[ \frac{2(1-\alpha_i)}{\mu(1+\alpha_i)\varepsilon^2} \right]^{(1-\alpha_i)/(1+\alpha_i)} L_i^{2/(1+\alpha_i)} \right\}.$$

140 Then it holds that

$$141 \quad f(\mathbf{v}_{k+1}) \leq f(\mathbf{v}_k) + \langle \nabla f(\mathbf{v}_k), \mathbf{v}_{k+1} - \mathbf{v}_k \rangle + \frac{1}{2\tau} \|\mathbf{v}_{k+1} - \mathbf{v}_k\|^2 + \frac{\mu\varepsilon^2}{4},$$

142 which, after a suitable rearrangement, can be equivalently written as

$$143 \quad (2.2) \quad \langle \nabla f(\mathbf{v}_k), \mathbf{v}_k - \mathbf{v}_{k+1} \rangle \leq f(\mathbf{v}_k) - f(\mathbf{v}_{k+1}) + \frac{\mu\varepsilon^2}{4} + \frac{1}{2\tau} \|\mathbf{v}_{k+1} - \mathbf{v}_k\|^2.$$

144 Recall that  $f^* = f(\mathbf{u}^*)$ . By virtue of the strong convexity of  $f$ , we can obtain that

$$145 \quad (2.3) \quad \langle \nabla f(\mathbf{v}_k), \mathbf{u}^* - \mathbf{v}_k \rangle \leq f^* - f(\mathbf{v}_k) - \frac{\mu}{2} \|\mathbf{v}_k - \mathbf{u}^*\|^2.$$

146 The optimality condition of the projection problem defining  $\mathbf{v}_{k+1}$  yields that

$$147 \quad \langle \mathbf{v}_{k+1} - \mathbf{v}_k + \tau \nabla f(\mathbf{v}_k), \mathbf{u} - \mathbf{v}_{k+1} \rangle \geq 0,$$

148 for all  $\mathbf{u} \in \Omega$ . Upon taking  $\mathbf{u} = \mathbf{u}^*$ , we have

$$149 \quad \begin{aligned} \langle \mathbf{v}_{k+1} - \mathbf{v}_k, \mathbf{v}_{k+1} - \mathbf{u}^* \rangle &\leq \tau \langle \nabla f(\mathbf{v}_k), \mathbf{u}^* - \mathbf{v}_{k+1} \rangle \\ &= \tau \langle \nabla f(\mathbf{v}_k), \mathbf{u}^* - \mathbf{v}_k \rangle + \tau \langle \nabla f(\mathbf{v}_k), \mathbf{v}_k - \mathbf{v}_{k+1} \rangle, \end{aligned}$$

150 which together with (2.2) and (2.3) implies that

$$151 \quad \begin{aligned} \langle \mathbf{v}_{k+1} - \mathbf{v}_k, \mathbf{v}_{k+1} - \mathbf{u}^* \rangle &\leq \tau \left( f^* - f(\mathbf{v}_{k+1}) + \frac{\mu\varepsilon^2}{4} \right) - \frac{\mu\tau}{2} \|\mathbf{v}_k - \mathbf{u}^*\|^2 \\ &\quad + \frac{1}{2} \|\mathbf{v}_{k+1} - \mathbf{v}_k\|^2. \end{aligned}$$

152 Moreover, it can be readily verified that

$$153 \quad (2.4) \quad \begin{aligned} \|\mathbf{v}_{k+1} - \mathbf{u}^*\|^2 &= \|\mathbf{v}_{k+1} - \mathbf{v}_k + \mathbf{v}_k - \mathbf{u}^*\|^2 \\ &= \|\mathbf{v}_k - \mathbf{u}^*\|^2 + 2 \langle \mathbf{v}_{k+1} - \mathbf{v}_k, \mathbf{v}_k - \mathbf{u}^* \rangle + \|\mathbf{v}_{k+1} - \mathbf{v}_k\|^2 \\ &= \|\mathbf{v}_k - \mathbf{u}^*\|^2 + 2 \langle \mathbf{v}_{k+1} - \mathbf{v}_k, \mathbf{v}_{k+1} - \mathbf{u}^* \rangle - \|\mathbf{v}_{k+1} - \mathbf{v}_k\|^2. \end{aligned}$$

154 Collecting the above two relationships together, we arrive at

$$155 \quad \|\mathbf{v}_{k+1} - \mathbf{u}^*\|^2 \leq (1 - \mu\tau) \|\mathbf{v}_k - \mathbf{u}^*\|^2 + 2\tau \left( f^* - f(\mathbf{v}_{k+1}) + \frac{\mu\varepsilon^2}{4} \right).$$

156 From the construction of  $\mathbf{u}_k$  in Algorithm 1, it then follows that  $f(\mathbf{v}_l) \geq f(\mathbf{u}_k)$  for  
157 all  $l \in \{1, 2, \dots, k\}$ . Let  $C_k = \sum_{l=1}^k (1 - \mu\tau)^{l-1}$  be a constant. Applying the above  
158 relationship recursively for  $k$  times leads to that

$$159 \quad \begin{aligned} \|\mathbf{v}_k - \mathbf{u}^*\|^2 &\leq (1 - \mu\tau)^k \|\mathbf{u}_0 - \mathbf{u}^*\|^2 + 2\tau \sum_{l=1}^k (1 - \mu\tau)^{l-1} \left( f^* - f(\mathbf{v}_l) + \frac{\mu\varepsilon^2}{4} \right) \\ &\leq (1 - \mu\tau)^k \|\mathbf{u}_0 - \mathbf{u}^*\|^2 + 2\tau \left( f^* - f(\mathbf{u}_k) + \frac{\mu\varepsilon^2}{4} \right) C_k, \end{aligned}$$

160 which together with  $\|\mathbf{v}_k - \mathbf{u}^*\| \geq 0$  and  $C_k \geq 1$  implies that

$$161 \quad f(\mathbf{u}_k) - f^* \leq \frac{(1 - \mu\tau)^k}{2\tau C_k} \|\mathbf{u}_0 - \mathbf{u}^*\|^2 + \frac{\mu\varepsilon^2}{4} \leq \frac{(1 - \mu\tau)^k}{2\tau} \|\mathbf{u}_0 - \mathbf{u}^*\|^2 + \frac{\mu\varepsilon^2}{4}.$$

162 According to the strong convexity of  $f$  and the optimality condition of problem (1.1),  
163 we have

$$164 \quad (2.5) \quad f(\mathbf{u}_k) - f^* \geq \langle \nabla f(\mathbf{u}^*), \mathbf{u}_k - \mathbf{u}^* \rangle + \frac{\mu}{2} \|\mathbf{u}_k - \mathbf{u}^*\|^2 \geq \frac{\mu}{2} \|\mathbf{u}_k - \mathbf{u}^*\|^2.$$

165 Hence, it holds that

$$166 \quad \begin{aligned} \|\mathbf{u}_k - \mathbf{u}^*\|^2 &\leq \frac{2}{\mu} (f(\mathbf{u}_k) - f^*) \leq \frac{(1 - \mu\tau)^k}{\mu\tau} \|\mathbf{u}_0 - \mathbf{u}^*\|^2 + \frac{\varepsilon^2}{2} \\ &\leq \frac{M \|\mathbf{u}_0 - \mathbf{u}^*\|^2}{\mu\varepsilon^{2(1-\hat{\alpha})/(1+\hat{\alpha})}} \left( 1 - \frac{\mu}{M} \varepsilon^{2(1-\hat{\alpha})/(1+\hat{\alpha})} \right)^k + \frac{\varepsilon^2}{2}. \end{aligned}$$

167 We denote by  $K_\varepsilon^*$  the smallest iteration number  $k$  such that  $\|\mathbf{u}_k - \mathbf{u}^*\| \leq \varepsilon$ . Then  
168 solving the inequality  $M \|\mathbf{u}_0 - \mathbf{u}^*\|^2 \varepsilon^{-2(1-\hat{\alpha})/(1+\hat{\alpha})} (1 - \mu\varepsilon^{2(1-\hat{\alpha})/(1+\hat{\alpha})}/M)^k / \mu \leq \varepsilon^2/2$   
169 indicates that

$$170 \quad \begin{aligned} K_\varepsilon^* &\leq \frac{4 \log((2M \|\mathbf{u}_0 - \mathbf{u}^*\|^2 / \mu)^{(1+\hat{\alpha})/4} / \varepsilon)}{-\log(1 - \mu\varepsilon^{2(1-\hat{\alpha})/(1+\hat{\alpha})}/M)(1 + \hat{\alpha})} \\ &\leq \frac{4M \log((2M \|\mathbf{u}_0 - \mathbf{u}^*\|^2 / \mu)^{(1+\hat{\alpha})/4} / \varepsilon)}{\mu(1 + \hat{\alpha})\varepsilon^{2(1-\hat{\alpha})/(1+\hat{\alpha})}}. \end{aligned}$$

171 The proof is completed.  $\square$

172 Theorem 2.2 demonstrates that the iteration complexity of Algorithm 1 with a  
173 fixed stepsize is  $O(\log(\varepsilon^{-1})\varepsilon^{2(\hat{\alpha}-1)/(1+\hat{\alpha})})$  for problem (1.1). This complexity result  
174 generalizes the classical linear convergence when  $\hat{\alpha} = 1$ , which highlights the perfor-  
175 mance degradation incurred by non-Lipschitz gradients.

176 **3. Universal Primal Gradient Method.** The fixed stepsize  $\tau$  chosen in Algo-  
177 rithm 1 depends on the parameters  $\alpha_i$  and  $L_i$  for all  $i \in [m]$ , which are often unknown  
178 and hard to estimate in practice. To address this issue, we adopt the universal primal  
179 gradient method (UPGM) proposed by Nesterov [10] to solve problem (1.1). This

**Algorithm 2:** Universal Primal Gradient Method (UPGM).**Input:**  $\varepsilon > 0$ .Initialize  $\mathbf{u}_0 = \mathbf{v}_0 \in \Omega$  and  $\rho_0 > 0$ .**for**  $k = 0, 1, 2, \dots$  **do**  **for**  $j_k = 0, 1, 2, \dots$  **do**  
    Compute

$$\mathbf{v}_{k+1} = \Pi_{\Omega} \left( \mathbf{v}_k - \frac{1}{2^{j_k} \rho_k} \nabla f(\mathbf{v}_k) \right).$$

**If**  $\mathbf{v}_{k+1}$  satisfies the following line-search condition,

$$(3.1) \quad \begin{aligned} f(\mathbf{v}_{k+1}) &\leq f(\mathbf{v}_k) + \langle \nabla f(\mathbf{v}_k), \mathbf{v}_{k+1} - \mathbf{v}_k \rangle \\ &+ \frac{2^{j_k} \rho_k}{2} \|\mathbf{v}_{k+1} - \mathbf{v}_k\|^2 + \frac{\mu \varepsilon^2}{4}, \end{aligned}$$

**then** break.  Update  $\rho_{k+1} = 2^{j_k} \rho_k$ .

Set

$$\mathbf{u}_{k+1} = \begin{cases} \mathbf{v}_{k+1}, & \text{if } f(\mathbf{v}_{k+1}) \leq f(\mathbf{u}_k), \\ \mathbf{u}_k, & \text{otherwise.} \end{cases}$$

**Output:**  $\mathbf{u}_{k+1}$ .

180 method incorporates a line-search procedure to adaptively determine the stepsize at  
 181 each iteration, and its overall framework is outlined in Algorithm 2.

182 Next, we establish the iteration complexity of Algorithm 2, which remains on the  
 183 same order as that of the projected gradient descent method with a fixed stepsize.

184 **THEOREM 3.1.** *Let  $\varepsilon \in (0, 1)$  be a sufficiently small constant. Then after at most*

$$185 \quad O \left( \log \left( \frac{M^{(1+\hat{\alpha})/4}}{\varepsilon} \right) \frac{M}{\varepsilon^{2(1-\hat{\alpha})/(1+\hat{\alpha})}} \right)$$

186 iterations, Algorithm 2 will attain an iterate  $\mathbf{u}_k \in \Omega$  satisfying that  $\|\mathbf{u}_k - \mathbf{u}^*\| \leq \varepsilon$ .

187 *Proof.* Obviously, there exists  $j_k \in \mathbb{N}$  such that

$$188 \quad 2^{j_k} \rho_k \geq \max_{i \in [m]} \left\{ \left[ \frac{2(1-\alpha_i)}{\mu(1+\alpha_i)\varepsilon^2} \right]^{(1-\alpha_i)/(1+\alpha_i)} L_i^{2/(1+\alpha_i)} \right\}.$$

189 By invoking the results of Proposition 2.1, we know that condition (3.1) is satisfied.  
 190 Hence, the line-search step in Algorithm 2 can be terminated after a finite number of  
 191 trials and the required number of trials  $j_k$  satisfies

$$192 \quad (3.2) \quad 2^{j_k} \rho_k \leq 2 \max_{i \in [m]} \left\{ \left[ \frac{2(1-\alpha_i)}{\mu(1+\alpha_i)\varepsilon^2} \right]^{(1-\alpha_i)/(1+\alpha_i)} L_i^{2/(1+\alpha_i)} \right\} \leq \frac{2M}{\varepsilon^{2(1-\hat{\alpha})/(1+\hat{\alpha})}},$$

193 where  $M > 0$  is a constant defined in (2.1). Moreover, the line-search condition (3.1)

194 directly yields that

195 (3.3) 
$$\langle \nabla f(\mathbf{v}_k), \mathbf{v}_k - \mathbf{v}_{k+1} \rangle \leq f(\mathbf{v}_k) - f(\mathbf{v}_{k+1}) + \frac{2^{j_k} \rho_k}{2} \|\mathbf{v}_{k+1} - \mathbf{v}_k\|^2 + \frac{\mu \varepsilon^2}{4}.$$

196 According to the optimality condition of the projection problem defining  $\mathbf{v}_{k+1}$ , we  
197 have

198 
$$\left\langle \mathbf{v}_{k+1} - \mathbf{v}_k + \frac{1}{2^{j_k} \rho_k} \nabla f(\mathbf{v}_k), \mathbf{u}^* - \mathbf{v}_{k+1} \right\rangle \geq 0,$$

199 which further implies that

200 
$$\begin{aligned} \langle \mathbf{v}_{k+1} - \mathbf{v}_k, \mathbf{v}_{k+1} - \mathbf{u}^* \rangle &\leq \frac{1}{2^{j_k} \rho_k} \langle \nabla f(\mathbf{v}_k), \mathbf{u}^* - \mathbf{v}_{k+1} \rangle \\ &\leq \frac{1}{2^{j_k} \rho_k} \langle \nabla f(\mathbf{v}_k), \mathbf{u}^* - \mathbf{v}_k \rangle + \frac{1}{2^{j_k} \rho_k} \langle \nabla f(\mathbf{v}_k), \mathbf{v}_k - \mathbf{v}_{k+1} \rangle. \end{aligned}$$

201 Substituting (2.3) and (3.3) into the above relationship leads to that

202 
$$\begin{aligned} \langle \mathbf{v}_{k+1} - \mathbf{v}_k, \mathbf{v}_{k+1} - \mathbf{u}^* \rangle &\leq \frac{1}{2^{j_k} \rho_k} \left( f^* - f(\mathbf{v}_{k+1}) + \frac{\mu \varepsilon^2}{4} \right) \\ &\quad + \frac{1}{2} \|\mathbf{v}_{k+1} - \mathbf{v}_k\|^2 - \frac{\mu}{2^{j_k+1} \rho_k} \|\mathbf{v}_k - \mathbf{u}^*\|^2, \end{aligned}$$

203 Thus, it follows from relationship (2.4) that

204 
$$\begin{aligned} \|\mathbf{v}_{k+1} - \mathbf{u}^*\|^2 &\leq \left( 1 - \frac{\mu}{2^{j_k} \rho_k} \right) \|\mathbf{v}_k - \mathbf{u}^*\|^2 + \frac{2}{2^{j_k} \rho_k} \left( f^* - f(\mathbf{v}_{k+1}) + \frac{\mu \varepsilon^2}{4} \right) \\ &\leq \left( 1 - \frac{\mu \varepsilon^{2(1-\hat{\alpha})/(1+\hat{\alpha})}}{2M} \right) \|\mathbf{v}_k - \mathbf{u}^*\|^2 + \frac{2}{\rho_0} \left( f^* - f(\mathbf{v}_{k+1}) + \frac{\mu \varepsilon^2}{4} \right), \end{aligned}$$

205 where the last inequality comes from (3.2) and  $2^{j_k} \rho_k \geq \rho_0$ . The remaining part of  
206 the proof follows the same line of reasoning as that of Theorem 2.2 and is therefore  
207 omitted here for the sake of brevity.  $\square$

208 We end this section by estimating the total number of line-search steps required  
209 by Algorithm 2.

210 COROLLARY 3.2. *Let  $\varepsilon \in (0, 1)$  be a sufficiently small constant. Then Algorithm 2  
211 requires at most*

212 
$$O \left( \log \left( \frac{M^{(1+\hat{\alpha})/4}}{\varepsilon} \right) \frac{M}{\varepsilon^{2(1-\hat{\alpha})/(1+\hat{\alpha})}} \right)$$

213 line-search steps for the generated sequence  $\{\mathbf{u}_k\}$  to satisfy  $\|\mathbf{u}_k - \mathbf{u}^*\| \leq \varepsilon$ .

214 *Proof.* Let  $N_k$  be the total number of line-search steps after  $k$  iterations in Algo-  
215 rithm 2. From the update rule  $\rho_{k+1} = 2^{j_k} \rho_k$ , we can obtain that  $j_k = \log \rho_{k+1} - \log \rho_k$ .  
216 Then a straightforward verification reveals that

217 (3.4) 
$$N_k = \sum_{l=0}^k (j_l + 1) = k + 1 + \log \rho_{k+1} - \log \rho_0,$$

218 which together with relationship (3.2) implies that

$$\begin{aligned} 219 \quad N_k &\leq k + \log\left(\frac{2M}{\varepsilon^{2(1-\hat{\alpha})/(1+\hat{\alpha})}}\right) - \log\rho_0 \\ &\leq k + \frac{2(1-\hat{\alpha})}{1+\hat{\alpha}} \log\left(\frac{1}{\varepsilon}\right) + \log\left(\frac{2M}{\rho_0}\right) + 1. \end{aligned}$$

220 By invoking the results of Theorem 3.1, we conclude that Algorithm 2 requires at  
221 most  $O(\log(\varepsilon^{-1})\varepsilon^{2(\hat{\alpha}-1)/(1+\hat{\alpha})})$  line-search steps, which completes the proof.  $\square$

222 At each iteration of Algorithm 2, we evaluate both the function value and the  
223 gradient at  $\mathbf{v}_k$ . In addition, an extra function evaluation at  $\mathbf{v}_{k+1,j_k}$  is involved during  
224 each line-search step. Therefore, Theorem 3.1 and Corollary 3.2 together reveal that  
225 the total number of function and gradient evaluations required by Algorithm 2 is  
226  $O(\log(\varepsilon^{-1})\varepsilon^{2(\hat{\alpha}-1)/(1+\hat{\alpha})})$ .

227 **4. Universal Fast Gradient Method.** To obtain a sharper complexity bound,  
228 we devise, in this section, a universal fast gradient method (UFGM) tailored to prob-  
229 lem (1.1). The proposed scheme, summarized in Algorithm 3, exhibits slight but  
230 essential differences from the algorithm introduced by Nesterov [10] to exploit the  
231 strong convexity of the objective function.

232 The following lemma illustrates that the line-search process in (4.4) is well-defined,  
233 which is guaranteed to terminate in a finite number of trials.

234 **LEMMA 4.1.** *There exists an integer  $j_k \in \mathbb{N}$  such that the line-search condition  
235 (4.4) is satisfied in Algorithm 3.*

236 *Proof.* It follows from the definition of  $\eta_k$  and  $\nu_k \leq 1$  that

$$237 \quad \eta_k = \frac{\nu_k}{1+\nu_k} \geq \frac{\nu_k}{2}, \quad \text{and} \quad \frac{\mu}{\nu_k^2} = 2^{j_k} \rho_k.$$

238 Recall that  $\hat{\alpha} = \min_{i \in [m]} \alpha_i \in (0, 1]$ . Then we have

$$\begin{aligned} 239 \quad \frac{\mu}{\nu_k^2} \eta_k^{(1-\hat{\alpha})/(1+\hat{\alpha})} &\geq \frac{2^{j_k} \rho_k}{2^{(1-\hat{\alpha})/(1+\hat{\alpha})}} \nu_k^{(1-\hat{\alpha})/(1+\hat{\alpha})} \\ &= \frac{2^{j_k} \rho_k}{2^{(1-\hat{\alpha})/(1+\hat{\alpha})}} \left[ \frac{\mu}{2^{j_k} \rho_k} \right]^{(1-\hat{\alpha})/(2(1+\hat{\alpha}))} \\ &= \frac{\mu^{(1-\hat{\alpha})/(2(1+\hat{\alpha}))}}{2^{(1-\hat{\alpha})/(1+\hat{\alpha})}} [2^{j_k} \rho_k]^{(1+3\hat{\alpha})/(2(1+\hat{\alpha}))}, \end{aligned}$$

240 where the first equality comes from the definition of  $\nu_k$ . Now it is clear that

$$241 \quad \frac{\mu}{\nu_k^2} \eta_k^{(1-\hat{\alpha})/(1+\hat{\alpha})} \rightarrow \infty,$$

242 as  $j_k \rightarrow \infty$ . Thus, there exists  $j_k \in \mathbb{N}$  such that

$$243 \quad (4.6) \quad \frac{\mu}{\nu_k^2} \eta_k^{(1-\hat{\alpha})/(1+\hat{\alpha})} \geq \max_{i \in [m]} \left\{ \left[ \frac{2(1-\alpha_i)}{\mu(1+\alpha_i)\varepsilon^2} \right]^{(1-\alpha_i)/(1+\alpha_i)} L_i^{2/(1+\alpha_i)} \right\},$$

**Algorithm 3:** Universal Fast Gradient Method (UFGM).**Input:**  $\varepsilon > 0$ .Initialize  $\mathbf{u}_0 = \mathbf{w}_0 \in \Omega$  and  $\rho_0 \geq \mu$ .**for**  $k = 0, 1, 2, \dots$  **do**    **for**  $j_k = 0, 1, 2, \dots$  **do**        Set  $\nu_k = \sqrt{\mu/(2^{j_k} \rho_k)}$  and  $\eta_k = \nu_k/(1 + \nu_k)$ .

Compute

(4.1) 
$$\mathbf{v}_k = (1 - \eta_k)\mathbf{u}_k + \eta_k \Pi_{\Omega}(\mathbf{w}_k),$$

and

(4.2) 
$$\mathbf{z}_k = \Pi_{\Omega} \left( \Pi_{\Omega}(\mathbf{w}_k) - \frac{\nu_k}{\mu} \nabla f(\mathbf{v}_k) \right).$$

Set

(4.3) 
$$\mathbf{u}_{k+1} = (1 - \eta_k)\mathbf{u}_k + \eta_k \mathbf{z}_k.$$

**If**  $\mathbf{u}_{k+1}$  satisfies the following line-search condition,

(4.4) 
$$\begin{aligned} f(\mathbf{u}_{k+1}) &\leq f(\mathbf{v}_k) + \langle \nabla f(\mathbf{v}_k), \mathbf{u}_{k+1} - \mathbf{v}_k \rangle \\ &+ \frac{\mu}{2\nu_k^2} \|\mathbf{u}_{k+1} - \mathbf{v}_k\|^2 + \frac{\eta_k \mu \varepsilon^2}{4}, \end{aligned}$$

**then** break.Set  $\rho_{k+1} = 2^{j_k} \rho_k$  and update  $\mathbf{w}_{k+1}$  by

(4.5) 
$$\mathbf{w}_{k+1} = (1 - \eta_k)\mathbf{w}_k + \eta_k \mathbf{v}_k - \frac{\eta_k}{\mu} \nabla f(\mathbf{v}_k).$$

**Output:**  $\mathbf{u}_{k+1}$ .

244 which further implies that

$$\begin{aligned} \frac{\mu}{\nu_k^2} &\geq \frac{1}{\eta_k^{(1-\hat{\alpha})/(1+\hat{\alpha})}} \max_{i \in [m]} \left\{ \left[ \frac{2(1-\alpha_i)}{\mu(1+\alpha_i)\varepsilon^2} \right]^{(1-\alpha_i)/(1+\alpha_i)} L_i^{2/(1+\alpha_i)} \right\} \\ 245 \quad &\geq \max_{i \in [m]} \left\{ \left[ \frac{2(1-\alpha_i)}{\eta_k \mu(1+\alpha_i)\varepsilon^2} \right]^{(1-\alpha_i)/(1+\alpha_i)} L_i^{2/(1+\alpha_i)} \right\}. \end{aligned}$$

246 As a direct consequence of Proposition 2.1, we can proceed to show that the line-search  
247 condition (4.4) is satisfied, which completes the proof.  $\square$ 248 *Remark 4.2.* When the parameters of problem (1.1) are fully specified, Algo-  
249 rithm 3 may alternatively be implemented with a fixed stepsize. Recall that  $M > 0$   
250 is a constant defined in (2.1). By invoking the result of Lemma 4.1, we can fix

251 
$$\nu_k = 2 \left[ \frac{\mu}{4M} \right]^{(1+\hat{\alpha})/(1+3\hat{\alpha})} \varepsilon^{2(1-\hat{\alpha})/(1+3\hat{\alpha})},$$

252 and dispense with the parameter  $\rho_k$  and the line-search procedure in (4.4). Under

253 this choice, Algorithm 3 continues to enjoy the same iteration complexity established  
 254 later.

255 We now introduce the estimating sequences associated with Algorithm 3, which  
 256 play a crucial role in our subsequent analysis.

257 LEMMA 4.3. *Let  $\{\sigma_k\}$  be a sequence of positive constants defined recursively by*

258 (4.7) 
$$\sigma_{k+1} = (1 + \nu_k)\sigma_k,$$

259 with  $\sigma_0 = 1$ . And let  $\{\phi_k\}$  be a sequence of functions defined recursively by

260 (4.8) 
$$\begin{aligned} \phi_{k+1}(\mathbf{u}) &= \phi_k(\mathbf{u}) - \nu_k\sigma_k f^* + \nu_k\sigma_k f(\mathbf{v}_k) + \nu_k\sigma_k \langle \nabla f(\mathbf{v}_k), \mathbf{u} - \mathbf{v}_k \rangle \\ &\quad + \frac{\nu_k\sigma_k\mu}{2} \|\mathbf{u} - \mathbf{v}_k\|^2, \end{aligned}$$

261 with  $\phi_0(\mathbf{u}) = c_0 + \sigma_0\mu \|\mathbf{u} - \mathbf{w}_0\|^2 / 2$  for  $c_0 = f(\mathbf{u}_0) - f^* - \mu\varepsilon^2/4$  and  $\mathbf{w}_0 \in \Omega$ . Then,  
 262 for all  $k \in \mathbb{N}$ , the function  $\phi_k$  preserves the following canonical form,

263 (4.9) 
$$\phi_k(\mathbf{u}) = c_k + \frac{\sigma_k\mu}{2} \|\mathbf{u} - \mathbf{w}_k\|^2,$$

264 where  $\{c_k\}$  is a sequence of real numbers and  $\{\mathbf{w}_k\}$  is defined recursively by (4.5).

265 Proof. We first prove that  $\nabla^2\phi_k = \sigma_k\mu I$  for all  $k \in \mathbb{N}$  by induction. It is evident  
 266 that  $\nabla^2\phi_0 = \sigma_0\mu I$ . Now we assume that  $\nabla^2\phi_k = \sigma_k\mu I$  for some  $k$ . Then relationships  
 267 (4.7) and (4.8) imply that

268 
$$\nabla^2\phi_{k+1} = \nabla^2\phi_k + \nu_k\sigma_k\mu I = \sigma_k\mu I + \nu_k\sigma_k\mu I = \sigma_{k+1}\mu I.$$

269 Thus, we know that  $\nabla^2\phi_k = \sigma_k\mu I$  for all  $k \in \mathbb{N}$ , which, in turn, justifies the canonical  
 270 form of  $\phi_k$  in (4.9).

271 Next, by combining two relationships (4.8) and (4.9) together, we can obtain that

272 
$$\begin{aligned} \phi_{k+1}(\mathbf{u}) &= c_k + \frac{\sigma_k\mu}{2} \|\mathbf{u} - \mathbf{w}_k\|^2 - \nu_k\sigma_k f^* + \nu_k\sigma_k f(\mathbf{v}_k) \\ &\quad + \nu_k\sigma_k \langle \nabla f(\mathbf{v}_k), \mathbf{u} - \mathbf{v}_k \rangle + \frac{\nu_k\sigma_k\mu}{2} \|\mathbf{u} - \mathbf{v}_k\|^2. \end{aligned}$$

273 Since  $\mathbf{w}_{k+1}$  is a global minimizer of  $\phi_{k+1}$  over  $\mathbb{R}^n$ , the first-order optimality condition  
 274 yields that

275 
$$\begin{aligned} 0 &= \nabla\phi_{k+1}(\mathbf{w}_{k+1}) = \sigma_k\mu(\mathbf{w}_{k+1} - \mathbf{w}_k) + \nu_k\sigma_k\nabla f(\mathbf{v}_k) + \nu_k\sigma_k\mu(\mathbf{w}_{k+1} - \mathbf{v}_k) \\ &= (1 + \nu_k)\sigma_k\mu\mathbf{w}_{k+1} - \sigma_k\mu\mathbf{w}_k - \nu_k\sigma_k\mu\mathbf{v}_k + \nu_k\sigma_k\nabla f(\mathbf{v}_k), \end{aligned}$$

276 from which the closed-form expression of  $\mathbf{w}_{k+1}$  in (4.5) can be derived. The proof is  
 277 completed.  $\square$

278 The following lemma characterizes the relationship between the objective function  
 279 of problem (1.1) and the estimating sequences.

280 LEMMA 4.4. *Let  $\sigma_k$  and  $\{\phi_k\}$  be the sequences defined in Lemma 4.3. Then we  
 281 have*

282 (4.10) 
$$\phi_k(\mathbf{u}) \leq \sigma_k(f(\mathbf{u}) - f^*) + \phi_0(\mathbf{u}),$$

283 for all  $\mathbf{u} \in \Omega$  and  $k \in \mathbb{N}$ .

284     *Proof.* We prove that  $\{\phi_k\}$  and  $\{\sigma_k\}$  satisfy relationship (4.10) by induction. It  
 285     is obvious that (4.10) holds for  $k = 0$  since  $f(\mathbf{u}) \geq f^*$  for any  $\mathbf{u} \in \Omega$ . Now we assume  
 286     that (4.10) holds for some  $k \in \mathbb{N}$ . It follows from the strong convexity of  $f$  that

$$287 \quad f(\mathbf{u}) \geq f(\mathbf{v}_k) + \langle \nabla f(\mathbf{v}_k), \mathbf{u} - \mathbf{v}_k \rangle + \frac{\mu}{2} \|\mathbf{u} - \mathbf{v}_k\|^2,$$

288     for all  $\mathbf{u} \in \Omega$ . Then substituting the above relationship into (4.8) leads to that

$$\begin{aligned} 289 \quad \phi_{k+1}(\mathbf{u}) &\leq \phi_k(\mathbf{u}) - \nu_k \sigma_k f^* + \nu_k \sigma_k f(\mathbf{u}) \\ &\leq \sigma_k(f(\mathbf{u}) - f^*) + \phi_0(\mathbf{u}) + \nu_k \sigma_k(f(\mathbf{u}) - f^*) \\ &= \sigma_{k+1}(f(\mathbf{u}) - f^*) + \phi_0(\mathbf{u}), \end{aligned}$$

290     which indicates that (4.10) also holds for  $k + 1$ . We complete the proof.  $\square$

291     Next, we proceed to show that the function value error of Algorithm 3 is controlled  
 292     by the estimating sequences.

293     PROPOSITION 4.5. *Let  $\{\sigma_k\}$  and  $\{\phi_k\}$  be the sequences defined in Lemma 4.3.  
 294     Then the sequence  $\{\mathbf{u}_k\}$  generated by Algorithm 3 satisfies*

$$295 \quad (4.11) \quad f(\mathbf{u}_k) - f^* \leq \frac{1}{\sigma_k} \phi_0(\mathbf{u}^*) + \frac{\mu \varepsilon^2}{4},$$

296     for all  $k \in \mathbb{N}$ .

297     *Proof.* Let  $\phi_k^* := \min_{\mathbf{u} \in \Omega} \phi_k(\mathbf{u})$ . We first prove by induction that

$$298 \quad (4.12) \quad \sigma_k \left( f(\mathbf{u}_k) - f^* - \frac{\mu \varepsilon^2}{4} \right) \leq \phi_k^*,$$

299     for any  $k \in \mathbb{N}$ . It is clear that (4.12) holds for  $k = 0$  since  $\sigma_0 = 1$  and  $\phi_0^* = \phi_0(\mathbf{w}_0) =$   
 300      $f(\mathbf{u}_0) - f^* - \mu \varepsilon^2 / 4$ . Now we assume that (4.12) holds for some  $k \in \mathbb{N}$  and investigate  
 301     the situation for  $k + 1$ .

302     From the canonical form (4.9), it follows that  $\phi_k$  is a strongly convex function  
 303     and  $\Pi_\Omega(\mathbf{w}_k) = \arg \min_{\mathbf{u} \in \Omega} \phi_k(\mathbf{u})$ . By invoking the result of [11, Corollary 2.2.1], we  
 304     have

$$\begin{aligned} 305 \quad \phi_k(\mathbf{u}) &\geq \phi_k^* + \frac{\sigma_k \mu}{2} \|\mathbf{u} - \Pi_\Omega(\mathbf{w}_k)\|^2 \\ &\geq \sigma_k \left( f(\mathbf{u}_k) - f^* - \frac{\mu \varepsilon^2}{4} \right) + \frac{\sigma_k \mu}{2} \|\mathbf{u} - \Pi_\Omega(\mathbf{w}_k)\|^2, \end{aligned}$$

306     for all  $\mathbf{u} \in \Omega$ . Then relationship (4.8) yields that

$$\begin{aligned} 307 \quad \phi_{k+1}(\mathbf{u}) &\geq \sigma_k \left( f(\mathbf{u}_k) - f^* - \frac{\mu \varepsilon^2}{4} \right) + \frac{\sigma_k \mu}{2} \|\mathbf{u} - \Pi_\Omega(\mathbf{w}_k)\|^2 - \nu_k \sigma_k f^* \\ &\quad + \nu_k \sigma_k f(\mathbf{v}_k) + \nu_k \sigma_k \langle \nabla f(\mathbf{v}_k), \mathbf{u} - \mathbf{v}_k \rangle + \frac{\nu_k \sigma_k \mu}{2} \|\mathbf{u} - \mathbf{v}_k\|^2 \\ &\geq \sigma_{k+1} (f(\mathbf{v}_k) - f^*) - \frac{\sigma_k \mu \varepsilon^2}{4} + \langle \nabla f(\mathbf{v}_k), \sigma_k \mathbf{u}_k - \sigma_{k+1} \mathbf{v}_k \rangle \\ &\quad + \nu_k \sigma_k \langle \nabla f(\mathbf{v}_k), \mathbf{u} \rangle + \frac{\sigma_k \mu}{2} \|\mathbf{u} - \Pi_\Omega(\mathbf{w}_k)\|^2 \\ &= \sigma_{k+1} (f(\mathbf{v}_k) - f^*) - \frac{\sigma_k \mu \varepsilon^2}{4} + \nu_k \sigma_k \langle \nabla f(\mathbf{v}_k), \mathbf{u} - \Pi_\Omega(\mathbf{w}_k) \rangle \\ &\quad + \frac{\sigma_k \mu}{2} \|\mathbf{u} - \Pi_\Omega(\mathbf{w}_k)\|^2, \end{aligned}$$

308 where the second inequality comes from the strong convexity of  $f$  and (4.7), and the  
 309 last equality holds due to the definition of  $\mathbf{v}_k$  in (4.1). According to the definition of  
 310  $\mathbf{z}_k$  in (4.2), we can obtain that

$$\begin{aligned} & \nu_k \sigma_k \langle \nabla f(\mathbf{v}_k), \mathbf{u} - \Pi_\Omega(\mathbf{w}_k) \rangle + \frac{\sigma_k \mu}{2} \|\mathbf{u} - \Pi_\Omega(\mathbf{w}_k)\|^2 \\ &= \frac{\sigma_k \mu}{2} \left\| \mathbf{u} - \left( \Pi_\Omega(\mathbf{w}_k) - \frac{\nu_k}{\mu} \nabla f(\mathbf{v}_k) \right) \right\|^2 - \frac{\nu_k^2 \sigma_k}{2\mu} \|\nabla f(\mathbf{v}_k)\|^2 \\ &\geq \frac{\sigma_k \mu}{2} \left\| \mathbf{z}_k - \left( \Pi_\Omega(\mathbf{w}_k) - \frac{\nu_k}{\mu} \nabla f(\mathbf{v}_k) \right) \right\|^2 - \frac{\nu_k^2 \sigma_k}{2\mu} \|\nabla f(\mathbf{v}_k)\|^2 \\ &= \nu_k \sigma_k \langle \nabla f(\mathbf{v}_k), \mathbf{z}_k - \Pi_\Omega(\mathbf{w}_k) \rangle + \frac{\sigma_k \mu}{2} \|\mathbf{z}_k - \Pi_\Omega(\mathbf{w}_k)\|^2. \end{aligned}$$

312 As a result, it holds that

$$\begin{aligned} & \phi_{k+1}(\mathbf{u}) \geq \sigma_{k+1} (f(\mathbf{v}_k) - f^*) - \frac{\sigma_k \mu \varepsilon^2}{4} + \nu_k \sigma_k \langle \nabla f(\mathbf{v}_k), \mathbf{z}_k - \Pi_\Omega(\mathbf{w}_k) \rangle \\ & \quad + \frac{\sigma_k \mu}{2} \|\mathbf{z}_k - \Pi_\Omega(\mathbf{w}_k)\|^2, \end{aligned} \tag{4.13}$$

314 for all  $\mathbf{u} \in \Omega$ . From the definitions of  $\mathbf{v}_k$  and  $\mathbf{u}_{k+1}$  in (4.1) and (4.3), it can be derived  
 315 that  $\mathbf{z}_k - \Pi_\Omega(\mathbf{w}_k) = (\mathbf{u}_{k+1} - \mathbf{v}_k)/\eta_k$ . Substituting this relationship into (4.13) and  
 316 taking  $\mathbf{u} = \Pi_\Omega(\mathbf{w}_{k+1})$ , we arrive at

$$\frac{\phi_{k+1}^*}{\sigma_{k+1}} \geq f(\mathbf{v}_k) - f^* + \langle \nabla f(\mathbf{v}_k), \mathbf{u}_{k+1} - \mathbf{v}_k \rangle + \frac{\mu}{2\nu_k^2} \|\mathbf{u}_{k+1} - \mathbf{v}_k\|^2 - \frac{(1 - \eta_k)\mu \varepsilon^2}{4},$$

318 which together with the line-search condition (4.4) implies that

$$\frac{\phi_{k+1}^*}{\sigma_{k+1}} \geq f(\mathbf{u}_{k+1}) - f^* - \frac{\eta_k \mu \varepsilon^2}{4} - \frac{(1 - \eta_k)\mu \varepsilon^2}{4} = f(\mathbf{u}_{k+1}) - f^* - \frac{\mu \varepsilon^2}{4}.$$

320 Therefore, relationship (4.12) also holds for  $k + 1$ .

321 Finally, by collecting two relationships (4.10) and (4.12) together, we can obtain  
 322 that

$$\begin{aligned} & \sigma_k \left( f(\mathbf{u}_k) - f^* - \frac{\mu \varepsilon^2}{4} \right) \leq \min_{\mathbf{u} \in \Omega} \phi_k(\mathbf{u}) \leq \min_{\mathbf{u} \in \Omega} \{ \sigma_k(f(\mathbf{u}) - f^*) + \phi_0(\mathbf{u}) \} \\ & \leq \sigma_k(f(\mathbf{u}^*) - f^*) + \phi_0(\mathbf{u}^*) \\ & = \phi_0(\mathbf{u}^*), \end{aligned}$$

324 which completes the proof.  $\square$

325 With the above preparatory results in place, we are now in a position to establish  
 326 the iteration complexity of Algorithm 3, as articulated in the theorem below.

327 **THEOREM 4.6.** *Let  $\varepsilon \in (0, 1)$  be a sufficiently small constant. Then after at most*

$$O \left( \log \left( \frac{1}{\varepsilon} \right) \frac{M^{(1+\hat{\alpha})/(1+3\hat{\alpha})}}{\varepsilon^{2(1-\hat{\alpha})/(1+3\hat{\alpha})}} \right)$$

329 iterations, Algorithm 3 will reach an iterate  $\mathbf{u}_k$  satisfying  $\|\mathbf{u}_k - \mathbf{u}^*\| \leq \varepsilon$ .

330     *Proof.* In view of relationship (4.6), the number of line-search steps  $j_k$  in (4.4)  
 331     satisfies

$$332 \quad \frac{\mu}{\nu_k^2} \eta_k^{(1-\hat{\alpha})/(1+\hat{\alpha})} \leq 2 \max_{i \in [m]} \left\{ \left[ \frac{2(1-\alpha_i)}{\mu(1+\alpha_i)\varepsilon^2} \right]^{(1-\alpha_i)/(1+\alpha_i)} L_i^{2/(1+\alpha_i)} \right\} \leq \frac{2M}{\varepsilon^{2(1-\hat{\alpha})/(1+\hat{\alpha})}},$$

333     where  $M > 0$  is a constant defined in (2.1). Since  $\eta_k = \nu_k/(1+\nu_k) \geq \nu_k/2$ , we arrive  
 334     at

$$335 \quad (4.14) \quad \frac{\nu_k^2}{\mu} \geq \frac{\varepsilon^{2(1-\hat{\alpha})/(1+\hat{\alpha})}}{2M} \eta_k^{(1-\hat{\alpha})/(1+\hat{\alpha})} \geq \frac{\varepsilon^{2(1-\hat{\alpha})/(1+\hat{\alpha})}}{2^{2/(1+\hat{\alpha})} M} \nu_k^{(1-\hat{\alpha})/(1+\hat{\alpha})}.$$

336     Let  $\omega > 0$  be a constant defined as

$$337 \quad \omega = \frac{1}{2^{2/(1+3\hat{\alpha})}} \left[ \frac{\mu}{M} \right]^{(1+\hat{\alpha})/(1+3\hat{\alpha})}.$$

338     Then it follows from relationship (4.14) that

$$339 \quad (4.15) \quad \nu_k \geq \omega \varepsilon^{2(1-\hat{\alpha})/(1+3\hat{\alpha})},$$

340     which further infers that

$$341 \quad \sigma_{k+1} = (1 + \nu_k) \sigma_k \geq \left( 1 + \omega \varepsilon^{2(1-\hat{\alpha})/(1+3\hat{\alpha})} \right) \sigma_k.$$

342     Applying the above inequality for  $k$  times recursively yields that

$$343 \quad \sigma_k \geq \left( 1 + \omega \varepsilon^{2(1-\hat{\alpha})/(1+3\hat{\alpha})} \right)^k.$$

344     As a direct consequence of (2.5) and (4.11), we can show that

$$345 \quad \begin{aligned} \|\mathbf{u}_k - \mathbf{u}^*\|^2 &\leq \frac{2}{\mu} (f(\mathbf{u}_k) - f^*) \leq \frac{2}{\mu} \left( \frac{1}{\sigma_k} \phi_0(\mathbf{u}^*) + \frac{\mu \varepsilon^2}{4} \right) \\ &\leq \chi \left( 1 + \omega \varepsilon^{2(1-\hat{\alpha})/(1+3\hat{\alpha})} \right)^{-k} + \frac{\varepsilon^2}{2}, \end{aligned}$$

346     where  $\chi = 2(f(\mathbf{u}_0) - f^*)/\mu + \|\mathbf{u}_0 - \mathbf{u}^*\|^2 > 0$  is a constant. Let  $K_\varepsilon^*$  be the small-  
 347     est iteration number  $k$  such that  $\|\mathbf{u}_k - \mathbf{u}^*\| \leq \varepsilon$ . By solving the inequality  $\chi(1 + \omega \varepsilon^{2(1-\hat{\alpha})/(1+3\hat{\alpha})})^{-k} \leq \varepsilon^2/2$ , we have

$$349 \quad K_\varepsilon^* \leq \log \left( \frac{\sqrt{2\chi}}{\varepsilon} \right) \frac{2}{\log(1 + \omega \varepsilon^{2(1-\hat{\alpha})/(1+3\hat{\alpha})})} \leq \log \left( \frac{\sqrt{2\chi}}{\varepsilon} \right) \frac{4}{\omega \varepsilon^{2(1-\hat{\alpha})/(1+3\hat{\alpha})}}.$$

350     The proof is completed.  $\square$

351     The complexity bound established in Theorem 4.6 is markedly lower than those  
 352     presented in Theorems 2.2 and 3.1, thereby highlighting the acceleration effect at-  
 353     tained by Algorithm 3. Finally, we demonstrate that the number of line-search steps  
 354     required by Algorithm 3 is also  $O(\log(\varepsilon^{-1}) \varepsilon^{2(\hat{\alpha}-1)/(1+3\hat{\alpha})})$ .

355     COROLLARY 4.7. *Let  $\varepsilon \in (0, 1)$  be a sufficiently small constant. Then, to achieve  
 356     an iterate  $\mathbf{u}_k$  satisfying  $\|\mathbf{u}_k - \mathbf{u}^*\| \leq \varepsilon$ , Algorithm 3 requires at most*

$$357 \quad O \left( \log \left( \frac{1}{\varepsilon} \right) \frac{M^{(1+\hat{\alpha})/(1+3\hat{\alpha})}}{\varepsilon^{2(1-\hat{\alpha})/(1+3\hat{\alpha})}} \right)$$

358 line-search steps.

359 *Proof.* It follows from relationship (4.14) that

$$360 \quad \rho_{k+1} = 2^{j_k} \rho_k = \frac{\mu}{\nu_k^2} \leq \frac{2^{2/(1+\hat{\alpha})} M}{\varepsilon^{2(1-\hat{\alpha})/(1+\hat{\alpha})}} \left[ \frac{1}{\nu_k} \right]^{(1-\hat{\alpha})/(1+\hat{\alpha})},$$

361 which together with (4.15) implies that

$$362 \quad \rho_{k+1} \leq \frac{2^{2/(1+\hat{\alpha})} M}{\varepsilon^{2(1-\hat{\alpha})/(1+\hat{\alpha})}} \left[ \frac{1}{\omega \varepsilon^{2(1-\hat{\alpha})/(1+3\hat{\alpha})}} \right]^{(1-\hat{\alpha})/(1+\hat{\alpha})} = \frac{2^{2/(1+\hat{\alpha})} M}{\omega^{(1-\hat{\alpha})/(1+\hat{\alpha})} \varepsilon^{4(1-\hat{\alpha})/(1+3\hat{\alpha})}}.$$

363 Let  $N_k$  be the total number of line-search steps after  $k$  iterations in Algorithm 3. In  
364 view of (3.4), we have

$$365 \quad \begin{aligned} N_k &\leq k + 1 + \log \left( \frac{2^{2/(1+\hat{\alpha})} M}{\omega^{(1-\hat{\alpha})/(1+\hat{\alpha})} \varepsilon^{4(1-\hat{\alpha})/(1+3\hat{\alpha})}} \right) - \log \rho_0 \\ &\leq k + \frac{4(1-\hat{\alpha})}{1+3\hat{\alpha}} \log \left( \frac{1}{\varepsilon} \right) + \log \left( \frac{2^{2/(1+\hat{\alpha})} M}{\omega^{(1-\hat{\alpha})/(1+\hat{\alpha})} \rho_0} \right) + 1. \end{aligned}$$

366 Consequently, Theorem 4.6 indicates that the total number of line-search steps in  
367 Algorithm 3 is at most  $O(\log(\varepsilon^{-1})\varepsilon^{2(\hat{\alpha}-1)/(1+3\hat{\alpha})})$ , which completes the proof.  $\square$

368 *Remark 4.8.* By an analogous argument, we can also prove that Algorithm 3  
369 requires at most  $O(\log(\varepsilon^{-1})\varepsilon^{(\hat{\alpha}-1)/(1+3\hat{\alpha})})$  iterations to generate an iterate  $\mathbf{u}_k$  such  
370 that  $f(\mathbf{u}_k) - f^* \leq \varepsilon$  for problem (1.1). Very recently, Doikov [8] has shown that,  
371 in the case  $m = 2$ , where  $f_1$  is a convex function with a Hölder continuous gradient  
372 and  $f_2(\mathbf{u}) = \|\mathbf{u}\|^2$ , the lower complexity bound for first-order methods is precisely  
373  $O(\log(\varepsilon^{-1})\varepsilon^{(\hat{\alpha}-1)/(1+3\hat{\alpha})})$  in terms of function value accuracy. This finding confirms  
374 that Algorithm 3 achieves the optimal iteration complexity.

375 **5. Numerical Experiments.** Preliminary numerical results are presented in  
376 this section to provide additional insights into the performance guarantees of the al-  
377 gorithms proposed in this paper. We aim to elucidate that the final error attained  
378 by the algorithm is influenced by both the stepsize and the Hölder exponent. The  
379 numerical experiments are conducted using Julia [4] (version 1.12) on an Apple Mac-  
380 intosh Mini with an M2 processor, 8 performance cores, and 32GB of memory. We  
381 have placed the Julia codes in the GitHub repository ([https://github.com/ctkelle/y/Grad\\_Des\\_CKW.jl](https://github.com/ctkelle/y/Grad_Des_CKW.jl)) with instructions for reproducing the figures. In this section,  
382 we set the spatial mesh width as  $h = 2^{-4}$  for the discretization of partial differential  
383 equations (PDEs). Then the dimension of the discretized problem is  $n = (h^{-1} - 1)^2$ .

385 **5.1. Two-dimensional PDE with a non-Lipschitz term.** Hölder continuous  
386 gradients arise naturally in PDEs involving non-Lipschitz nonlinearity [3, 14]. In this  
387 subsection, we introduce a numerical example from [3]. This problem is to solve the  
388 following two-dimensional PDE,

$$389 \quad (5.1) \quad \mathcal{F}(u) = -\Delta u + \gamma u_+^\alpha = 0,$$

390 where  $\alpha \in (0, 1)$ ,  $\gamma > 0$  is a constant and  $u_+ = \max\{u, 0\}$ . Discretizing (5.1) with the  
391 standard five point difference scheme [9] leads to the following nonlinear system,

$$392 \quad (5.2) \quad \mathbf{F}(\mathbf{u}) = \mathbf{A}\mathbf{u} + \gamma \mathbf{u}_+^\alpha - \mathbf{b} = 0,$$

393 where  $\mathbf{A} \in \mathbb{R}^{n \times n}$  is the discretization of  $-\Delta$  with zero boundary conditions,  $\mathbf{b} \in$   
 394  $\mathbb{R}^n$  encodes the boundary conditions, and  $\mathbf{u}_+^\alpha = \max\{\mathbf{u}, 0\}^\alpha$  is understood as a  
 395 component-wise operation.

396 We now modify the above problem to enable direct computation of errors in the  
 397 iterations. To this end, we follow [13, Example 4.4] and take as the exact solution the  
 398 function

$$399 \quad u^*(x, y) = \left(\frac{3r-1}{2}\right)^2 \max\left\{0, r - \frac{1}{3}\right\},$$

400 where  $r = \sqrt{x^2 + y^2}$ . We enforce the following boundary conditions,

$$401 \quad u(x, 1) = u^*(x, 1), u(x, 0) = u^*(x, 0), u(1, y) = u^*(1, y), u(0, y) = u^*(0, y),$$

402 for  $0 < x, y < 1$ . And these conditions are encoded into  $\mathbf{b}$ . Then our modified  
 403 equation is

$$404 \quad (5.3) \quad \mathbf{F}(\mathbf{u}) - \mathbf{c}^* = 0,$$

405 where  $\mathbf{c}^* = \mathbf{F}(\mathbf{u}^*)$ . The nonlinear system (5.3) corresponds to the optimality condition  
 406 of the following problem,

$$407 \quad (5.4) \quad \min_{\mathbf{u} \in \mathbb{R}^n} f(\mathbf{u}) = \frac{1}{2} \mathbf{u}^\top \mathbf{A} \mathbf{u} + \frac{\gamma}{1+\alpha} \mathbf{e}^\top \mathbf{u}_+^{1+\alpha} - (\mathbf{b} + \mathbf{c}^*)^\top \mathbf{u},$$

408 where  $\mathbf{e} \in \mathbb{R}^n$  is the vector of all ones.

409 The optimization model (5.4) is a special instance of problem (1.1) with  $\Omega = \mathbb{R}^n$ ,  
 410  $m = 2$ ,

$$411 \quad f_1(\mathbf{u}) = \mathbf{u}^\top \mathbf{A} \mathbf{u} - 2(\mathbf{b} + \mathbf{c}^*)^\top \mathbf{u}, \text{ and } f_2(\mathbf{u}) = \frac{2\gamma}{1+\alpha} \mathbf{e}^\top \mathbf{u}_+^{1+\alpha}.$$

412 It is clear that,  $\nabla f_1$  is Lipschitz continuous with the corresponding Lipschitz constant  
 413  $L_1 = 2 \|\mathbf{A}\|$ , and  $\nabla f_2$  is Hölder continuous with the Hölder exponent  $\alpha$  and  $L_2 = 2\gamma$   
 414 from

$$415 \quad \|\nabla f_2(\mathbf{u}) - \nabla f_2(\mathbf{v})\| = 2\gamma \|\mathbf{u}_+^\alpha - \mathbf{v}_+^\alpha\| \leq 2\gamma \|\mathbf{u} - \mathbf{v}\|^\alpha,$$

416 for all  $\mathbf{u}, \mathbf{v} \in \mathbb{R}^n$ . Moreover, the function  $f = (f_1 + f_2)/2$  is  $\lambda(\mathbf{A})$ -strongly convex,  
 417 where  $\lambda(\mathbf{A})$  is the smallest eigenvalue of the symmetric positive definite matrix  $\mathbf{A}$ .  
 418 Let  $\mathbf{u}^*$  be the vector obtained by evaluating  $u^*$  at the interior grid points. Then  $\mathbf{u}^*$   
 419 serves as the unique global minimizer of problem (5.4).

420 In the subsequent experiments, we use the solution of  $\mathbf{A}\mathbf{u}_0 = \mathbf{b}$  as the initial  
 421 iterate. This is the discretization of Laplace's equation with the boundary conditions.  
 422 In this way, we ensure that the entire iteration satisfies the boundary conditions.

423 **5.1.1. Numerical results for Algorithm 1.** In the first experiment, we scrutinize  
 424 the performance of Algorithm 1 under different stepsizes for problem (5.4) with  
 425  $\alpha = 0.5$  and  $\gamma = 0.5$ . Specifically, Algorithm 1 is tested for stepsizes of the form  
 426  $\tau = \tau_0 h^2$ , where  $\tau_0$  is taken from the set  $\{0.2, 0.1, 0.05, 0.01\}$ . The corresponding nu-  
 427 mercial results, presented in Figure 1(a), illustrate the decay of the distance between  
 428 the iterates and the global minimizer over iterations. It can be observed that a larger  
 429 stepsize facilitates a more rapid descent in the iterations.

430 In the second experiment, we vary the Hölder exponent  $\alpha$  over the values in  
 431  $\{0.1, 0.2, 0.5, 0.8\}$ , while fixing  $\tau_0 = 0.1$ . Figure 1(b) similarly tracks the decay of  
 432 the distance to the global minimizer over iterations. It is evident that, as the value  
 433 of  $\alpha$  decreases, the final error attained by Algorithm 1 increases under the same  
 434 stepsize. Therefore, the associated optimization problems become increasingly ill-  
 435 conditioned and thus more challenging to solve for smaller values of  $\alpha$ . These findings  
 436 offer empirical support for our theoretical analysis. In Figure 1(b), and in sever  
 437 others, the thick lines are artifacts of small rapid oscillations in the error norm which  
 438 reflect stagnation in the iteration.

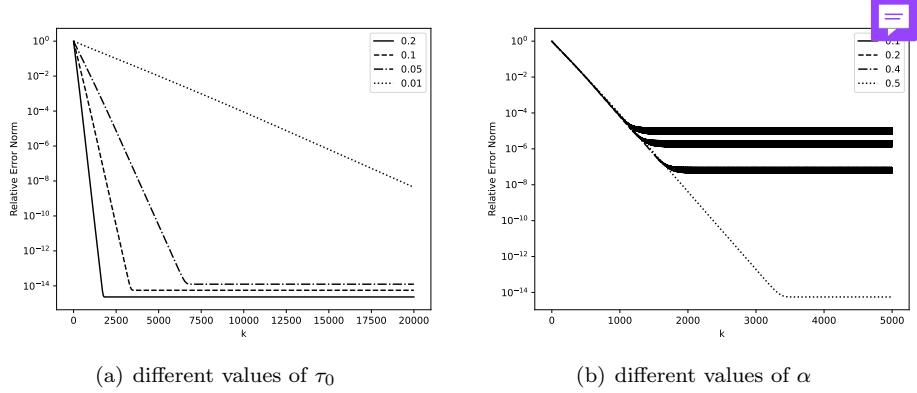


FIG. 1. Numerical performance of Algorithm 1 for problem (5.4).

439 **5.1.2. Numerical results for Algorithm 2.** We repeat the study in subsec-  
 440 tion 5.1.1 for Algorithm 2 by varying the values of the Hölder exponent  $\alpha$ . We set  
 441  $\varepsilon = 10^{-6}$  and  $\mu = 2\pi^2$  in Algorithm 2, which is a lower estimate for the smallest  
 442 eigenvalue of  $\mathbf{A}$ . The stepsize is initialized to  $20h^2$  in the line-search procedure. The  
 443 corresponding numerical results are depicted in Figure 2. Comparing Figure 2 to Fig-  
 444 ure 1(b) shows the benefits of the line-search procedure in Algorithm 2, which does  
 445 not need to manually adjust the value of  $\tau_0$  to converge for a given value of  $\varepsilon$ .

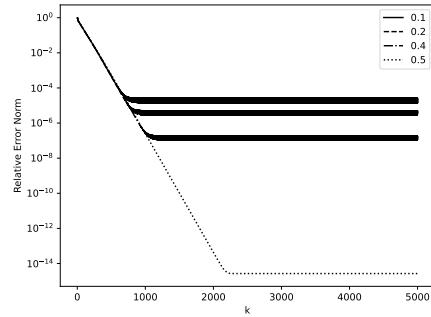


FIG. 2. Numerical performance of Algorithm 2 for problem (5.4) with different values of  $\alpha$ .

446 **5.1.3. Numerical results for Algorithm 3.** We report the numerical perfor-  
 447 mance of Algorithm 3 on two experiments. Guided by the observation in Remark 4.2,  
 448 we test Algorithm 3 with a fixed stepsize  $\nu = \tau_0 h^2$ . We first use the values for  $\tau_0$

449 from Figure 1. In this way we can directly compare the performance of Algorithm 3  
 450 with that of Algorithm 1. The corresponding results, shown in Figure 3, are poor.  
 451 The reason for this is that we are not exploiting the ability of Algorithm 3 to use  
 452 larger stepsizes. Consequently, we consider larger values for  $\tau_0$  in Figure 4(a) and set  
 453  $\tau_0 = 20$  in Figure 4(b). The convergence is much better in all cases.

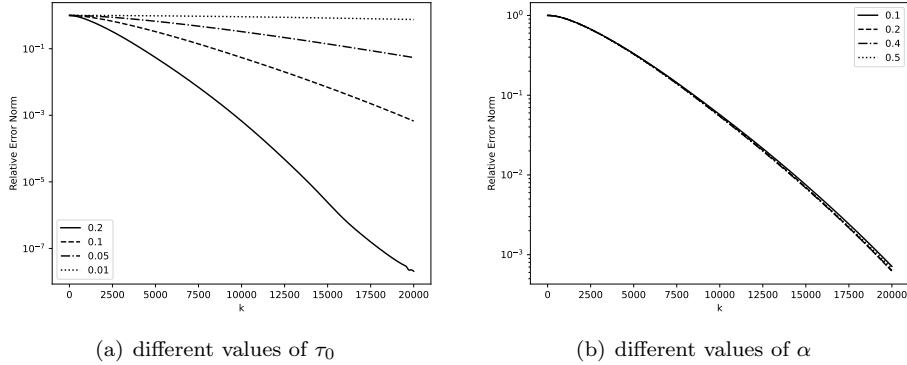


FIG. 3. Numerical performance of Algorithm 3 for problem (5.4) with smaller stepsizes.

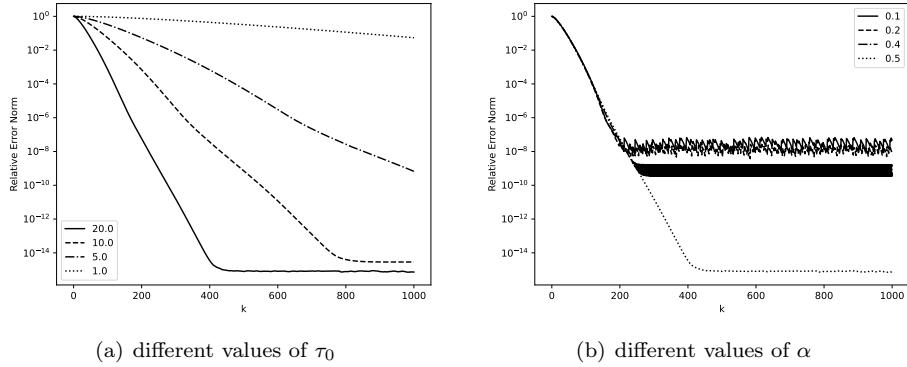


FIG. 4. Numerical performance of Algorithm 3 for problem (5.4) with larger stepsizes.

**454      5.2. Semi-linear elliptic problem with a constraint.** We consider a second  
 455 numerical example motivated by a semi-linear elliptic problem with a constraint on  
 456 the solution in a certain set [14]. Let

$$457 \quad (5.5) \qquad \qquad \qquad \mathcal{H}(u) = -\Delta u + \delta |u|^\alpha \operatorname{sign}(u) - |u|^{p-1} u,$$

458 on  $D = (0, 1)^2$  with the boundary condition  $u(x, y) = 0.5 - \sin(x)\sin(y)$  on  $\partial D$ . Here,  
 459  $\alpha \in (0, 1)$ ,  $p > 1$ , and  $\delta > p/\alpha$  are three constants. We consider the variational  
 460 inequality that is to find  $u^* \in [-1, 1]$  such that

$$\mathcal{H}(u^*)(u - u^*) \geq 0,$$

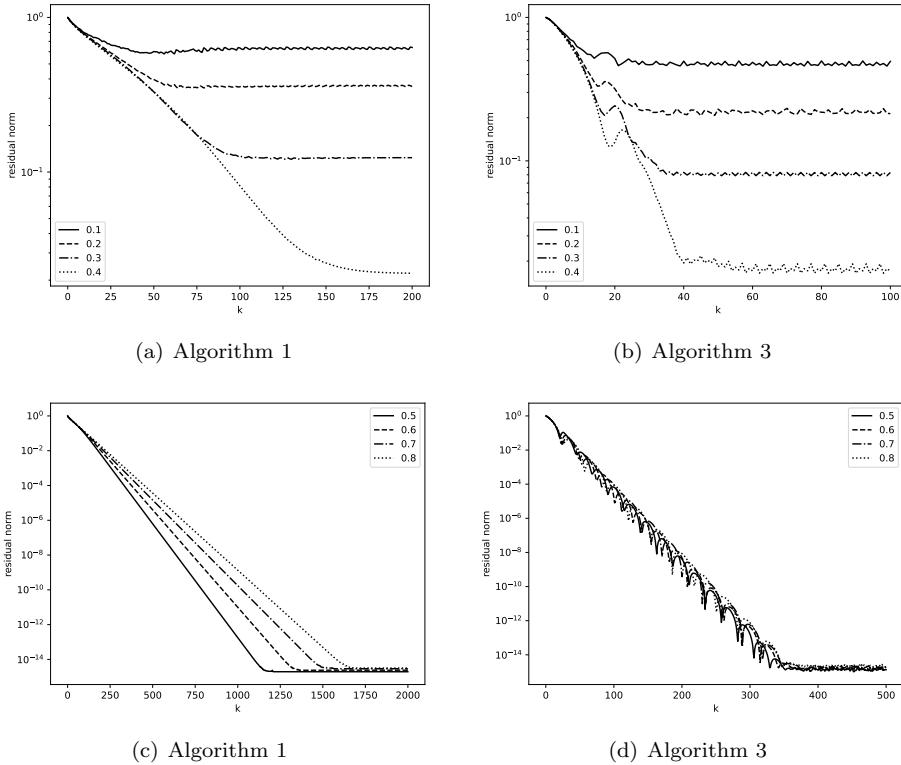


FIG. 5. Numerical performance of Algorithm 1 and Algorithm 3 for problem (5.8) with different values of  $\alpha$ .

for any  $u \in [-1, 1]$ . This problem is equivalent to the following nonlinear equation,

$$463 \quad (5.6) \quad 0 = \mathcal{F}(u) := \begin{cases} \mathcal{H}(u), & \text{if } u - \mathcal{H}(u) \in [-1, 1], \\ u - 1, & \text{if } u - \mathcal{H}(u) \geq 1, \\ u + 1, & \text{otherwise.} \end{cases}$$

464 By discretizing (5.5) with the standard five point difference scheme [9], problem (5.6)  
 465 leads to the following system of nonlinear equations,

$$466 \quad (5.7) \quad 0 = \mathbf{F}(\mathbf{u}) := \mathbf{u} - \Pi_{\mathbf{U}} \left( \mathbf{u} - \tau \left( \mathbf{A}\mathbf{u} + \delta |\mathbf{u}|^\alpha \operatorname{sign}(\mathbf{u}) - |\mathbf{u}|^{p-1} \mathbf{u} - \mathbf{b} \right) \right),$$

467 where  $\mathbf{U} = [-1, 1]^n$ ,  $\tau > 0$  is a constant,  $\mathbf{A} \in \mathbb{R}^{n \times n}$  is a symmetric positive definite  
 468 matrix, and  $\mathbf{b} \in \mathbb{R}^n$  encodes the boundary conditions. Note that (5.7) is the optimality  
 469 condition of the following problem,

$$470 \quad (5.8) \quad \min_{\mathbf{u} \in \mathbb{U}} \quad f(\mathbf{u}) := \frac{1}{2} \mathbf{u}^\top \mathbf{A} \mathbf{u} + \frac{\delta}{1+\alpha} \mathbf{e}^\top |\mathbf{u}|^{1+\alpha} - \frac{1}{1+p} \mathbf{e}^\top |\mathbf{u}|^{1+p} - \mathbf{b}^\top \mathbf{u}.$$

471 The Hessian matrix of  $f$  at  $\mathbf{u}$  with  $\mathbf{u}_i \neq 0$  ( $i = 1, \dots, n$ ) has the form

$$\nabla^2 f(\mathbf{u}) = \mathbf{A} + \delta\alpha \text{Diag}\left(|\mathbf{u}|^{\alpha-1}\right) - p \text{Diag}\left(|\mathbf{u}|^{p-1}\right),$$

473 Since  $\delta > p/\alpha$ ,  $\nabla^2 f(\mathbf{u})$  is symmetric positive definite for any  $\mathbf{u} \in \mathbf{U}$  with  $\mathbf{u}_i \neq 0$  ( $i = 1, \dots, n$ ). Hence, the function  $f$  is  $\mu$ -strongly convex in  $\mathbf{U}$  with  $\mu = \lambda(\mathbf{A})$  and the  
 474 system (5.7) has a unique solution in  $\mathbf{U}$ . The optimization model (5.8) is a special  
 475 instance of problem (1.1) with  $\Omega = \mathbf{U}$ ,  $m = 2$ ,

$$477 \quad f_1(\mathbf{u}) = \mathbf{u}^\top \mathbf{A} \mathbf{u} - 2\mathbf{b}^\top \mathbf{u} - \frac{2}{1+p} \mathbf{e}^\top |\mathbf{u}|^{1+p}, \text{ and } f_2(\mathbf{u}) = \frac{2\delta}{1+\alpha} \mathbf{e}^\top |\mathbf{u}|^{1+\alpha}.$$

478 It is clear that Assumption 1.1 (ii) holds with  $\alpha_1 = 1$ ,  $L_1 = 2\|\mathbf{A}\| + 2p$ ,  $\alpha_2 = \alpha$ , and  
 479  $L_2 = 2\delta\alpha$ .

480 In this example, we do not have an analytic solution and we only plot the residual  
 481 norm  $\|\mathbf{F}(\mathbf{u})\|$  with  $\tau$  being the stepsize. We compare the performance of Algorithm 1  
 482 and Algorithm 3 on problem (5.8) with  $p = 1.5$  and  $\delta = 20$ . The stepsizes of Algo-  
 483 rithm 1 and Algorithm 3 are set to  $\tau = 0.1h^2$  and  $\tau = 20h^2$ , respectively. Figure 5(a)  
 484 and Figure 5(c) present the performance of Algorithm 1 for  $\alpha \in \{0.1, 0.2, 0.3, 0.4\}$  and  
 485  $\alpha \in \{0.5, 0.6, 0.7, 0.8\}$ , respectively. In a similar vein, Figure 5(b) and Figure 5(d) il-  
 486 lustrate the behavior of Algorithm 3 across the same ranges of  $\alpha$ . Similar as the  
 487 case in subsection 5.1, problems where the exponent  $\alpha$  for the non-Lipschitz term in  
 488 the gradients is small are difficult. In particular, one cannot drive the residual to a  
 489 small value. For larger values of  $\alpha$ , both algorithms demonstrate strong performance.  
 490 Furthermore, Algorithm 3 exhibits a faster convergence rate, benefiting from the use  
 491 of a larger stepsize.

492 **6. Conclusion.** In this paper, we consider a class of strongly convex constrained  
 493 optimization problems of the form (1.1). Example 1.2 shows that although each com-  
 494 ponent function  $f_i$  of the objective function  $f$  admits a Hölder continuous gradient  
 495 with an component  $\alpha_i \in (0, 1]$ , the gradient of  $f$  is not necessarily Hölder continuous.  
 496 To establish the iteration complexity of the projected gradient descent methods for  
 497 this class of problems, we use the parameter  $\hat{\alpha} = \min_{i \in [m]} \alpha_i$  to determine the com-  
 498 plexity bound. Algorithm 1 is a new version of projected gradient method for prob-  
 499 lem (1.1) with an appropriately fixed stepsize. Theorem 2.2 shows that Algorithm 1  
 500 can find an iterate in the feasible set  $\Omega$  with a distance to the global minimizer less  
 501 than  $\varepsilon$  at most  $O(\log(\varepsilon^{-1})\varepsilon^{2(\hat{\alpha}-1)/(1+\hat{\alpha})})$  iterations. This recovers the classical com-  
 502 plexity result when  $\hat{\alpha} = 1$  and reveals the additional difficulty imposed by the weaker  
 503 smoothness of the objective function for  $\hat{\alpha} < 1$ . Algorithm 2 is a modification of Algo-  
 504 rithm 1 for problems where the parameters  $\alpha_i$  and  $L_i$  are difficult to estimate for the  
 505 stepsize. In Algorithm 3, the stepsize is updated by the universal scheme at each iter-  
 506 ation, which improves the complexity bound to  $O(\log(\varepsilon^{-1})\varepsilon^{2(\hat{\alpha}-1)/(1+3\hat{\alpha})})$ . Numerical  
 507 experiments are conducted to validate our theoretical findings, demonstrating the ex-  
 508 pected behavior of projected gradient descent methods under different stepsizes and  
 509 Hölder exponents. These results offer new insights into the performance guarantees  
 510 of the classic projected gradient descent methods for a broader class of optimization  
 511 problems with non-Lipschitz gradients.

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