A STOCHASTIC DERIVATIVE FREE OPTIMIZATION
METHOD WITH MOMENTUM

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ABSTRACT

We consider the problem of unconstrained minimization of a smooth objective function in \( \mathbb{R}^d \) in setting where only function evaluations are possible. We propose and analyze stochastic zeroth-order method with heavy ball momentum. In particular, we propose, \( \text{SMTP} \), a momentum version of the stochastic three-point method (\( \text{STP} \)) Bergou et al. (2019). We show new complexity results for non-convex, convex and strongly convex functions. We test our method on a collection of learning to continuous control tasks on several MuJoCo Todorov et al. (2012) environments with varying difficulty and compare against \( \text{STP} \), other state-of-the-art derivative-free optimization algorithms and against policy gradient methods. \( \text{SMTP} \) significantly outperforms \( \text{STP} \) and all other methods that we considered in our numerical experiments. Our second contribution is \( \text{SMTP} \) with importance sampling which we call \( \text{SMTP-IS} \). We provide convergence analysis of this method for non-convex, convex and strongly convex objectives.

1 INTRODUCTION

In this paper, we consider the following minimization problem

\[
\min_{x \in \mathbb{R}^d} f(x),
\]

where \( f: \mathbb{R}^d \to \mathbb{R} \) is "smooth" but not necessarily a convex function in a Derivative-Free Optimization (DFO) setting where only function evaluations are possible. The function \( f \) is bounded from below by \( f(x^*) \) where \( x^* \) is a minimizer. Lastly and throughout the paper, we assume that \( f \) is \( L \)-smooth.

DFO. In DFO setting Conn et al. (2009); Kolda et al. (2003), the derivatives of the objective function \( f \) are not accessible. That is they are either impractical to evaluate, noisy (function \( f \) is noisy) (Chen 2015) or they are simply not available at all. In standard applications of DFO, evaluations of \( f \) are only accessible through simulations of black-box engine or software as in reinforcement learning and continuous control environments Todorov et al. (2012). This setting of optimization problems appears also in applications from computational medicine Marsden et al. (2008) and fluid dynamics Allaire (2001); Haslinger & Máckinen (2003); Mohammadi & Pironneau (2001) to localization Marsden et al. (2004; 2007) and continuous control Mania et al. (2018); Salimans et al. (2017) to name a few.

The literature on DFO for solving (1) is long and rich. The first approaches were based on deterministic direct search (DDS) and they span half a century of work Hooke & Jeeves (1961); Su (1979); Torczon

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Our contributions can be summarized into three folds.

- **First ZO method with heavy ball momentum.** Motivated by practical effectiveness of first-order momentum heavy ball method, we introduce momentum into STP method and...
We use $\| \cdot \|$ to define $\ell_p$-norm of the vector $x \in \mathbb{R}^d$: $\| x \|_p \overset{\text{def}}{=} \left( \sum_{i=1}^d |x_i|^p \right)^{1/p}$ for $p \geq 1$ and $\| x \|_\infty \overset{\text{def}}{=} \max_{i \in [d]} |x_i|$ where $x_i$ is the $i$-th component of vector $x$, $[d] = \{1, 2, \ldots, d \}$. Operator $\mathbb{E}[\cdot]$ denotes mathematical expectation with respect to all randomness and $\mathbb{E}_{x \sim D}[\cdot]$ denotes conditional expectation w.r.t. randomness coming from random vector $s$ which is sampled from probability distribution $D$ on $\mathbb{R}^d$. To denote standard inner product of two vectors $x, y \in \mathbb{R}^d$ we use $\langle x, y \rangle \overset{\text{def}}{=} \sum_{i=1}^d x_i y_i$, $e_i$ denotes $i$-th coordinate vector from standard basis in $\mathbb{R}^d$, i.e. $x = \sum_{i=1}^d x_i e_i$. We use $\| \cdot \|^*$ to define the conjugate norm for the norm $\| \cdot \|$: $\| x \|^* \overset{\text{def}}{=} \max \{ \langle a, x \rangle \mid a \in \mathbb{R}^d, \| a \| \leq 1 \}$.

As we mention in the introduction we assume throughout the paper that the objective function $f$ is $L$-smooth.\footnote{We will use thinner assumption in Section 4.}
We put our attention on Polyak’s heavy ball method where the update rule could be written in the form (2019) where we propose an importance sampling that improves the leading constant marked in red. Note that one possible view on gradient descent is not the best algorithm to solve unconstrained smooth minimization problems and that all assumptions listed are in addition to Assumption 2.1. We notice that for SMTP IS \( \| \cdot \|_\infty = \| \cdot \|_{\infty} \) in non-convex and strongly convex cases. \( R_0 < \infty \) is the radius in \( \| \cdot \|_{\infty} \)-norm of a bounded level set where the exact definition is given in Assumption 3.2. We see that for SMTP IS \( \| \cdot \|_D = \| \cdot \|_1 \) and \( \| \cdot \|_D^* = \| \cdot \|_{\infty} \) in non-convex and strongly convex cases and \( \| \cdot \|_D = \| \cdot \|_2 \) in the strongly convex case.

Assumption 2.1. (L-smoothness) We say that \( f \) is L-smooth if
\[
\| \nabla f(x) - \nabla f(y) \|_2 \leq L \| x - y \|_2 \quad \forall x, y \in \mathbb{R}^d.
\] (2)

From this definition one can obtain
\[
| f(y) - f(x) - \langle \nabla f(x), y - x \rangle | \leq \frac{L}{2} \| y - x \|_2^2, \quad \forall x, y \in \mathbb{R}^d,
\] (3)

and if additionally \( f \) is convex, i.e. \( f(y) \geq f(x) + \langle \nabla f(x), y - x \rangle \), we have
\[
\| \nabla f(x) \|_2^2 \leq 2L(f(x) - f(x^*)) \quad \forall x \in \mathbb{R}^d.
\] (4)

### 3 Stochastic Momentum Three Points (SMTP)

Our analysis of SMTP is based on the following key assumption.

Assumption 3.1. The probability distribution \( D \) on \( \mathbb{R}^d \) satisfies the following properties:

1. The quantity \( \gamma_D \) defined as \( \mathbb{E}_{s \sim D} \| s \|_2 \) is finite.
2. There is a constant \( \mu_D > 0 \) for a norm \( \| \cdot \|_D \) in \( \mathbb{R}^d \) such that for all \( g \in \mathbb{R}^d \)
\[
\mathbb{E}_{s \sim D} | g, s | \geq \mu_D \| g \|_D.
\] (5)

Some examples of distributions that meet above assumption are described in Lemma 3.4 from Bergou et al. (2019). For convenience we provide the statement of the lemma in the Appendix (see Lemma F.1).

Recall that one possible view on STP [Bergou et al. (2019)] is as following. If we substitute gradient \( \nabla f(x_k) \) in the update rule for the gradient descent \( x_k^{k+1} = x_k - \gamma_k \nabla f(x_k) \) by \( \pm s_k \) where \( s_k \) is sampled from distribution \( D \) satisfied Assumption 3.1 and then select \( x_k^{k+1} \) as the best point in terms of functional value among \( x_k, x_k - \gamma_k s_k, x_k + \gamma_k s_k \) we will get exactly SMTP method. However, gradient descent is not the best algorithm to solve unconstrained smooth minimization problems and the natural idea is to try to perform the same substitution-trick with more efficient first-order methods than gradient descent.

We put our attention on Polyak’s heavy ball method where the update rule could be written in the following form:
\[
v^{k+1} = v_k - \beta v_k - \nabla f(x_k), \quad x^{k+1} = x_k - \gamma_k v_k.
\] (6)

As in STP, we substitute \( \nabla f(x_k) \) by \( \pm s_k \) and consider new sequences \( \{ v^{k+1}_+ \}_{k \geq 0} \) and \( \{ v^{k+1}_- \}_{k \geq 0} \) defined in the Algorithm 1. However, it is not straightforward how to choose next \( x^{k+1} \) and \( v^{k+1} \) and

| Assumptions on f | SMTP Complexity | SMTP IS Complexity |
|------------------|-----------------|-------------------|
| None             | \( \frac{2\rho_0 L + \rho D}{\rho^2} \ln(\frac{2\rho}{\rho_0}) \) | \( \frac{2\rho_0 L e_1 + \rho D}{\rho e_1} \ln(\frac{2\rho}{\rho_0}) \) |
| Convex, \( R_0 < \infty \) | \( \frac{L^2 \gamma_0 R^2 D^2}{\rho^2} \ln(\frac{2\rho}{\rho_0}) \) | \( \frac{2\rho_0 L e_1 + \rho D}{\rho e_1} \ln(\frac{2\rho}{\rho_0}) \) |
| \( \mu \)-strongly convex | \( \frac{L}{\mu} \ln(\frac{2\rho}{\rho_0}) \) | \( \frac{L e_1}{\mu} \ln(\frac{2\rho}{\rho_0}) \) |

Table 1: Summary of the derived new complexity results of SMTP and SMTP IS. The complexities for SMTP are under a generic sampling distribution \( D \) satisfying Assumption 3.1 while for SMTP IS are under an arbitrary discrete sampling from a set of coordinate directions following Bibi et al. (2019) where we propose an importance sampling that improves the leading constant marked in red. Notice that for \( r_0 = f(x_0) - f(x^*) \) and that all assumptions listed are in addition to Assumption 2.1. Complexity means number of iterations in order to guarantee \( \mathbb{E}\| \nabla f(z^K) \|_D \leq \epsilon \) for the non-convex case, \( \mathbb{E}\| f(\zeta^K) - f(x^*) \| \leq \epsilon \) for convex and strongly convex cases. \( R_0 < \infty \) is the radius in \( \| \cdot \|_\infty \)-norm of a bounded level set where the exact definition is given in Assumption 3.2. We see that for SMTP IS \( \| \cdot \|_D = \| \cdot \|_1 \) and \( \| \cdot \|_D^* = \| \cdot \|_{\infty} \) in non-convex and strongly convex cases and \( \| \cdot \|_D = \| \cdot \|_2 \) in the strongly convex case.
the virtual iterates analysis [Yang et al. (2016)] hints the update rule. We consider new iterates \( z_k^{k+1} = x^{k+1} - \frac{\gamma_k}{2(1-\beta)} z^k \) and \( z_k^{k+1} = x^{k+1} - \frac{\gamma_k}{2(1-\beta)} z^k \) and define \( z_{k+1} \) as \( \arg\min \{ f(z^k), f(z^{k+1}), f(z^{k+1}) \} \).

Next we update \( z_k \) and \( v^k \) in order to have the same relationship between \( z_{k+1}, x_{k+1} \) and \( v^k \) as between \( z_{k+1}, x_{k+1} \) and \( v^k \) as well as \( z_{k+1}, x_{k+1} \) and \( v^k \). Such scheme allows easily apply virtual iterates analysis and generalize Key Lemma from [Bergou et al. (2019)] which is the main tool in the analysis of SMTP.

By definition of \( z_{k+1} \), we get that the sequence \( \{ f(z^k) \}_{k \geq 0} \) is monotone:

\[
f(z^{k+1}) \leq f(z^k) \quad \forall k \geq 0.
\]

Now, we establish the key result which will be used to prove the main complexity results and remaining theorems in this section.

**Lemma 3.1.** Assume that \( f \) is \( L \)-smooth and \( \mathcal{D} \) satisfies Assumption 3.1. Then for the iterates of SMTP the following inequalities hold:

\[
f(z^{k+1}) \leq f(z^k) - \frac{\gamma_k}{1-\beta} \| \nabla f(z^k), s^k \| + \frac{L(\gamma_k)^2}{2(1-\beta)^2} \| s^k \|^2_2
\]

\[
\text{and}
\]

\[
\mathbb{E}_{z^k \sim \mathcal{D}} [f(z^{k+1})] \leq f(z^k) - \frac{\gamma_k \mu_D}{1-\beta} \| \nabla f(z^k) \|_D + \frac{L(\gamma_k)^2 \gamma_D}{2(1-\beta)^2}.
\]

### 3.1 Non-Convex Case

In this section, we show our complexity results for Algorithm 1 in the case when \( f \) is allowed to be non-convex. In particular, we show that SMTP in Algorithm 1 guarantees complexity bounds with the same order as classical bounds, i.e. \( 1/\sqrt{K} \), where \( K \) is the number of iterations, in the literature. We notice that query complexity (i.e. number of oracle calls) of SMTP coincides with its iteration complexity up to numerical constant factor. For clarity and completeness, proofs are left for the appendix.

**Theorem 3.1.** Let Assumptions 2.1 and 3.1 be satisfied. Let SMTP with \( \gamma_k \equiv \gamma > 0 \) produce points \( \{ z^0, z^1, \ldots, z^{K-1} \} \) and \( z^K \) is chosen uniformly at random among them. Then

\[
\mathbb{E} [\| \nabla f(z^K) \|_D] \leq \frac{(1-\beta)(f(x^0) - f(x^*))}{K \gamma_D} + \frac{L \gamma_D}{2 \mu_D (1-\beta)}.
\]

Moreover, if we choose \( \gamma = \frac{\gamma_0}{\sqrt{K}} \), the complexity (10) reduces to

\[
\mathbb{E} [\| \nabla f(z^K) \|_D] \leq \frac{1}{\sqrt{K}} \left( \frac{(1-\beta)(f(x^0) - f(x^*))}{\gamma_0 \mu_D} + \frac{L \gamma_0 \gamma_D}{2 \mu_D (1-\beta)} \right).
\]

Then \( \gamma_0 = \sqrt{\frac{2(1-\beta)^2 (f(x^0) - f(x^*))}{L \gamma_D}} \) minimizes the right-hand side of (11) and for this choice we have

\[
\mathbb{E} [\| \nabla f(z^K) \|_D] \leq \frac{\sqrt{2} (f(x^0) - f(x^*)) L \gamma_D}{\mu_D \sqrt{K}}.
\]

In other words, the above theorem states that SMTP converges no worse than STP for non-convex problems to the stationary point. In the next sections we also show that theoretical convergence guarantees for SMTP are not worse than for STP for convex and strongly convex problems. However, in practice SMTP significantly outperforms STP. So, the relationship between SMTP and STP correlates with the known in the literature relationship between Polyak’s heavy ball method and gradient descent.

### 3.2 Convex Case

In this section, we present our complexity results for Algorithm 1 when \( f \) is convex. In particular, we show that this method guarantees complexity bounds with the same order as classical bounds, i.e. \( 1/K \), in the literature. We will need the following additional assumption in the sequel.
**Assumption 3.2.** We assume that $f$ is convex, has a minimizer $x^*$ and has bounded level set at $x^0$:
\[
R_0 \overset{\text{def}}{=} \max \left\{ \|x - x^*\|_D^2 \mid f(x) \leq f(x^0) \right\} < +\infty, \tag{13}\]
where $\|x\|_D = \max \{ \langle x, \xi \rangle \mid \|x\|_D \leq 1 \}$ defines the dual norm to $\| \cdot \|_D$.

From the above assumption and Cauchy-Schwartz inequality we get the following implication:
\[
f(x) \leq f(x_0) \Rightarrow f(x) - f(x^*) \leq \langle \nabla f(x), x - x^* \rangle \leq \|\nabla f(x)\|_D \|x - x^*\|_D \leq R_0 \|\nabla f(x)\|_D, \tag{14}\]
which implies
\[
\|\nabla f(x)\|_D \geq \frac{f(x) - f(x^*)}{R_0} \quad \forall x : f(x) \leq f(x_0). \tag{14}\]

**Theorem 3.2** (Constant stepsize). Let Assumptions 2.1, 3.1 and 3.2 be satisfied. If we set $\gamma^k = \gamma \in (1 - \beta)R_0 / \mu_D$, then for the iterates of SMTP method the following inequality holds:
\[
\mathbb{E} \left[f(z^k) - f(x^*)\right] \leq \left(1 - \frac{\gamma \mu_D}{(1 - \beta)R_0}\right)^k \left(f(x^0) - f(x^*)\right) + \frac{L \gamma \mu_D R_0}{2(1 - \beta) \mu_D}. \tag{15}\]

If we choose $\gamma = \frac{\varepsilon (1 - \beta) \mu_D}{L \gamma \mu_D R_0}$ for some $0 < \varepsilon \leq \frac{L \gamma \mu_D R_0}{2(1 - \beta) \mu_D}$ and run SMTP for $k = K$ iterations where
\[
K = \frac{1}{\varepsilon} \frac{L \gamma \mu_D R_0}{2(1 - \beta) \mu_D} \ln \left(\frac{2(\varepsilon f(0) - f(x^*))}{\varepsilon}\right), \tag{16}\]
then we will get $\mathbb{E} \left[f(z^K)\right] - f(x^*) \leq \varepsilon$.

In order to get rid of factor $\ln \left(\frac{2(\varepsilon f(0) - f(x^*))}{\varepsilon}\right)$ in the complexity we consider decreasing stepizes.

**Theorem 3.3** (Decreasing stepizes). Let Assumptions 2.1, 3.1 and 3.2 be satisfied. If we set $\gamma^k = \frac{2}{\alpha k + \beta}$, where $\alpha = \frac{\mu_D}{(1 - \beta)R_0}$ and $\theta \geq \frac{2}{\alpha}$, then for the iterates of SMTP method the following inequality holds:
\[
\mathbb{E} \left[f(z^k) - f(x^*)\right] \leq \frac{1}{\eta k + 1} \max \left\{ f(x^0) - f(x^*), \frac{2L \gamma D R_0}{\alpha \theta (1 - \beta)^2} \right\}, \tag{17}\]
where $\eta \overset{\text{def}}{=} \frac{\alpha}{\theta}$. Then, if we choose $\gamma^k = \frac{2}{\alpha k + \beta}$ where $\alpha = \frac{\mu_D}{(1 - \beta)R_0}$ and run SMTP for $k = K$ iterations where
\[
K = \frac{1}{\varepsilon} \frac{2R_0^2}{\mu_D^2} \max \left\{ (1 - \beta)^2 (f(x^0) - f(x^*)), L \gamma D \right\} - \frac{2(1 - \beta)^2 R_0^2}{\mu_D^2}, \quad \varepsilon > 0, \tag{18}\]
we get $\mathbb{E} \left[f(z^K)\right] - f(x^*) \leq \varepsilon$.

We notice that if we choose $\beta$ sufficiently close to 1, we will obtain from the formula (18) that $K \approx \frac{2R_0^2 L \gamma D}{\varepsilon \mu_D^2}$.

3.3 **STRONGLY CONVEX CASE**

In this section we present our complexity results for Algorithm I when $f$ is $\mu$-strongly convex.

**Assumption 3.3.** We assume that $f$ is $\mu$-strongly convex with respect to the norm $\| \cdot \|_D^2$:
\[
f(y) \geq f(x) + \langle \nabla f(x), y - x \rangle + \frac{\mu}{2} \|y - x\|_D^2, \quad \forall x, y \in \mathbb{R}^d. \tag{19}\]

It is well known that strong convexity implies
\[
\|\nabla f(x)\|_D^2 \geq 2 \mu \left(f(x) - f(x^*)\right). \tag{20}\]
Theorem 3.4 (Solution-dependent stepsizes). Let Assumptions 2.1, 3.1, 3.3 and 3.4 be satisfied. If we set \( \gamma_k = \left(1 - \beta \right) \theta_k \mu_\Delta \sqrt{2 \mu(f(z^k) - f(x^*))} \) for some \( \theta_k \in (0, 2) \) such that \( \theta = \inf_{k \geq 0} \{ 2\theta_k - \gamma D \theta_k^2 \} \in (0, L/(\mu_\Delta \mu)) \), then for the iterates of SMTP, the following inequality holds:

\[
E[f(z^k)] - f(x^*) \leq \left(1 - \theta \mu_\Delta^2 \mu L \right)^k (f(x^0) - f(x^*)) .
\]

Then, if we run SMTP for \( k = K \) iterations where

\[
K = \frac{\kappa}{\theta \mu_\Delta^2} \ln \left( \frac{f(x^0) - f(x^*)}{\varepsilon} \right), \quad \varepsilon > 0,
\]

where \( \kappa \equiv \frac{L}{\mu} \) is the condition number of the objective, we will get \( E[f(z^K)] - f(x^*) \leq \varepsilon \).

Note that the previous result uses stepsizes that depends on the optimal solution \( f(x^*) \) which is often not known in practice. The next theorem removes this drawback without spoiling the convergence rate. However, we need an additional assumption on the distribution \( D \) and one extra function evaluation.

Assumption 3.4. We assume that for all \( s \sim D \) we have \( \|s\|_2 = 1 \).

Theorem 3.5 (Solution-free stepsizes). Let Assumptions 2.1, 3.1, 3.3 and 3.4 be satisfied. If additionally we compute \( f(z^k + ts^k) \), set \( \gamma_k = (1 - \beta) \|f(z^k + ts^k) - f(z^k)\|/ (Lt) \) for \( t > 0 \) and assume that \( D \) is such that \( \mu_\Delta \leq L/\mu \), then for the iterates of SMTP the following inequality holds:

\[
E[f(z^k)] - f(x^*) \leq \left(1 - \frac{\mu_\Delta^2 L}{\mu} \right)^k (f(x^0) - f(x^*)) + \frac{L^2 t^2 \mu^2}{8 \mu_\Delta^2} .
\]

Moreover, for any \( \varepsilon > 0 \) if we set \( t \) such that

\[
0 < t \leq \sqrt{\frac{4 \varepsilon \mu_\Delta^2}{L^2}},
\]

and run SMTP for \( k = K \) iterations where

\[
K = \frac{\kappa}{\mu_\Delta^2} \ln \left( \frac{2(f(x^0) - f(x^*))}{\varepsilon} \right),
\]

where \( \kappa \equiv \frac{L}{\mu} \) is the condition number of the objective, we will have \( E[f(z^K)] - f(x^*) \leq \varepsilon \).

4 Stochastic Momentum Three Points with Importance Sampling (SMTP_IS)

In this section we consider another assumption, in a similar spirit to [Bibi et al., 2019], on the objective.

Assumption 4.1 (Coordinate-wise \( L \)-smoothness). We assume that the objective \( f \) has coordinate-wise Lipschitz gradient, with Lipschitz constants \( L_1, \ldots, L_d > 0 \), i.e.

\[
f(x + he_i) \leq f(x) + \nabla_i f(x) h + \frac{L_i h^2}{2}, \quad \forall x \in \mathbb{R}^d, h \in \mathbb{R},
\]

where \( \nabla_i f(x) \) is \( i \)-th partial derivative of \( f \) at the point \( x \).

For this kind of problems we modify SMTP and present SMTP_IS method in Algorithm 2. In general, the idea behind methods with importance sampling and, in particular, behind SMTP_IS is to adjust probabilities of sampling in such a way that gives better convergence guarantees. In the case when \( f \) satisfies coordinate-wise \( L \)-smoothness and Lipschitz constants \( L_i \) are known it is natural to sample direction \( s^k = \varepsilon_i \) with probability depending on \( L_i \) (e.g. proportional to \( L_i \)). One can find more detailed discussion of the importance sampling in [Zhao & Zhang, 2015] and [Richtárik & Takáč, 2016].

Now, we establish the key result which will be used to prove the main complexity results of SMTP_IS.
work in Bibi et al. (2019), we use Algorithm 2

\begin{algorithm}[H]
\caption{SMTP$_{\text{IS}}$: Stochastic Momentum Three Points with Importance Sampling}
\textbf{Require:} stepsizes parameters $w_1, \ldots, w_n > 0$, probabilities $p_1, \ldots, p_n > 0$ summing to 1, starting point $x^0 \in \mathbb{R}^d$, $0 \leq \beta < 1$ — momentum parameter

1: Set $v^0 = 0$ and $z^0 = x^0$
2: \textbf{for} $k = 0, 1, \ldots$ \textbf{do}
3: \hspace{1em} Select $i_k = i$ with probability $p_i > 0$
4: \hspace{1em} Choose stepsize $\gamma_i^k$ proportional to $\frac{1}{w_i}$
5: \hspace{1em} Let $v^k = \beta v^{k-1} + e_{i_k}$ and $\nu^k = \beta v^{k-1} - e_{i_k}$
6: \hspace{1em} Let $x^{k+1} = x^k - \frac{\gamma_i^k}{1-\beta} v^k$ and $x^{k+1} = x^k - \frac{\gamma_i^k}{1-\beta} \nu^k$
7: \hspace{1em} Let $z^{k+1} = x^{k+1} = \gamma_i^k y^k$ and $z^{k+1} = x^{k+1} - \frac{\gamma_i^k}{1-\beta} v^k$
8: \hspace{1em} Set $z^{k+1} = \arg\min \{ f(z^k), f(x^{k+1}), f(z^{k+1}) \}$
9: \hspace{1em} Set $x^{k+1} = \begin{cases} x^{k+1}, & \text{if } z^{k+1} = z^{k+1} \\ x^{k+1}, & \text{if } z^{k+1} = z^{k} \end{cases}$ and $v^{k+1} = \begin{cases} v^{k+1}, & \text{if } z^{k+1} = z^{k+1} \\ v^{k+1}, & \text{if } z^{k+1} = z^{k+1} \\ v^k, & \text{if } z^{k+1} = z^{k} \end{cases}$
10: \textbf{end for}
\end{algorithm}

Lemma 4.1. Assume that $f$ satisfies Assumption [4.7] Then for the iterates of SMTP$_{\text{IS}}$ the following inequalities hold:

$$f(z^{k+1}) \leq f(z^k) - \frac{\gamma_i^k}{1-\beta} |\nabla_i f(z^k)| + \frac{L_{ik} (\gamma_i^k)^2}{2(1-\beta)^2}$$

and

$$E_{z^k \sim D} [f(z^{k+1})] \leq f(z^k) - \frac{1}{1-\beta} E [\gamma_i^k |\nabla_i f(z^k)| | z^k] + \frac{1}{2(1-\beta)^2} E [L_{ik} (\gamma_i^k)^2 | z^k].$$

Due to the page limitation, we provide the complexity results of SMTP$_{\text{IS}}$ in the Appendix.

5 Experiments

Experimental Setup. We conduct extensive experiments on challenging non-convex problems on the continuous control task from the MuJoCo suit [Todorov et al. (2012)]. In particular, we address the problem of model-free control of a dynamical system. Policy gradient methods for model-free reinforcement learning algorithms provide an off-the-shelf model-free approach to learn how to control a dynamical system and are often benchmarked in a simulator. We compare our proposed momentum stochastic three points method SMTP and the momentum with importance sampling version SMTP$_{\text{IS}}$ against state-of-art DFO based methods as SMTP$_{\text{IS}}$ [Bibi et al. (2019)] and ARS [Mania et al. (2018)]. Moreover, we also compare against classical policy gradient methods as TRPO [Schulman et al. (2015)] and NG [Rajeswaran et al. (2017)]. We conduct experiments on several environments with varying difficulty Swimmer-v1, Hopper-v1, HalfCheetah-v1, Ant-v1, and Humanoid-v1.

Note that due to the stochastic nature of problem where $f$ is stochastic, we use the mean of the function values of $f(x^k), f(x^k)$, see Algorithm 1 over K observations. Similar to the work in [Bibi et al. (2019)], we use $K = 2$ for Swimmer-v1, $K = 4$ for both Hopper-v1 and HalfCheetah-v1, $K = 40$ for Ant-v1 and Humanoid-v1. Similar to [Bibi et al. (2019)], these values were chosen based on the validation performance over the grid that $K \in \{ 1, 2, 4, 8, 16 \}$ for the smaller dimensional problems Swimmer-v1, Hopper-v1, HalfCheetah-v1 and $K \in \{ 20, 40, 80, 120 \}$ for larger dimensional problems Ant-v1, and Humanoid-v1. As for the momentum term, for SMTP we set $\beta = 0.5$. For SMTP$_{\text{IS}}$, as the smoothness constants are not available for continuous control, we use the coordinate smoothness constants of a $\theta$ parameterized smooth function $f_{\theta}$ (multi-layer perceptron) that estimates $f$. In particular, consider running any DFO for $n$ steps; with the queried sampled $\{ x_i, f(x_i) \}_{i=1}^n$, we estimate $f$ by solving $\theta_{n+1} = \arg\min \sum_i (f(x_i) - f(x_i; \theta))^2$. See [Bibi et al. (2019)] for further implementation details.

3The code will be made available online upon acceptance of this work.
Figure 1: SMTP is far superior to STP on all 5 different MuJoCo tasks particularly on the high dimensional Humanoid-v1 problem. The horizontal dashed lines are the thresholds used in Table 2 to demonstrate complexity of each method.

Table 2: For each MuJoCo task, we report the average number of episodes required to achieve a predefined reward threshold. Results for our method is averaged over five random seeds, the rest is copied from (Mania et al., 2018) (N/A means the method failed to reach the threshold. UNK means the results is unknown since they are not reported in the literature.)

| Threshold | STP | STP-IS | SMTP | SMTP-IS | ARS(V1-t) | ARS(V2-t) | NG-lin | TRPO-nn |
|-----------|-----|--------|------|---------|-----------|-----------|--------|---------|
| Swimmer-v1 | 325 | 330 | 110 | 80 | 100 | 100 | 427 | 1450 | N/A |
| Hopper-v1 | 3120 | 3970 | 2400 | 1264 | 1408 | 51840 | 1973 | 13920 | 10000 |
| HalfCheetah-v1 | 3430 | 13760 | 4420 | 1872 | 1624 | 8106 | 1707 | 11250 | 4250 |
| Ant-v1 | 3580 | 107220 | 43860 | 19890 | 14420 | 58133 | 20800 | 39240 | 73500 |
| Humanoid-v1 | 6000 | N/A | 530200 | 161230 | 207160 | N/A | 142600 | 130000 | UNK |

as we follow the same experimental procedure. In contrast to STP-IS, our method (SMTP) does not required sampling from directions in the canonical basis; hence, we use directions from standard Normal distribution in each iteration. For SMTP-IS, we follow a similar procedure as Bibi et al. (2019) and sample from columns of a random matrix B.

Similar to the standard practice, we perform all experiments with 5 different initialization and measure the average reward, in continuous control we are maximizing the reward function $f$, and best and worst run per iteration. We compare algorithms in terms of reward vs. sample complexity.

**Comparison Against STP.** Our method improves sample complexity of STP and STP-IS significantly. Especially for high dimensional problems like Ant-v1 and Humanoid-v1, sample efficiency of SMTP is at least as twice as the STP. Moreover, SMTP-IS helps in some experiments by improving over SMTP. However, this is not consistent in all environments. We believe this is largely due to the fact that SMTP-IS can only handle sampling from canonical basis similar to STP-IS.

**Comparison Against State-of-The-Art.** We compare our method with state-of-the-art DFO and policy gradient algorithms. For the environments, Swimmer-v1, Hopper-v1, HalfCheetah-v1 and Ant-v1, our method outperforms the state-of-the-art results. Whereas for Humanoid-v1, our methods results in a comparable sample complexity.

### 6 Conclusion

We have proposed, SMTP, the first heavy ball momentum DFO based algorithm with convergence rates for non-convex, convex and strongly convex functions under generic sampling direction. We specialize the sampling to the set of coordinate bases and further improve rates by proposing a momentum and importance sampling version SMPT-IS with new convergence rates for non-convex, convex and strongly convex functions too. We conduct large number of experiments on the task of
controlling dynamical systems. We outperform two different policy gradient methods and achieve comparable or better performance to the best DFO algorithm (ARS) on the respective environments.

REFERENCES

G. Allaire. Shape Optimization by the Homogenization Method. Springer, New York, USA, 2001.

N. Baba. Convergence of a random optimization method for constrained optimization problems. Journal of Optimization Theory and Applications, 33:1–11, 1981.

El Houcine Bergou, Eduard Gorbunov, and Peter Richtárik. Stochastic three points method for unconstrained smooth minimization. arXiv preprint arXiv:1902.03591, 2019.

Adel Bibi, El Houcine Bergou, Ozan Sener, Bernard Ghanem, and Peter Richtárik. Stochastic derivative-free optimization method with importance sampling. arXiv preprint arXiv:1902.01272, 2019.

Ruobing Chen. Stochastic derivative-free optimization of noisy functions. PhD thesis at Lehigh University, 2015.

A. R. Conn, K. Scheinberg, and L. N. Vicente. Introduction to Derivative-Free Optimization. SIAM, Philadelphia, PA, USA, 2009.

M. A. Diniz-Ehrhardt, J. M. Martinez, and M. Raydan. A derivative-free nonmonotone line-search technique for unconstrained optimization. Journal of Optimization Theory and Applications, 219:383–397, 2008.

Mahdi Dodangeh and Luis N Vicente. Worst case complexity of direct search under convexity. Mathematical Programming, 155(1-2):307–332, 2016.

C. Dorea. Expected number of steps of a random optimization method. Journal of Optimization Theory and Applications, 39:165–171, 1983.

Pavel Dvurechensky, Alexander Gasnikov, and Alexander Tiurin. Randomized similar triangles method: A unifying framework for accelerated randomized optimization methods (coordinate descent, directional search, derivative-free method). arXiv preprint arXiv:1707.08486, 2017.

Euhanna Ghadimi, Hamid Reza Feyzmahdavian, and Mikael Johansson. Global convergence of the heavy-ball method for convex optimization. In 2015 European Control Conference (ECC), pp. 310–315. IEEE, 2015.

Saeed Ghadimi and Guanghui Lan. Stochastic first-and zeroth-order methods for nonconvex stochastic programming. SIAM Journal on Optimization, 23(4):2341–2368, 2013.

Saeed Ghadimi, Guanghui Lan, and Hongchao Zhang. Mini-batch stochastic approximation methods for nonconvex stochastic composite optimization. Mathematical Programming, 155(1-2):267–305, 2016.

E. Gorbunov, P. Dvurechensky, and A. Gasnikov. An accelerated method for derivative-free smooth stochastic convex optimization. arXiv preprint arXiv:1802.09022, 2018.

S. Gratton, C. W. Royer, L. N. Vicente, and Z. Zhang. Direct search based on probabilistic descent. SIAM Journal on Optimization, 25(3):1515–1541, 2015.

J. Haslinger and R.A.E. Mäckinen. Introduction to Shape Optimization: Theory, Approximation, and Computation. SIAM, Philadelphia, PA, USA, 2003.

R. Hooke and T.A. Jeeves. Direct search solution of numerical and statistical problems. J. Assoc. Comput. Mach, 8:212–229, 1961.

V. G. Karmanov. Convergence estimates for iterative minimization methods. USSR Computational Mathematics and Mathematical Physics, 14:1–13, 1974a.

V. G. Karmanov. On convergence of a random search method in convex minimization problems. Theory of Probability and its applications, 19:788–794, 1974b.

T. G. Kolda, R. M. Lewis, and V. J. Torczon. Optimization by direct search: New perspectives on some classical and modern methods. SIAM Review, 45:385–482, 2003.

Laurent Lessard, Benjamin Recht, and Andrew Packard. Analysis and design of optimization algorithms via integral quadratic constraints. SIAM Journal on Optimization, 26(1):57–95, 2016.
Nicolas Loizou and Peter Richtárik. Momentum and stochastic momentum for stochastic gradient, newton, proximal point and subspace descent methods. *arXiv preprint arXiv:1712.09677*, 2017.

Horia Mania, Aurelia Guy, and Benjamin Recht. Simple random search provides a competitive approach to reinforcement learning. *arXiv preprint arXiv:1803.07055*, 2018.

A. L. Marsden, M. Wang, J. E. Dennis, and P. Moin. Optimal aeroacoustic shape design using the surrogate management framework. *Optimization and Engineering*, 5:235–262, 2004.

A. L. Marsden, M. Wang, J. E. Dennis, and P. Moin. Trailering-edge noise reduction using derivative-free optimization and large-eddy simulation. *Journal of Fluid Mechanics*, 5:235–262, 2007.

A. L. Marsden, J. A. Feinstein, and C. A. Taylor. A computational framework for derivative-free optimization of cardiovascular geometries. *Computer Methods in Applied Mechanics and Engineering*, 197:1890–1905, 2008.

J. Matyas. Random optimization. *Automation and Remote Control*, 26:246–253, 1965.

Konstantin Mishchenko, Eduard Gorbunov, Martin Takáč, and Peter Richtárik. Distributed learning with compressed gradient differences. *arXiv preprint arXiv:1901.09269*, 2019.

B. Mohammadi and O. Pironneau. *Applied Shape Optimization for Fluids*. Clarendon Press, Oxford, 2001.

Y. Nesterov and V. Spokoiny. Random gradient-free minimization of convex functions. *Foundations of Computational Mathematics*, 17:527–566, 2017.

Boris T Polyak. Some methods of speeding up the convergence of iteration methods. *USSR Computational Mathematics and Mathematical Physics*, 4(5):1–17, 1964.

Aravind Rajeswaran, Kendall Lowrey, Emanuel V Todorov, and Sham M Kakade. Towards generalization and simplicity in continuous control. In *Advances in Neural Information Processing Systems*, pp. 6550–6561, 2017.

Peter Richtárik and Martin Takáč. On optimal probabilities in stochastic coordinate descent methods. *Optimization Letters*, 10(6):1233–1243, 2016.

Tim Salimans, Jonathan Ho, Xi Chen, Szymon Sidor, and Ilya Sutskever. Evolution strategies as a scalable alternative to reinforcement learning. *arXiv preprint arXiv:1703.03864*, 2017.

M. Sarma. On the convergence of the Baba and Dorea random optimization methods. *Journal of Optimization Theory and Applications*, 66:337–343, 1990.

John Schulman, Sergey Levine, Pieter Abbeel, Michael Jordan, and Philipp Moritz. Trust region policy optimization. In *International Conference on Machine Learning*, pp. 1889–1897, 2015.

S. U. Stich, C. L. Muller, and B. Gartner. Optimization of convex functions with random pursuit. *arXiv preprint arXiv:1111.0194*, 2011.

Sebastian U Stich. *Convex optimization with random pursuit*. PhD thesis, ETH Zurich, 2014a.

Sebastian Urban Stich. On low complexity acceleration techniques for randomized optimization. In *International Conference on Parallel Problem Solving from Nature*, pp. 130–140. Springer, 2014b.

Yu Wen Su. Positive basis and a class of direct search techniques. *Scientia Sinica (in Chinese)*, 9(S1):53–67, 1979.

Emanuel Todorov, Tom Erez, and Yuval Tassa. Mujoco: A physics engine for model-based control. In *Intelligent Robots and Systems (IROS)*, 2012 IEEE/RSJ International Conference on, pp. 5026–5033. IEEE, 2012.

Virginia Torczon. On the convergence of pattern search algorithms. *SIAM Journal on optimization*, 7(1):1–25, 1997.

Luís Nunes Vicente. Worst case complexity of direct search. *EURO Journal on Computational Optimization*, 1 (1-2):143–153, 2013.

Tianbao Yang, Qihang Lin, and Zhe Li. Unified convergence analysis of stochastic momentum methods for convex and non-convex optimization. *arXiv preprint arXiv:1604.03257*, 2016.

Peilin Zhao and Tong Zhang. Stochastic optimization with importance sampling for regularized loss minimization. In *international conference on machine learning*, pp. 1–9, 2015.
A Stochastic Derivative Free Optimization Method with Momentum

(Supplementary Material)

A Preliminaries

We first list the main assumptions.

Assumption A.1. (L-smoothness) We say that $f$ is $L$-smooth if:

$$\|\nabla f(x) - \nabla f(y)\|_2 \leq L\|x - y\|_2 \quad \forall x, y \in \mathbb{R}^d.$$  \hspace{1cm} (29)

Assumption A.2. The probability distribution $\mathcal{D}$ on $\mathbb{R}^d$ satisfies the following properties:

1. The quantity $\gamma_{\mathcal{D}} \overset{\text{def}}{=} \mathbb{E}_{s \sim \mathcal{D}} \|s\|_2^2$ is positive and finite.
2. There is a constant $\mu_{\mathcal{D}} > 0$ and norm $\|\cdot\|_{\mathcal{D}}$ on $\mathbb{R}^d$ such that for all $g \in \mathbb{R}^d$

$$\mathbb{E}_{s \sim \mathcal{D}} |\langle g, s \rangle| \geq \mu_{\mathcal{D}} \|g\|_D.$$  \hspace{1cm} (30)

We establish the key lemma which will be used to prove the theorems stated in the paper.

Lemma A.1. Assume that $f$ is $L$-smooth and $\mathcal{D}$ satisfies Assumption A.2. Then for the iterates of SMTP the following inequalities hold:

$$f(z^{k+1}) \leq f(z^k) - \frac{\gamma^k}{1 - \beta} \|\nabla f(z^k), s^k\| + \frac{L(\gamma^k)^2}{2(1 - \beta)^2} \|s^k\|_2^2$$  \hspace{1cm} (31)

and

$$\mathbb{E}_{s \sim \mathcal{D}} [f(z^{k+1})] \leq f(z^k) - \frac{\gamma^k \mu_{\mathcal{D}}}{1 - \beta} \|\nabla f(z^k)\|_D + \frac{L(\gamma^k)^2 \gamma_{\mathcal{D}}}{2(1 - \beta)^2}.$$  \hspace{1cm} (32)

Proof. By induction one can show that

$$z^k = x^k - \frac{\gamma^k \beta}{1 - \beta} v^{k-1}.$$  \hspace{1cm} (33)

That is, for $k = 0$ this recurrence holds and update rules for $z^k, x^k$ and $v^{k-1}$ do not brake it. From this we get

$$z^k_{+1} = x^k_{+1} - \frac{\gamma^k \beta}{1 - \beta} v^k_{+} = x^k - \gamma^k v^k_{+} - \frac{\gamma^k \beta}{1 - \beta} v^k_{+} = x^k - \gamma^k v^k_{+} = x^k - \frac{\gamma^k \beta}{1 - \beta} v^{k-1} - \frac{\gamma^k}{1 - \beta} s^k.$$  \hspace{1cm} (34)

Similarly,

$$z^k_{-1} = x^k_{-1} - \frac{\gamma^k \beta}{1 - \beta} v^k_{-} = x^k - \gamma^k v^k_{-} - \frac{\gamma^k \beta}{1 - \beta} v^k_{-} = x^k - \gamma^k v^k_{-} = x^k - \frac{\gamma^k \beta}{1 - \beta} v^{k-1} + \frac{\gamma^k}{1 - \beta} s^k.$$  \hspace{1cm} (35)
It implies that
\[
 f(z_{k+1}^+) \leq f(z^k) + \langle \nabla f(z^k), z_{k+1}^k - z_k \rangle + \frac{L}{2} \|z_{k+1}^k - z_k\|^2
 = f(z^k) - \frac{\gamma_k}{1 - \beta} \langle \nabla f(z^k), s^k \rangle + \frac{L(\gamma_k)^2}{2(1 - \beta)^2} \|s^k\|^2
\]
and
\[
 f(z_{k+1}^-) \leq f(z^k) + \frac{\gamma_k}{1 - \beta} \langle \nabla f(z^k), s^k \rangle + \frac{L(\gamma_k)^2}{2(1 - \beta)^2} \|s^k\|^2.
\]
Unifying these two inequalities we get
\[
 f(z^{k+1}) \leq \min \{ f(z_{k+1}^+), f(z_{k+1}^-) \} = f(z^k) - \frac{\gamma_k}{1 - \beta} \langle \nabla f(z^k), s^k \rangle + \frac{L(\gamma_k)^2}{2(1 - \beta)^2} \|s^k\|^2,
\]
which proves (31). Finally, taking the expectation \( \mathbb{E}_{s^k \sim \mathcal{D}} \) of both sides of the previous inequality and invoking Assumption A.2, we obtain
\[
 \mathbb{E}_{s^k \sim \mathcal{D}}[f(z^{k+1})] \leq f(z^k) - \frac{\gamma_k \mu_D}{1 - \beta} \|\nabla f(z^k)\|_D + \frac{L(\gamma_k)^2 \gamma_D}{2(1 - \beta)^2}.
\]
\[\Box\]

**B Non-Convex Case**

**Theorem B.1.** Let Assumptions A.1 and A.2 be satisfied. Let SMTP with \( \gamma_k \equiv \gamma > 0 \) produce points \( \{z^0, z^1, \ldots, z^{K-1}\} \) and \( z^K \) is chosen uniformly at random among them. Then
\[
 \mathbb{E} \left[ \|\nabla f(z^K)\|_D \right] \leq \frac{(1 - \beta)(f(x^0) - f(x^*))}{K \gamma \mu_D} + \frac{L \gamma_D}{2 \mu_D (1 - \beta)}. \tag{34}
\]
Moreover, if we choose \( \gamma = \frac{2\mu_D}{K^\frac{1}{2}} \) the complexity (34) reduces to
\[
 \mathbb{E} \left[ \|\nabla f(z^K)\|_D \right] \leq \frac{1}{\sqrt{K}} \left( \frac{(1 - \beta)(f(z^0) - f(x^*))}{\gamma_0 \mu_D} + \frac{L \gamma_0 \gamma_D}{2 \mu_D (1 - \beta)} \right). \tag{35}
\]
Then \( \gamma_0 = \sqrt{\frac{2(1 - \beta)^2(f(x^0) - f(x^*)) L \gamma_D}{K \mu_D}} \) minimizes the right-hand side of (35) and for this choice we have
\[
 \mathbb{E} \left[ \|\nabla f(z^K)\|_D \right] \leq \sqrt{2} \frac{(f(x^0) - f(x^*)) L \gamma_D}{\mu_D \sqrt{K}}. \tag{36}
\]

**Proof.** Taking full expectation from both sides of inequality (32) we get
\[
 \mathbb{E} \left[ \|\nabla f(z^k)\|_D \right] \leq \frac{(1 - \beta) \mathbb{E} \left[ f(z^k) - f(z^{k+1}) \right]}{\gamma \mu_D} + \frac{L \gamma_D}{2 \mu_D (1 - \beta)}.
\]
Further, summing up the results for \( k = 0, 1, \ldots, K - 1 \), dividing both sides of the obtained inequality by \( K \) and using tower property of the mathematical expectation we get
\[
 \mathbb{E} \left[ \|\nabla f(z^K)\|_D \right] = \frac{1}{K} \sum_{k=0}^{K-1} \mathbb{E} \left[ \|\nabla f(z^k)\|_D \right] \leq \frac{(1 - \beta)(f(z^0) - f(x^*))}{K \gamma \mu_D} + \frac{L \gamma_D}{2 \mu_D (1 - \beta)}.
\]
The last part where \( \gamma = \frac{2\mu_D}{K^\frac{1}{2}} \) is straightforward. \[\Box\]
C CONVEX CASE

Assumption C.1. We assume that $f$ is convex, has a minimizer $x^*$ and has bounded level set at $x^0$:

$$R_0 \overset{\text{def}}{=} \max \{ \|x - x^*\|_D^* \mid f(x) \leq f(x^0) \} < +\infty,$$  \hfill (37)

where $\|\xi\|_D^* \overset{\text{def}}{=} \max \{ \langle \xi, x \rangle \mid \|x\|_D \leq 1 \}$ defines the dual norm to $\| \cdot \|_D$.

Theorem C.1 (Constant stepsize). Let Assumptions A.1, A.2 and C.1 be satisfied. If we set $\gamma^k \equiv \gamma < \frac{(1 - \beta)R_0}{\mu^2_D}$, then for the iterates of SMTP method the following inequality holds:

$$E[f(z^k) - f(x^*)] \leq \left(1 - \frac{\gamma \mu_D}{(1 - \beta)R_0}\right)^k (f(x^0) - f(x^*)) + \frac{L\gamma \mu_D R_0}{2(1 - \beta)\mu_D^2}. \hfill (38)$$

If we choose $\gamma = \frac{\varepsilon(1 - \beta)\mu_D}{L\gamma \mu_D R_0}$ for some $0 < \varepsilon \leq \frac{L\gamma R_0^2}{\mu_D^2}$ and run SMTP for $k = K$ iterations where

$$K = \frac{1}{\varepsilon} \frac{L\gamma R_0^2}{\mu^2_D} \ln \left(\frac{2(f(x^0) - f(x^*))}{\varepsilon}\right), \hfill (39)$$

then we will get $E[f(z^K)] - f(x^*) \leq \varepsilon$.

Proof. From \ref{eq:7} and monotonicity of $\{f(z^k)\}_{k \geq 0}$ we have

$$E_{z \sim D}[f(z^{k+1})] \leq f(z^k) - \frac{\gamma \mu_D}{(1 - \beta)R_0} \|\nabla f(z^k)\|_D + \frac{L\gamma^2 \mu_D}{2(1 - \beta)^2}$$

$$\leq f(z^k) - \frac{\gamma \mu_D}{(1 - \beta)R_0} (f(z^k) - f(x^*)) + \frac{L\gamma^2 \mu_D}{2(1 - \beta)^2}.$$  \hfill (14)

Taking full expectation, subtracting $f(x^*)$ from the both sides of the previous inequality and using the tower property of mathematical expectation we get

$$E[f(z^{k+1}) - f(x^*)] \leq \left(1 - \frac{\gamma \mu_D}{(1 - \beta)R_0}\right) E[f(z^k) - f(x^*)] + \frac{L\gamma^2 \mu_D}{2(1 - \beta)^2}. \hfill (40)$$

Since $\gamma < \frac{(1 - \beta)R_0}{\mu^2_D}$ the term $1 - \frac{\gamma \mu_D}{(1 - \beta)R_0}$ is positive and we can unroll the recurrence \ref{eq:5}:

$$E[f(z^k) - f(x^*)] \leq \left(1 - \frac{\gamma \mu_D}{(1 - \beta)R_0}\right)^k (f(x^0) - f(x^*)) + \frac{L\gamma^2 \mu_D}{2(1 - \beta)^2} \sum_{l=0}^{k-1} \left(1 - \frac{\gamma \mu_D}{(1 - \beta)R_0}\right)^l$$

$$\leq \left(1 - \frac{\gamma \mu_D}{(1 - \beta)R_0}\right)^k (f(x^0) - f(x^*)) + \frac{L\gamma^2 \mu_D}{2(1 - \beta)^2} \sum_{l=0}^{\infty} \left(1 - \frac{\gamma \mu_D}{(1 - \beta)R_0}\right)^l$$

$$\leq \left(1 - \frac{\gamma \mu_D}{(1 - \beta)R_0}\right)^k (f(x^0) - f(x^*)) + \frac{L\gamma \mu_D R_0}{\mu^2_D} \frac{(1 - \beta)R_0}{\mu^2_D}.$$  \hfill (14)

Lastly, putting $\gamma = \frac{\varepsilon(1 - \beta)\mu_D}{L\gamma \mu_D R_0}$ and $k = K$ from \ref{eq:6} in \ref{eq:5} we have

$$E[f(z^K)] - f(x^*) = \left(1 - \frac{\varepsilon \mu_D^2}{L\gamma \mu_D R_0^2}\right)^K (f(x^0) - f(x^*)) + \varepsilon$$

$$\leq \exp \left\{-K \cdot \frac{\varepsilon \mu_D^2}{L\gamma \mu_D R_0^2}\right\} (f(x^0) - f(x^*)) + \varepsilon$$

$$\leq \frac{\varepsilon}{2} + \frac{\varepsilon}{2} = \varepsilon. \hfill (\Box)$$
Next we use technical lemma from [Mishchenko et al. (2019)]. We provide the original proof for completeness.

**Lemma C.1** (Lemma 6 from [Mishchenko et al. (2019)]). Let a sequence \( \{a^k\}_{k \geq 0} \) satisfy inequality \( a^{k+1} \leq (1 - \gamma^k \alpha) a^k + (\gamma^k)^2 N \) for any positive \( \gamma^k \leq \gamma_0 \) with some constants \( \alpha > 0 \), \( N > 0 \), \( \gamma_0 > 0 \). Further, let \( \theta \geq \frac{2}{\gamma_0} \) and take \( C \) such that \( N \leq \frac{\alpha \theta}{4} C \) and \( a_0 \leq C \). Then, it holds

\[
a_k \leq \frac{C}{\theta k + 1}
\]

if we set \( \gamma^k = \frac{2}{\alpha_k + \theta} \).

**Proof.** We will show the inequality for \( a^k \) by induction. Since inequality \( a_0 \leq C \) is one of our assumptions, we have the initial step of the induction. To prove the inductive step, consider

\[
a^{k+1} \leq (1 - \gamma^k \alpha) a^k + (\gamma^k)^2 N \leq \left( 1 - \frac{2\alpha}{\alpha k + \theta} \right) \theta C + \theta \alpha \frac{C}{(\alpha k + \theta)^2}.
\]

To show that the right-hand side is upper bounded by \( \frac{\theta C}{\alpha (k+1) + \theta} \), one needs to have, after multiplying both sides by \((\alpha k + \theta)(\alpha k + \alpha + \theta)(\theta C)^{-1}\),

\[
\left( 1 - \frac{2\alpha}{\alpha k + \theta} \right) (\alpha k + \alpha + \theta) + \alpha \frac{\alpha k + \alpha + \theta}{\alpha k + \theta} \leq \alpha k + \theta,
\]

which is equivalent to

\[
\alpha - \alpha \frac{\alpha k + \alpha + \theta}{\alpha k + \theta} \leq 0.
\]

The last inequality is trivially satisfied for all \( k \geq 0 \).

**Theorem C.2** (Decreasing stepsizes). Let Assumptions [A.1] [A.2] and [C.1] be satisfied. If we set \( \gamma^k = \frac{2 \alpha}{\alpha^2 k + 2} \), where \( \alpha = \frac{\mu_D}{(1 - \beta) R_0} \) and \( \theta \geq \frac{2}{\alpha} \), then for the iterates of SMTP method the following inequality holds:

\[
E \left[ f(z^k) \right] - f(x^*) \leq \frac{1}{\eta k + 1} \max \left\{ f(x^0) - f(x^*), \frac{2L \gamma_D}{\alpha \theta (1 - \beta)^2} \right\},
\]

(41)

where \( \eta \equiv \frac{\alpha}{\theta} \). Then, if we choose \( \gamma^k = \frac{2 \alpha}{\alpha^2 k + 2} \) where \( \alpha = \frac{\mu_D}{(1 - \beta) R_0} \) and run SMTP for \( k = K \) iterations where

\[
K = \frac{1}{\varepsilon} \cdot 2 \frac{R_0^2}{\mu_D^2} \max \left\{ (1 - \beta)^2 (f(x^0) - f(x^*)), L \gamma_D \right\} - \frac{2(1 - \beta)^2 R_0^2}{\mu_D^2}, \quad \varepsilon > 0,
\]

(42)

we get \( E \left[ f(z^K) \right] - f(x^*) \leq \varepsilon \).

**Proof.** In [40] we proved that

\[
E \left[ f(z^{k+1}) - f(x^*) \right] \leq \left( 1 - \frac{\gamma \mu_D}{(1 - \beta) R_0} \right) E \left[ f(z^k) - f(x^*) \right] + \frac{L \gamma_D^2}{2(1 - \beta)^2}.
\]

Having that, we can apply Lemma C.1 to the sequence \( E \left[ f(z^k) - f(x^*) \right] \). The constants for the lemma are: \( N = \frac{L \gamma_D^2}{2(1 - \beta) R_0} \), \( \alpha = \frac{\mu_D}{(1 - \beta) R_0} \) and \( C = \max \left\{ f(x^0) - f(x^*), \frac{L \gamma_D^2}{2(1 - \beta)^2 R_0} \right\} \). Lastly, choosing \( \gamma^k = \frac{2 \alpha}{\alpha^2 k + 2} \) is equivalent to the choice \( \theta = \frac{2}{\alpha} \). In this case, we have \( \alpha \theta = 2 \), \( C = \max \left\{ f(x^0) - f(x^*), \frac{L \gamma_D^2}{2(1 - \beta) R_0} \right\} \) and \( \eta = \frac{\alpha}{\theta} = \frac{\alpha^2}{2} = \frac{\mu_D^2}{2(1 - \beta) R_0} \). Putting these parameters and \( K \) from (42) in (41) we get the result.

\[\square\]
D Strongly Convex Case

Assumption D.1. We assume that $f$ is $\mu$-strongly convex with respect to the norm $\| \cdot \|_D^2$:

$$f(y) \geq f(x) + \langle \nabla f(x), y - x \rangle + \frac{\mu}{2} \|y - x\|_D^2, \quad \forall x, y \in \mathbb{R}^d.$$  \hspace{1cm} (43)

It is well known that strong convexity implies

$$\|\nabla f(x)\|_D^2 \geq 2\mu (f(x) - f(x^*)).$$  \hspace{1cm} (44)

Theorem D.1 (Solution-dependent stepsizes). Let Assumptions A.1, A.2 and D.1 be satisfied. If we set

$$\gamma^k = \frac{(1-\beta)\theta k \mu}{L} \sqrt{2\mu(f(z^k) - f(x^*))}$$

for some $\theta_k \in (0, 2)$ such that $\theta = \inf_{k \geq 0} \{2\theta_k - \gamma D^2 \theta_k^2\} \in \left(0, \frac{L}{\mu^2} \right)$, then for the iterates of SMTP the following inequality holds:

$$E[f(z^k)] - f(x^*) \leq \left(1 - \frac{\theta_k^2 \mu^2}{L} \right)^k (f(x^0) - f(x^*)).$$ \hspace{1cm} (45)

If we run SMTP for $k = K$ iterations where

$$K = \frac{\kappa}{\theta \mu^2} \ln \left(\frac{f(x^0) - f(x^*)}{\varepsilon}\right), \quad \varepsilon > 0,$$  \hspace{1cm} (46)

where $\kappa \equiv \frac{L}{\mu}$ is the condition number of the objective, we will get $E[f(z^K)] - f(x^*) \leq \varepsilon$.

Proof. From (32) and $\gamma^k = \frac{\theta k \mu^2}{L} \sqrt{2\mu(f(z^k) - f(x^*))}$ we have

$$E_{s^k \sim D}[f(z^{k+1})] - f(x^*) \leq f(z^k) - f(x^*) - \frac{\gamma^k \mu \|\nabla f(z^k)\|_D}{1-\beta} + \frac{L(\gamma^k)^2 \gamma D^2}{2(1-\beta)^2}$$

$$\leq f(z^k) - f(x^*) - \frac{\gamma^k \mu \|\nabla f(z^k)\|_D}{1-\beta} \sqrt{2\mu(f(z^k) - f(x^*))}$$

$$+ \frac{\gamma D^2 \theta^2 \mu^2}{L} (f(z^k) - f(x^*))$$

$$\leq f(z^k) - f(x^*) - \frac{2\theta^2 \mu^2 \|\nabla f(z^k)\|_D}{L} (f(z^k) - f(x^*))$$

$$+ \frac{\gamma D^2 \theta^2 \mu^2}{L} (f(z^k) - f(x^*))$$

$$\leq \left(1 - (2\theta_k - \gamma D^2 \theta_k^2 \mu^2 \|\nabla f(z^k)\|_D) \right) (f(z^k) - f(x^*)).$$

Using $\theta = \inf_{k \geq 0} \{2\theta_k - \gamma D^2 \theta_k^2\} \in \left(0, \frac{L}{\mu^2} \right)$ and taking the full expectation from the previous inequality we get

$$E[f(z^{k+1})] - f(x^*) \leq \left(1 - \frac{\theta_k^2 \mu^2}{L} \right) E[f(z^k) - f(x^*)]$$

$$\leq \left(1 - \frac{\theta_k^2 \mu^2}{L} \right)^k (f(x^0) - f(x^*)).$$

Lastly, from (45) we have

$$E[f(z^K)] - f(x^*) \leq \left(1 - \frac{\theta_k^2 \mu^2}{L} \right)^K (f(x^0) - f(x^*))$$

$$\leq \exp \left\{-K \frac{\theta_k^2 \mu^2}{L} \right\} (f(x^0) - f(x^*))$$

$$\leq \varepsilon.$$

$\square$
Assumption D.2. We assume that for all $s \sim \mathcal{D}$ we have $\|s\|_2 = 1$.

Theorem D.2 (Solution-free stepsizes). Let Assumptions A.1, A.2, D.1 and D.2 be satisfied. If additionally we compute $f(z^k + ts^k)$, set $\gamma^k = \frac{1}{L t} \langle f(z^k + ts^k) - f(z^k) \rangle$ for $t > 0$ and assume that $\mathcal{D}$ is such that $\mu_2^2 \leq \frac{1}{\mu}$, then for the iterates of SMTP the following inequality holds:

$$
E \left[ f(z^k) \right] - f(x^*) \leq \left( 1 - \frac{\mu_2^2 \mu}{L} \right)^k \left( f(x^0) - f(x^*) \right) + \frac{L^2 t^2}{8 \mu_2^2 \mu}.
$$

(47)

Moreover, for any $\varepsilon > 0$ if we set $t$ such that

$$
0 < t \leq \sqrt{\frac{4 \varepsilon \mu_2^2 \mu}{L^2}},
$$

(48)

and run SMTP for $k = K$ iterations where

$$
K = \frac{\kappa}{\mu_2^2} \ln \left( \frac{2(f(x^0) - f(x^*))}{\varepsilon} \right),
$$

(49)

where $\kappa \equiv \frac{L}{\mu}$ is the condition number of $f$, we will have $E \left[ f(z^K) \right] - f(x^*) \leq \varepsilon$.

Proof. Recall that from (31) we have

$$
f(z^{k+1}) \leq f(z^k) - \frac{\gamma^k}{1 - \beta} |\langle \nabla f(z^k), s^k \rangle| + \frac{L(\gamma^k)^2}{2(1 - \beta)^2}.
$$

If we minimize the right hand side of the previous inequality as a function of $\gamma^k$, we will get that the optimal choice in this sense is $\gamma^k_{\text{opt}} = \frac{(1 - \beta)}{L t} |\langle \nabla f(z^k), s^k \rangle|$. However, this stepsize is impractical for derivative-free optimization, since it requires to know $\nabla f(z^k)$. The natural way to handle this is to approximate directional derivative $\langle \nabla f(z^k), s^k \rangle$ by finite difference $\frac{f(z^k + ts^k) - f(z^k)}{t}$ and that is what we do. We choose $\gamma^k = \frac{(1 - \beta)}{L t} |\langle \nabla f(z^k), s^k \rangle| = \frac{(1 - \beta)}{L t} |\langle \nabla f(z^k), s^k \rangle| = \frac{L t^2}{4} |\langle \nabla f(z^k), s^k \rangle| \equiv \gamma^k_{\text{opt}} + \delta^k$. From this we get

$$
f(z^{k+1}) \leq f(z^k) - \frac{|\langle \nabla f(z^k), s^k \rangle|^2}{2L} + \frac{L}{2(1 - \beta)^2} (\delta^k)^2.
$$

Next we estimate $|\delta^k|:

$$
|\delta^k| = \frac{(1 - \beta)}{Lt} \left| f(z^k + ts^k) - f(z^k) \right| - |\langle \nabla f(z^k), ts^k \rangle| \\
\leq \frac{(1 - \beta)}{Lt} \left| f(z^k + ts^k) - f(z^k) - \langle \nabla f(z^k), ts^k \rangle \right| \\
\leq \frac{(1 - \beta)}{Lt} \cdot \frac{L}{2} \|ts^k\|^2 = \frac{(1 - \beta) t}{2}.
$$

It implies that

$$
f(z^{k+1}) \leq f(z^k) - \frac{|\langle \nabla f(z^k), s^k \rangle|^2}{2L} + \frac{L}{2(1 - \beta)^2} \cdot \frac{(1 - \beta)^2 t^2}{4} \\
= f(z^k) - \frac{|\langle \nabla f(z^k), s^k \rangle|^2}{2L} + \frac{Lt^2}{8}.
$$

and after taking full expectation from the both sides of the obtained inequality we get

$$
E \left[ f(z^{k+1}) - f(x^*) \right] \leq E \left[ f(z^k) - f(x^*) \right] - \frac{1}{2L} E \left[ |\langle \nabla f(z^k), s^k \rangle|^2 \right] + \frac{Lt^2}{8}.
$$

Note that from the tower property of mathematical expectation and Jensen’s inequality we have

$$
E \left[ |\langle \nabla f(z^k), s^k \rangle|^2 \right] = E \left[ E_{s^k \sim \mathcal{D}} \left[ |\langle \nabla f(z^k), s^k \rangle|^2 \mid s^k \right] \right] \\
\geq E \left[ \left( E_{s^k \sim \mathcal{D}} \left[ |\langle \nabla f(z^k), s^k \rangle| \mid s^k \right] \right)^2 \right] \\
\geq E \left[ \mu_2^2 \|\nabla f(z^k)\|_D^2 \right] \geq 2 \mu_2^2 \mu E \left[ f(z^k) - f(x^*) \right].
$$

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Putting all together we get
\[
E[f(z^{k+1}) - f(x^*)] \leq \left( 1 - \frac{\mu_D^2 \mu}{L} \right) E[f(z^k) - f(x^*)] + \frac{Lt^2}{8}.
\]

Due to \( \mu_D^2 \leq \frac{L}{\mu} \) we have
\[
E[f(z^k) - f(x^*)] \leq \left( 1 - \frac{\mu_D^2 \mu}{L} \right)^k (f(x^0) - f(x^*)) + \frac{Lt^2}{8} \sum_{l=0}^{k-1} \left( 1 - \frac{\mu_D^2 \mu}{L} \right)^l
\]
\[
\leq \left( 1 - \frac{\mu_D^2 \mu}{L} \right)^k (f(x^0) - f(x^*)) + \frac{Lt^2}{8} \sum_{l=0}^{\infty} \left( 1 - \frac{\mu_D^2 \mu}{L} \right)^l
\]
\[
= \left( 1 - \frac{\mu_D^2 \mu}{L} \right)^k (f(x^0) - f(x^*)) + \frac{L^2 t^2}{8 \mu_D^2 \mu}.
\]

Lastly, from (47) we have
\[
E[f(z^K)] - f(x^*) \leq \left( 1 - \frac{\mu_D^2 \mu}{L} \right)^K (f(x^0) - f(x^*)) + \frac{L^2 t^2}{8 \mu_D^2 \mu}
\]
\[
\leq \exp \left\{ -K \frac{\mu_D^2 \mu}{L} \right\} (f(x^0) - f(x^*)) + \frac{\varepsilon}{2}
\]
\[
\leq \frac{\varepsilon}{2} + \frac{\varepsilon}{2} = \varepsilon.
\]

\[\Box\]
SMTP_IS: Stochastic Momentum Three Points with Importance Sampling

Again by definition of $z^{k+1}$ we get that the sequence $\{f(z^k)\}_{k \geq 0}$ is monotone:

$$f(z^{k+1}) \leq f(z^k) \quad \forall k \geq 0.$$  \hspace{1cm} (50)

**Lemma E.1.** Assume that $f$ satisfies Assumption 4.1. Then for the iterates of SMTP_IS the following inequalities hold:

$$f(z^{k+1}) \leq f(z^k) - \frac{\gamma_k}{1 - \beta} \| \nabla_i f(z^k) \| + \frac{L_{ik}(\gamma_k)^2}{2(1 - \beta)^2}$$  \hspace{1cm} (51)

and

$$\mathbb{E}_{z_k \sim \mathcal{D}} \left[ f(z^{k+1}) \right] \leq f(z^k) - \frac{1}{1 - \beta} \mathbb{E} \left[ \gamma_i \| \nabla_i f(z^k) \| \mid z^k \right] + \frac{1}{2(1 - \beta)^2} \mathbb{E} \left[ L_{ik}(\gamma_i)^2 \mid z^k \right].$$  \hspace{1cm} (52)

**Proof.** In the similar way as in Lemma A.1 one can show that

$$z^k = z^{k-1} - \frac{\gamma_k}{1 - \beta} e_i,$$  \hspace{1cm} (53)

and

$$z^k = z^{k+1} - \frac{\gamma_k}{1 - \beta} e_i,$$

$$z^{k+1} = z^{k} + \frac{\gamma_k}{1 - \beta} e_i.$$

It implies that

$$f(z^{k+1}) \leq f(z^k) - \frac{\gamma_k}{1 - \beta} \| \nabla_i f(z^k) \| + \frac{L_{ik}(\gamma_k)^2}{2(1 - \beta)^2}$$

and

$$f(z^{k+1}) \leq f(z^k) + \frac{\gamma_k}{1 - \beta} \| \nabla_i f(z^k) \| + \frac{L_{ik}(\gamma_k)^2}{2(1 - \beta)^2}.$$

Unifying these two inequalities we get

$$f(z^{k+1}) \leq \min \{ f(z^{k+1}), f(z^{k+1}) \} = f(z^k) - \frac{\gamma_k}{1 - \beta} \| \nabla_i f(z^k) \| + \frac{L_{ik}(\gamma_k)^2}{2(1 - \beta)^2},$$

which proves (51). Finally, taking the expectation $\mathbb{E} \left[ \cdot \mid z^k \right]$ conditioned on $z^k$ from the both sides of the previous inequality we obtain

$$\mathbb{E} \left[ f(z^{k+1}) \mid z^k \right] \leq f(z^k) - \frac{1}{1 - \beta} \mathbb{E} \left[ \gamma_i \| \nabla_i f(z^k) \| \mid z^k \right] + \frac{1}{2(1 - \beta)^2} \mathbb{E} \left[ L_{ik}(\gamma_i)^2 \mid z^k \right].$$

\[\square\]

**E.1 Non-convex Case**

**Theorem E.1.** Assume that $f$ satisfies Assumption 4.1. Let SMTP_IS with $\gamma_i = \frac{1}{w_i}$ for some $\gamma > 0$ produce points $\{z^0, z^1, \ldots, z^{K-1}\}$ and $z^K$ is chosen uniformly at random among them. Then

$$\mathbb{E} \left[ \| \nabla f(z^K) \| \right] \leq \frac{(1 - \beta)(f(z^0) - f(x^*))}{K \gamma \min_{i=1, \ldots, d} \frac{E_i}{w_i}} + \frac{\gamma}{2(1 - \beta)} \min_{i=1, \ldots, d} \frac{E_i}{w_i} \sum_{i=1}^d \frac{L_i p_i}{w_i^2}.$$  \hspace{1cm} (54)
Moreover, if we choose \( \gamma = \frac{\gamma_0}{\sqrt{K}} \), then
\[
\mathbb{E} \left[ \| \nabla f(z^K) \|_1 \right] \leq \frac{1}{\sqrt{K}} \min_{i=1,\ldots,d} \frac{p_i}{w_i} \left( \frac{(1-\beta)(f(x^0) - f(x^*))}{\gamma_0} + \frac{\gamma_0}{2(1-\beta)} \sum_{i=1}^{d} \frac{L_i p_i}{w_i^2} \right). \tag{55}
\]

Note that if we choose \( \gamma_0 = \sqrt{\frac{2(1-\beta)^2(f(x^0) - f(x^*))}{\sum_{i=1}^{d} L_i p_i w_i}} \) in order to minimize right-hand side of (55), we will get
\[
\mathbb{E} \left[ \| \nabla f(z^K) \|_1 \right] \leq \frac{\sqrt{2 (f(x^0) - f(x^*)) \sum_{i=1}^{d} \frac{L_i p_i}{w_i^2}}}{\sqrt{K}} \min_{i=1,\ldots,d} \frac{p_i}{w_i}. \tag{56}
\]

Note that for \( p_i = L_i / \sum_i^d L_i \) with \( w_i = L_i \) we have that the rates improves to
\[
\mathbb{E} \left[ \| \nabla f(z^K) \|_1 \right] \leq \frac{2(f(x^0) - f(x^*)) d \sum_{i=1}^{d} L_i}{\sqrt{K}}. \tag{57}
\]

Proof. Recall that from (52) we have
\[
\mathbb{E} \left[ f(z^{k+1}) \mid z^k \right] \leq f(z^k) - \frac{1}{1-\beta} \mathbb{E} \left[ \gamma_i^k \nabla_i f(z^k) \mid z^k \right] + \frac{1}{2(1-\beta)^2} \mathbb{E} \left[ L_{ik} (\gamma_i^k)^2 \mid z^k \right]. \tag{58}
\]

Using our choice \( \gamma_i^k = \frac{\gamma}{w_{ik}} \) we derive
\[
\mathbb{E} \left[ \gamma_i^k \nabla_i f(z^k) \mid z^k \right] = \gamma \sum_{i=1}^{d} \frac{p_i}{w_i} \nabla_i f(z^k) \geq \gamma \| \nabla f(z^k) \|_1 \min_{i=1,\ldots,d} \frac{p_i}{w_i}
\]
and
\[
\mathbb{E} \left[ L_{ik} (\gamma_i^k)^2 \mid z^k \right] = \gamma^2 \sum_{i=1}^{d} \frac{L_i p_i}{w_i^2}.
\]

Putting it in (58) and taking full expectation from the both sides of obtained inequality we get
\[
\mathbb{E} \left[ f(z^{k+1}) \right] \leq \mathbb{E} \left[ f(z^k) \right] - \gamma \left( \min_{i=1,\ldots,d} \frac{p_i}{w_i} \frac{1}{1-\beta} \mathbb{E} \| \nabla f(z^k) \|_1 \right) + \gamma^2 \sum_{i=1}^{d} \frac{L_i p_i}{w_i^2},
\]
whence
\[
\| \nabla f(z^k) \|_1 \leq \frac{(1-\beta) \mathbb{E} \left[ f(z^k) \right] - \mathbb{E} \left[ f(z^{k+1}) \right]}{\gamma \left( \min_{i=1,\ldots,d} \frac{p_i}{w_i} \right)} + \frac{\gamma^2}{2(1-\beta)^2} \sum_{i=1}^{d} \frac{L_i p_i}{w_i^2}.
\]

Summing up previous inequality for \( k = 0, 1, \ldots, K-1 \) and dividing both sides of the result by \( K \), we get
\[
\frac{1}{K} \sum_{k=0}^{K-1} \mathbb{E} \left[ \| \nabla f(z^k) \|_1 \right] \leq \frac{(1-\beta)(f(x^0) - f(x^*))}{K \gamma \left( \min_{i=1,\ldots,d} \frac{p_i}{w_i} \right)} + \frac{\gamma^2}{2(1-\beta)^2} \sum_{i=1}^{d} \frac{L_i p_i}{w_i^2}.
\]

It remains to notice that \( \frac{1}{K} \sum_{k=0}^{K-1} \mathbb{E} \left[ \| \nabla f(z^k) \|_1 \right] = \mathbb{E} \left[ \| \nabla f(z^K) \|_1 \right] \). The last part where \( \gamma = \frac{\gamma_0}{\sqrt{K}} \) is straightforward. \( \square \)
E.2  Convex Case

As for SMTP to tackle convex problems by SMTP-IS we use Assumption 3.2 with \( \| \cdot \|_D = \| \cdot \|_1 \). Note that in this case \( R_0 = \max \{ \| x - x^\ast \|_\infty \mid f(x) \leq f(x^0) \} \).

**Theorem E.2** (Constant stepsize). Let Assumptions 3.2 and 4.1 be satisfied. If we set \( \gamma^k_i = \frac{\beta}{w_i} \) such that \( 0 < \gamma \leq \frac{(1-\beta)R_0}{\min_{i=1,\ldots,d} w_i} \), then for the iterates of SMTP-IS the method the following inequality holds:

\[
E[f(z^k) - f(x^\ast)] \leq \left( 1 - \gamma \frac{\min_{i=1,\ldots,d} w_i}{(1-\beta)R_0} \right)^k (f(z^0) - f(x^\ast)) + \frac{\gamma R_0}{2(1-\beta)} \min_{i=1,\ldots,d} w_i \sum_{i=1}^d L_i p_i w_i^2. \tag{59}
\]

Moreover, if we choose \( \gamma = \frac{\varepsilon(1-\beta)}{R_0 \sum_{i=1}^d L_i w_i^2} \) for some \( 0 < \varepsilon \leq \frac{R_0^2 \sum_{i=1}^d L_i p_i w_i^2}{\min_{i=1,\ldots,d} w_i^2} \) and run SMTP-IS for \( k = K \) iterations where

\[
K = \frac{1}{\varepsilon} \frac{R_0^2 d \sum_{i=1}^d L_i p_i w_i^2}{\min_{i=1,\ldots,d} w_i^2} \ln \left( \frac{2(f(x^0) - f(x^\ast))}{\varepsilon} \right), \tag{60}
\]

we will get \( E[f(z^K)] - f(x^\ast) \leq \varepsilon \). Moreover, for \( p_i = L_i/\sum_{i=1}^d L_i \), with \( w_i = L_i \), the rate improves to

\[
K = \frac{1}{\varepsilon} \frac{R_0^2 d \sum_{i=1}^d L_i \ln(2(f(x^0) - f(x^\ast))}{\varepsilon}. \tag{61}
\]

**Proof.** Recall that from (52) we have

\[
E[f(z^{k+1}) \mid z^k] \leq f(z^k) - \frac{1}{1-\beta} E[\gamma^k_i \nabla_i f(z^k) \mid z^k] + \frac{1}{2(1-\beta)^2} E[L_{ik}(\gamma^k_i)^2 \mid z^k]. \tag{62}
\]

Using our choice \( \gamma^k_i = \frac{\beta}{w_i} \) we derive

\[
E[\gamma^k_i \nabla_i f(z^k) \mid z^k] = \gamma \sum_{i=1}^d \frac{p_i}{w_i} \nabla_i f(z^k) \geq \gamma \| \nabla f(z^k) \|_1 \min_{i=1,\ldots,d} \frac{p_i}{w_i}
\]

\[
\overset{\text{(53)}}{=} \frac{\gamma}{R_0} \min_{i=1,\ldots,d} \frac{p_i}{w_i} (f(z^k) - f(x^\ast))
\]

and

\[
E[L_{ik}(\gamma^k_i)^2 \mid z^k] = \gamma^2 \sum_{i=1}^d \frac{L_ip_i}{w_i^2}.
\]

Putting it in (62) and taking full expectation from the both sides of obtained inequality we get

\[
E[f(z^{k+1}) - f(x^\ast)] \leq \left( 1 - \gamma \frac{\min_{i=1,\ldots,d} w_i}{(1-\beta)R_0} \right) E[f(z^k) - f(x^\ast)] + \frac{\gamma^2}{2(1-\beta)^2} \sum_{i=1}^d \frac{L_ip_i}{w_i^2}. \tag{63}
\]
Due to our choice of $\gamma \leq \frac{(1-\beta)R_0}{\min_{i=1,\ldots,d} \frac{p_i}{w_i}}$, we have that the factor $\left(1 - \frac{\gamma}{(1-\beta)R_0} \min_{i=1,\ldots,d} \frac{p_i}{w_i}\right)$ is non-negative and, therefore,

$$
\mathbb{E}[f(z^k) - f(x^*)] \leq \left(1 - \frac{\gamma}{(1-\beta)R_0} \min_{i=1,\ldots,d} \frac{p_i}{w_i}\right)^k (f(z^0) - f(x^*)) + \left(1 - \frac{\gamma}{(1-\beta)R_0} \min_{i=1,\ldots,d} \frac{p_i}{w_i}\right)^{k-1} \sum_{i=0}^{k-1} \left(1 - \frac{\gamma}{(1-\beta)R_0} \min_{i=1,\ldots,d} \frac{p_i}{w_i}\right)^i
$$

where $\gamma \leq \eta \leq \frac{\beta}{2\alpha}$. Moreover, if we choose $\gamma = \frac{2\alpha}{\alpha^2 + 2\theta}$, where $\alpha = \frac{\min_{i=1,\ldots,d} \frac{p_i}{w_i}}{(1-\beta)R_0}$ and $\theta \geq \frac{\alpha}{2}$, then for the iterates of SMTP\_IS method the following inequality holds:

$$
\mathbb{E}[f(z^k)] - f(x^*) = \left(1 - \frac{\gamma}{(1-\beta)R_0} \min_{i=1,\ldots,d} \frac{p_i}{w_i}\right)^k (f(z^0) - f(x^*)) + \frac{\gamma R_0}{2(1-\beta)} \min_{i=1,\ldots,d} \frac{p_i}{w_i} \sum_{i=1}^{d} L_i p_i \leq \exp\left\{-K \cdot \frac{\varepsilon}{2} \right\} (f(z^0) - f(x^*)) + \frac{\varepsilon}{2}
$$

Thus, we have that the factor

$$
\mathbb{E}[f(z^k)] - f(x^*) \leq \mathbb{E}[f(z^{k+1})] - f(x^*) \leq \varepsilon.
$$

**Theorem E.3 (Decreasing stepsizes).** Let Assumptions 3.2 and 4.1 be satisfied. If we set $\gamma^k = \frac{\gamma^k}{w_{i_k}}$ and $\gamma^k = \frac{2\alpha}{\alpha^2 + \theta}$, where $\alpha = \frac{\min_{i=1,\ldots,d} \frac{p_i}{w_i}}{(1-\beta)R_0}$ and $\theta \geq \frac{\alpha}{2}$, then for the iterates of SMTP\_IS method the following inequality holds:

$$
\mathbb{E}[f(z^k)] - f(x^*) \leq \frac{1}{\eta k + 1} \max \left\{ f(x^0) - f(x^*), \frac{2}{\alpha\theta(1-\beta)^2} \sum_{i=1}^{d} L_i p_i \right\},
$$

where $\eta \equiv \frac{\alpha}{\beta}$. Moreover, if we choose $\gamma^k = \frac{2\alpha}{\alpha^2 + \theta^2 k^2}$, where $\alpha = \frac{\min_{i=1,\ldots,d} \frac{p_i}{w_i}}{(1-\beta)R_0}$ and run SMTP\_IS for $k = K$ iterations where

$$
K = \frac{1}{\varepsilon} \cdot \min_{i=1,\ldots,d} \frac{p_i}{w_i} \max \left\{ (1-\beta)^2(f(x^0) - f(x^*)), \sum_{i=1}^{d} L_i p_i - \frac{2(1-\beta)^2 R_0^2}{\min_{i=1,\ldots,d} \frac{p_i}{w_i}}, \varepsilon > 0, \right\}
$$

we will get $\mathbb{E}[f(z^k)] - f(x^*) \leq \varepsilon$.

**Proof.** In (63) we proved that

$$
\mathbb{E}[f(z^{k+1}) - f(x^*)] \leq \left(1 - \frac{\gamma}{(1-\beta)R_0} \min_{i=1,\ldots,d} \frac{p_i}{w_i}\right) \mathbb{E}[f(z^k) - f(x^*)] + \frac{\gamma^2}{2(1-\beta)} \sum_{i=1}^{d} L_i p_i w_i^2.
$$


Having that, we can apply Lemma [C.1] to the sequence $E [f(z^k) - f(x^*)]$. The constants for the lemma are: $N = \frac{1}{2(1-\beta)^2} \sum_{i=1}^{d} \frac{L_{i} P_{i}}{w_{i}^{2}}$, $\alpha = \min_{i=1,\ldots,d} \frac{P_{i}}{w_{i}}$ and $C = \max\left\{ \frac{f(x^0) - f(x^*)}{\alpha(1-\beta)^2} \sum_{i=1}^{d} \frac{L_{i} P_{i}}{w_{i}^{2}} \right\}$. Lastly, note that choosing $\gamma^k = \frac{2\alpha}{\alpha^2 + 1}$ is equivalent to choice $\theta = \frac{2}{\alpha}$. In this case we have $\alpha \theta = 2$ and $C = \max\left\{ \frac{f(x^0) - f(x^*)}{(1-\beta)^2} \sum_{i=1}^{d} \frac{L_{i} P_{i}}{w_{i}^{2}} \right\}$ and $\eta \alpha = \frac{\alpha^2}{2} = \frac{\min_{i=1,\ldots,d} \frac{P_{i}^2}{w_{i}^{2}}}{2(1-\beta)^2 \sum_{i=1}^{d} \frac{L_{i} P_{i}}{w_{i}^{2}}}$. Putting these parameters and $K$ from (65) in the (64) we get the result. \qed

### E.3 Strongly Convex Case

**Theorem E.4** (Solution-dependent stepsizes). Let Assumptions [E.3] (with $\| \cdot \|_{\mathcal{F}} = \| \cdot \|_{1}$) and [4.1] be satisfied. If we set $\gamma^k = \frac{(1-\beta)\theta_k}{\min_{i=1,\ldots,d} \frac{P_{i}}{w_{i}}} \sqrt{2\mu(f(z^k) - f(x^*))}$ for some $\theta_k \in (0, 2)$ such that
\[
\theta = \inf_{k \geq 0} \left\{ 2\theta_k - \frac{\theta^2_k}{k} \right\} \in \left( 0, \frac{\mu \min_{i=1,\ldots,d} \frac{P_{i}^2}{w_{i}^{2}}}{\theta_k} \right),
\]
then for the iterates of SMTP IS method the following inequality holds:
\[
E [f(z^k)] - f(x^*) \leq \left( 1 - \frac{\theta \mu \min_{i=1,\ldots,d} \frac{P_{i}^2}{w_{i}^{2}}}{\sum_{i=1}^{d} \frac{L_{i} P_{i}}{w_{i}^{2}}} \right)^k (f(x^0) - f(x^*)), \quad (66)
\]
If we run SMTP IS for $k = K$ iterations where
\[
K = \frac{\theta \mu \min_{i=1,\ldots,d} \frac{P_{i}^2}{w_{i}^{2}}}{\theta_k \mu \min_{i=1,\ldots,d} \frac{P_{i}^2}{w_{i}^{2}}} \ln \left( \frac{f(x^0) - f(x^*)}{\varepsilon} \right), \quad \varepsilon > 0, \quad (67)
\]
we will get $E [f(z^K)] - f(x^*) \leq \varepsilon$.

**Proof.** Recall that from (52) we have
\[
E [f(z^{k+1}) \mid z^k] \leq f(z^k) - \frac{1}{1-\beta} E [\gamma^k \nabla_i f(z^k) \mid z^k] + \frac{1}{2(1-\beta)^2} E [L_{ik}(\gamma^k)^2 \mid z^k]. \quad (68)
\]
Using our choice $\gamma^k = \frac{(1-\beta)\theta_k}{\min_{i=1,\ldots,d} \frac{P_{i}}{w_{i}}} \sqrt{2\mu(f(z^k) - f(x^*))}$ we derive
\[
E [\gamma^k \nabla_i f(z^k) \mid z^k] = \frac{(1-\beta)\theta_k}{\min_{i=1,\ldots,d} \frac{P_{i}}{w_{i}}} \sqrt{2\mu(f(z^k) - f(x^*))} \sum_{i=1}^{d} \frac{P_{i}}{w_{i}} |\nabla_i f(z^k)| \geq \frac{(1-\beta)\theta_k}{\min_{i=1,\ldots,d} \frac{P_{i}}{w_{i}}} \sqrt{2\mu(f(z^k) - f(x^*))} \| \nabla f(z^k) \|_1 \geq \frac{2(1-\beta)\theta_k}{\min_{i=1,\ldots,d} \frac{P_{i}^2}{w_{i}^{2}}} \mu(f(z^k) - f(x^*))}
\]

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Theorem E.5

The previous result based on the choice of \(\gamma^k\) which depends on the \(f(z^k) - f(x^*)\) which is often unknown in practice. The next theorem does not have this drawback and makes it possible to obtain the same rate of convergence as in the previous theorem using one extra function evaluation.

Putting it in (68) and taking full expectation from the both sides of obtained inequality we get

\[
E \left[ f(z^{k+1}) - f(x^*) \right] \leq \left( 1 - (2\theta - \theta^2) \frac{\mu \min_{i=1,\ldots,d} \frac{\rho_i^2}{\mu_i}}{\sum_{i=1}^{d} \frac{L_i p_i}{\mu_i}} \right)^{k+1} \left( f(x^0) - f(x^*) \right).
\]

Lastly, from (66) we have

\[
E \left[ f(z^K) - f(x^*) \right] \leq \exp \left\{ -K \frac{\theta \mu \min_{i=1,\ldots,d} \frac{\rho_i^2}{\mu_i}}{\sum_{i=1}^{d} \frac{L_i p_i}{\mu_i}} \left( f(x^0) - f(x^*) \right) \right\} \leq \varepsilon.
\]

The previous result based on the choice of \(\gamma^k\) which depends on the \(f(z^k) - f(x^*)\) which is often unknown in practice. The next theorem does not have this drawback and makes it possible to obtain the same rate of convergence as in the previous theorem using one extra function evaluation.

Theorem E.5 (Solution-free stepsizes). Let Assumptions 3.3 (with \(\| \cdot \|_{\mathcal{D}} = \| \cdot \|_2\)) and 4.1 be satisfied.

If additionally we compute \(f(z^k + t e_i^k)\), set \(\gamma_i^k = \frac{(1-\beta)(f(z^k + t e_i^k) - f(z^k))}{L_i t}\) for \(t > 0\), then for the iterates of SMTP-IS method the following inequality holds:

\[
E \left[ f(z^k) - f(x^*) \right] \leq \left( 1 - \mu \min_{i=1,\ldots,d} \frac{p_i}{L_i} \right)^k \left( f(x^0) - f(x^*) \right) + \frac{\rho^2}{8\mu \min_{i=1,\ldots,d} \frac{p_i}{L_i}} \sum_{i=1}^{d} p_i L_i. \tag{69}
\]
Moreover, for any \( \varepsilon > 0 \) if we set \( t \) such that
\[
0 < t \leq \sqrt{\frac{4\varepsilon \mu}{\min_{i=1}^{d} \frac{E_i}{L_i}}},
\]
and run SMTP-IS for \( k = K \) iterations where
\[
K = \frac{1}{\mu \min_{i=1}^{d} \frac{E_i}{L_i}} \ln \left( \frac{2(f(x^0) - f(x^*))}{\varepsilon} \right),
\]
we will get \( \mathbb{E} \left[ f(z^K) \right] - f(x^*) \leq \varepsilon. \) Moreover, note that for \( p_i = L_i / \sum_i L_i \), with \( w_i = L_i \), the rate improves to
\[
K = \sum_{i=1}^{d} \frac{L_i}{\mu} \ln \left( \frac{2(f(x^0) - f(x^*))}{\varepsilon} \right).
\]

**Proof.** Recall that from (51) we have
\[
f(z^{k+1}) \leq f(z^k) - \frac{\gamma_k}{1 - \beta} |\nabla_{ik} f(z^k)| + \frac{L_{ik} (\gamma_k)^2}{2(1 - \beta)^2}.
\]
If we minimize the right hand side of the previous inequality as a function of \( \gamma_k \), we will get that the optimal choice in this sense is \( \gamma_{opt} = \frac{(1 - \beta)|\nabla_{ik} f(z^k)|}{L_{ik}} \). However, this stepsize is impractical for derivative-free optimization, since it requires to know \( \nabla_{ik} f(z^k) \). The natural way to handle this is to approximate directional derivative \( \nabla_{ik} f(z^k) \) by finite difference \( f(z^{k+te_{ik}}) - f(z^k) \) and that is what we do. We choose \( \gamma_k = \frac{(1 - \beta)|f(z^{k+te_{ik}}) - f(z^k)|}{L_{ik} t} = \frac{(1 - \beta)|\nabla_{ik} f(z^k)|}{L_{ik}} + \frac{t}{L_{ik}} |f(z^{k+te_{ik}}) - f(z^k)| - \frac{(1 - \beta)|\nabla_{ik} f(z^k)|}{L_{ik}} \) def \( \gamma_{opt} + \delta_t^k \). From this we get
\[
f(z^{k+1}) \leq f(z^k) - \frac{|\nabla_{ik} f(z^k)|^2}{2L_{ik}} + \frac{L_{ik}}{2(1 - \beta)^2} (\delta_t^k)^2.
\]
Next we estimate \( |\delta_t^k|\):
\[
|\delta_t^k| = \frac{(1 - \beta)}{L_{ik}} \left| f(z^{k+te_{ik}}) - f(z^k) - |\nabla_{ik} f(z^k)| t \right| \\
\leq \frac{(1 - \beta)}{L_{ik}} \left| f(z^{k+te_{ik}}) - f(z^k) - \nabla_{ik} f(z^k) t \right| \\
\leq \frac{\frac{1}{L_{ik}}}{\frac{1}{L_{ik}}} \frac{L_{ik} t^2}{2} = \frac{(1 - \beta)}{2} t.
\]
It implies that
\[
f(z^{k+1}) \leq f(z^k) - \frac{|\nabla_{ik} f(z^k)|^2}{2L_{ik}} + \frac{L_{ik}}{2(1 - \beta)^2} \frac{(1 - \beta)^2 t^2}{4} \\
= f(z^k) - \frac{|\nabla_{ik} f(z^k)|^2}{2L_{ik}} + \frac{L_{ik} t^2}{8}
\]
and after taking expectation \( \mathbb{E} [ \cdot | z^k] \) conditioned on \( z^k \) from the both sides of the obtained inequality we get
\[
\mathbb{E} [ f(z^{k+1}) | z^k] \leq f(z^k) - \frac{1}{2} \mathbb{E} \left[ \frac{|\nabla_{ik} f(z^k)|^2}{L_{ik}} \bigm| z^k \right] + \frac{t^2}{8} \mathbb{E} \left[ L_{ik} | z^k \right].
\]
Note that
\[
\mathbb{E} \left[ \frac{|\nabla_{ik} f(z^k)|^2}{L_{ik}} \bigm| z^k \right] = \sum_{i=1}^{d} \frac{p_i}{L_i} |\nabla_i f(z^k)|^2 \\
\geq \| \nabla f(z^k) \|_2^2 \min_{i=1}^{d} \frac{p_i}{L_i} \\
\geq 2\mu (f(z^k) - f(x^*)) \min_{i=1}^{d} \frac{p_i}{L_i},
\]
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We notice that for SMTP we give number of iterations in order to guarantee $E$ with $\text{SMTP}_{\text{IS}}$.

Taking full expectation from the previous inequality we get

$$E[f(z^{k+1}) - f(z^k)] \leq \left(1 - \mu \min_{i=1,\ldots,d} \frac{p_i}{L_i}\right)^k E[f(z^0) - f(x^*)] + \frac{1^2}{8} \sum_{i=1}^d p_i L_i.$$ 

Putting all together we get

$$E[f(z^{k+1}) | z^k] \leq f(z^k) - \mu \min_{i=1,\ldots,d} \frac{p_i}{L_i} (f(z^k) - f(x^*)) + \frac{1^2}{8} \sum_{i=1}^d p_i L_i.$$ 

Since $\mu \leq L_i$ for all $i = 1, \ldots, d$ we have

$$E[f(z^k) - f(x^*)] \leq \left(1 - \mu \min_{i=1,\ldots,d} \frac{p_i}{L_i}\right)^k (f(x^0) - f(x^*)) + \frac{1^2}{8} \sum_{i=1}^d p_i L_i.$$ 

Lastly, from (69) we have

$$E[f(z^K)] - f(x^*) \leq \left(1 - \mu \min_{i=1,\ldots,d} \frac{p_i}{L_i}\right)^K (f(x^0) - f(x^*)) + \frac{1^2}{8} \sum_{i=1}^d p_i L_i.$$ 

E.4 COMPARISON OF SMTP AND SMTP\_IS

Here we compare SMTP when $D$ is normal distribution with zero mean and $\frac{L}{\mu}$ covariance matrix with SMTP\_IS with probabilities $p_i = L_i / \sum_{i=1}^d L_i$. We choose such a distribution for SMTP since it shows the best dimension dependence among other distributions considered in Lemma 4.1. Note that if $f$ satisfies Assumption 4.1 it is $L$-smooth with $L = \max_{i=1,\ldots,d} L_i$. So, we always have that $\sum_{i=1}^d L_i \geq dL$.

Table 3 summarizes complexities in this case. We notice that for SMTP we have $\| \cdot \|_D = \| \cdot \|_2$. That is why one needs to compare SMTP with SMTP\_IS accurately. At the first glance, Table 3 says that for non-convex and convex cases we get an extra $d$ factor in the complexity of SMTP\_IS when $L_1 = \ldots = L_d = L$. However, it is natural since we use different norms for SMTP and SMTP\_IS. In the non-convex case for SMTP we give number of iterations in order to guarantee $E[\|\nabla f(z^K)\|_2] \leq \varepsilon$ while for SMTP\_IS we provide number of iterations in order to guarantee $E[\|\nabla f(z^K)\|_1] \leq \varepsilon$. From Holder’s inequality...

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Table 3: Comparison of SMTP with $D = N(0, \frac{1}{d})$ and SMTP-IS with $p_i = L_i / \sum_{l=1}^{d} L_l$. Here $r_0 = f(x^0) - f(x^*)$, $R_0, \ell_0$ corresponds to the $R_0$ from Assumption C.1 with $\| \cdot \|_D = \| \cdot \|_2$ and $R_0, \ell_\infty$ corresponds to the $\tilde{R}_0$ from Assumption C.1 with $\| \cdot \|_D = \| \cdot \|_1$.

\[ \| \cdot \|_1 \leq \sqrt{d} \| \cdot \|_2 \text{ and, therefore, in order to have } \mathbb{E} \left[ \| \nabla f(\pi^K) \|_1 \right] \leq \varepsilon \text{ for SMTP we need to ensure that } \mathbb{E} \left[ \| \nabla f(\pi^K) \|_2 \right] \leq \frac{\varepsilon}{\sqrt{d}}. \] That is, to guarantee $\mathbb{E} \left[ \| \nabla f(\pi^K) \|_1 \right] \leq \varepsilon$ SMTP for aforementioned distribution needs to perform $\frac{\pi d \alpha^2 L^2}{\varepsilon^2}$ iterations.

Analogously, in the convex case using Cauchy-Schwartz inequality $\| \cdot \|_2 \leq \sqrt{d} \| \cdot \|_\infty$ we have that $R_0, \ell_\infty \leq \sqrt{d} R_0, \ell_\infty$. Typically this inequality is tight and if we assume that $R_0, \ell_\infty \geq C R_0, \ell_\infty / \sqrt{d}$, we will get that SMTP-IS complexity is $\frac{R_0^2 \ell_0 \sum_{l=1}^{d} L_l}{\varepsilon} \ln \left( \frac{2r_0}{\varepsilon} \right)$ up to constant factor.

That is, in all cases SMTP-IS shows better complexity than SMTP up to some constant factor.

F Auxiliary Results

Lemma F.1 (Lemma 3.4 from Bergou et al. [2019]). Let $g \in \mathbb{R}^d$.

1. If $D$ is the uniform distribution on the unit sphere in $\mathbb{R}^d$, then

\[ \gamma_D = 1 \quad \text{and} \quad \mathbb{E}_{s \sim D} \left[ \langle g, s \rangle \right] \sim \frac{1}{\sqrt{2\pi d}} \| g \|_2. \] (73)

Hence, $D$ satisfies Assumption 3.1 with $\gamma_D = 1$, $\| \cdot \|_D = \| \cdot \|_2$ and $\mu_D \sim \frac{1}{\sqrt{2\pi d}}$.

2. If $D$ is the normal distribution with zero mean and identity over $d$ as covariance matrix (i.e. $s \sim N(0, \frac{1}{d}))$ then

\[ \gamma_D = 1 \quad \text{and} \quad \mathbb{E}_{s \sim D} \left[ \langle g, s \rangle \right] = \frac{\sqrt{d}}{\sqrt{2\pi d}} \| g \|_2. \] (74)

Hence, $D$ satisfies Assumption 3.1 with $\gamma_D = 1$, $\| \cdot \|_D = \| \cdot \|_2$ and $\mu_D = \frac{\sqrt{d}}{\sqrt{2\pi d}}$.

3. If $D$ is the uniform distribution on $\{ e_1, \ldots, e_d \}$, then

\[ \gamma_D = 1 \quad \text{and} \quad \mathbb{E}_{s \sim D} \left[ \langle g, s \rangle \right] = \frac{1}{d} \| g \|_1. \] (75)

Hence, $D$ satisfies Assumption 3.1 with $\gamma_D = 1$, $\| \cdot \|_D = \| \cdot \|_1$ and $\mu_D = \frac{1}{d}$.

4. If $D$ is an arbitrary distribution on $\{ e_1, \ldots, e_d \}$ given by $P \{ s = e_i \} = p_i > 0$, then

\[ \gamma_D = 1 \quad \text{and} \quad \mathbb{E}_{s \sim D} \left[ \langle g, s \rangle \right] = \| g \|_D \overset{\text{def}}{=} \sum_{i=1}^{d} p_i \| g_i \|_D. \] (76)

Hence, $D$ satisfies Assumption 3.1 with $\gamma_D = 1$ and $\mu_D = 1$.

5. If $D$ is a distribution on $D = \{ u_1, \ldots, u_d \}$ where $u_1, \ldots, u_d$ form an orthonormal basis of $\mathbb{R}^d$ and $P \{ s = d_i \} = p_i$, then

\[ \gamma_D = 1 \quad \text{and} \quad \mathbb{E}_{s \sim D} \left[ \langle g, s \rangle \right] = \| g \|_D \overset{\text{def}}{=} \sum_{i=1}^{d} p_i \| g_i \|. \] (77)
Hence, $D$ satisfies Assumption 3.1 with $\gamma_D = 1$ and $\mu_D = 1$. 