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# Fast Two-Time-Scale Noisy EM Algorithms

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## Abstract

Using the Expectation-Maximization (EM) algorithm is the most popular choice for current latent data model learning tasks. For today's modern and complex models, variants of the EM have been initially introduced by [16], using incremental updates to scale to large datasets, and by [20, 6], using Monte-Carlo (MC) approximations to bypass the impossible conditional expectation of the latent data for most nonconvex models. In this paper, we propose a general class of methods called Two-Time-Scale EM Methods based on double stages of stochastic updates to tackle an essential large and nonconvex optimization task for latent data models. We motivate the choice of a double dynamics by invoking the variance reduction virtue of each stage of the method on both sources of noise: the incremental update and the MC approximation. We establish finite-time and global convergence bounds for nonconvex objective functions. Numerical applications are also presented in this article to illustrate our findings.

## 1 Introduction

Learning latent data models is critical for modern machine learning problems, see [14] for references. We formulate the training of such model as an empirical risk minimization problem:

$$\min_{\theta \in \Theta} \bar{L}(\theta) := r(\theta) + L(\theta) \quad \text{with} \quad L(\theta) = \frac{1}{n} \sum_{i=1}^n L_i(\theta) := \frac{1}{n} \sum_{i=1}^n \{ -\log g(y_i; \theta) \}, \quad (1)$$

We denote the observations by  $\{y_i\}_{i=1}^n$ ,  $\Theta \subset \mathbb{R}^d$  is the convex parameters space. We consider a regularized model where  $r : \Theta \rightarrow \mathbb{R}$  is a smooth convex regularization function and for  $\theta \in \Theta$ ,  $g(y; \theta)$  is the (incomplete) likelihood of each individual observation. The objective function  $\bar{L}(\theta)$  is possibly *nonconvex* and is assumed to be lower bounded  $\bar{L}(\theta) > -\infty$  for all  $\theta \in \Theta$ .

In the latent variable model,  $g(y_i; \theta)$ , is the marginal of the complete data likelihood defined as  $f(z_i, y_i; \theta)$ , i.e.  $g(y_i; \theta) = \int_{\mathcal{Z}} f(z_i, y_i; \theta) \mu(dz_i)$ , where  $\{z_i\}_{i=1}^n$  are the latent variables. In this paper, we make the assumption of a complete model belonging to the curved exponential family:

$$f(z_i, y_i; \theta) = h(z_i, y_i) \exp \left( \langle S(z_i, y_i) | \phi(\theta) \rangle - \psi(\theta) \right), \quad (2)$$

where  $\psi(\theta)$ ,  $h(z_i, y_i)$  are scalar functions,  $\phi(\theta) \in \mathbb{R}^k$  is a vector function, and  $S(z_i, y_i) \in \mathbb{R}^k$  is the complete data sufficient statistics.

Full batch EM [7] is the method of reference for that kind of task and is a two steps procedure. The **E-step** amounts to computing the conditional expectation of the complete data sufficient statistics,

$$\bar{s}(\theta) = \frac{1}{n} \sum_{i=1}^n \bar{s}_i(\theta) \quad \text{where} \quad \bar{s}_i(\theta) = \int_{\mathcal{Z}} S(z_i, y_i) p(z_i | y_i; \theta) \mu(dz_i). \quad (3)$$

28 The M-step is given by

$$\text{M-step: } \hat{\boldsymbol{\theta}} = \bar{\boldsymbol{\theta}}(\bar{\mathbf{s}}(\boldsymbol{\theta})) := \arg \min_{\boldsymbol{\vartheta} \in \Theta} \{ \mathbf{r}(\boldsymbol{\vartheta}) + \psi(\boldsymbol{\vartheta}) - \langle \bar{\mathbf{s}}(\boldsymbol{\theta}) | \phi(\boldsymbol{\vartheta}) \rangle \}, \quad (4)$$

29 Two caveats of this method are the following: (a) with the explosion of data, the first step of the EM  
 30 is computationally inefficient as it requires a full pass over the dataset at each iteration and (b) the  
 31 complexity of modern models makes the expectation in (3) intractable. So far, both challenges have  
 32 been addressed separately, to the best of our knowledge, as detailed the sequel.

33 **Prior Work** Inspired by stochastic optimization procedures, [16] and [4] developed respectively an  
 34 incremental and an online variant of the E-step in models where the expectation is computable then  
 35 extensively used and studied in [17, 12, 3]. Some improvements of that methods have been provided  
 36 and analyzed, globally and in finite-time, in [9] where variance reduction techniques taken from the  
 37 optimization literature have been efficiently applied to scale the EM algorithm to large datasets.

38 Regarding the computation of the expectation under the posterior distribution, the first method was  
 39 the Monte-Carlo EM (MCEM) introduced in the seminal paper [20] where a MC approximation  
 40 for this expectation is computed. A variant of that method is the Stochastic Approximation of the  
 41 EM (SAEM) in [6] leveraging the power of Robbins-Monro type of update [19] to ensure pointwise  
 42 convergence of the vector of estimated parameters rather using a decreasing stepsize than increasing  
 43 the number of MC samples. The MCEM and the SAEM have been successfully applied in mixed  
 44 effects models [13, 8, 2] or to do inference for joint modeling of time to event data coming from  
 45 clinical trials in [5], among other applications. Recently, an incremental variant of the SAEM was  
 46 proposed in [11] showing positive empirical results but its analysis is limited to asymptotic consid-  
 47 eration. Gradient-based methods have been developed and analyzed in [21] but they remain out of  
 48 the scope of this paper as they tackle the high-dimensionality issue.

49 **Contributions** This paper *introduces* and *analyzes* a new class of methods which purpose is up-  
 50 date two proxies for target expected quantities in a two-time-scale manner. Those approximated  
 51 quantities are then used to optimize (1) for current modern examples and settings using EM-fashion  
 52 Maximization step. The main contributions of the paper are:

- 53 • We propose a two-time-scale method based on Stochastic Approximation (SA), to alleviate  
 54 the problem of MC computation, and on Incremental updates, to scale to large datasets.  
 55 We describe in details the edges of each level of our method based on variance reduction  
 56 arguments. The derivation of such class of algorithms has two advantages. First, it naturally  
 57 leverages variance reduction and Robbins-Monro type of updates to tackle large-scale and  
 58 highly nonlinear learning tasks. Then, it gives a simple formulation as a *scaled-gradient*  
 59 *method* which makes the global analysis and the implementation accessible.
- 60 • We also establish global (independent of the initialization) and finite-time (true at each  
 61 iteration) upper bounds on a classical suboptimality condition in the nonconvex literature,  
 62 *i.e.*, the second order moment of the gradient of the objective function.

63 In Section 2 we give rigorous mathematical definitions of the various updates used for both incre-  
 64 mental and Monte-Carlo EMs and we introduce the main class of new algorithms, based on two  
 65 different dynamics, we are proposing to analyze and compare to baselines algorithms. Section 3  
 66 presents the main theoretical guarantees of this newly introduced two-time-scale class of algorithms.  
 67 Results are given both in finite-time and in the nonconvex setting. Finally, we illustrate the advan-  
 68 tages of our method in Section 4 on two numerical experiments.

## 69 2 Two-Time-Scale Stochastic EM Algorithms

70 We recall and formalize in this section the different methods found in the literature that aim to solv-  
 71 ing the large-scale problem and the intractable expectation. We then provide the general framework  
 72 of our method that efficiently tackles the optimization problem (1).

### 73 2.1 Monte Carlo Integration and Stochastic Approximation

74 As mentioned in the introduction, for complex and possibly nonlinear models, the expectation under  
 75 the posterior distribution defined in (3) is not tractable. In that case, the first solution involves

76 computing a Monte Carlo integration of that latter term. For all  $i \in \llbracket 1, n \rrbracket$ , draw for  $m \in \llbracket 1, M \rrbracket$ ,  
 77 samples  $z_{i,m} \sim p(z_i|y_i; \theta)$  and compute the MC integration  $\tilde{s}$  of the deterministic quantity  $\bar{s}(\theta)$ :

$$\text{MC-step : } \tilde{s} = \frac{1}{n} \sum_{i=1}^n \frac{1}{M} \sum_{m=1}^M S(z_{i,m}, y_i) \quad (5)$$

78 and then update the parameter  $\hat{\theta} = \bar{\theta}(\tilde{s})$ . This algorithm bypasses the intractable expectation issue  
 79 but is rather computationally expensive in order to reach point wise convergence ( $M$  needs to be  
 80 large). An alternative to that stochastic algorithm is to use a Robbins-Monro (RM) type of update.  
 81 We denote, at iteration  $k$ , the following quantity

$$\tilde{S}^{(k+1)} = \frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(k+1)} = \frac{1}{n} \sum_{i=1}^n \frac{1}{M} \sum_{m=1}^M S(z_{i,m}^{(k)}, y_i) \quad \text{where} \quad z_{i,m}^{(k)} \sim p(z_i|y_i; \theta^{(k)}) \quad (6)$$

82 Then, the RM updated of the sufficient statistics  $\hat{s}^{(k+1)}$  reads:

$$\text{SA-step : } \hat{s}^{(k+1)} = \hat{s}^{(k)} + \gamma_{k+1}(\tilde{S}^{(k+1)} - \hat{s}^{(k)}) \quad (7)$$

83 where  $\{\gamma_k\}_{k>1} \in (0, 1)$  is a sequence of decreasing step sizes to ensure asymptotic convergence.  
 84 This is called the Stochastic Approximation of the EM (SAEM) and has been shown to converge to  
 85 a maximum likelihood of the observations under very general conditions [6]. In the simulation step  
 86 (6), since the loss function between the observed data  $y_i$  and the latent variable  $z_i$  can be nonconvex,  
 87 sampling from the posterior distribution  $p(z_i|y_i; \theta)$ , under the current model  $\theta$ , requires using an  
 88 inference algorithm. [10] proved almost sure convergence of the sequence of parameters obtained  
 89 by this algorithm coupled with an MCMC procedure during the simulation step. In simple scenarios,  
 90 the samples  $\{z_{i,m}\}_{m=0}^{M-1}$  are conditionally independent and identically distributed with distribution  
 91  $p(z_i, \theta)$ . Nevertheless, in most cases, sampling exactly from this distribution is not an option and the  
 92 Monte Carlo batch is sampled by Monte Carlo Markov Chains (MCMC) algorithm. In the SA-step,  
 93 the sequence of decreasing positive integers  $\{\gamma_k\}_{k>1}$  controls the convergence of the algorithm. In  
 94 practice,  $\gamma_k$  is set equal to 1 during the first few iterations to let the algorithm explore the parameter  
 95 space without memory and converge quickly to a neighborhood of the target estimate. The Stochastic  
 96 Approximation is performed during the remaining iterations where  $\gamma_k = 1/k^\alpha$ , where  $\alpha \in (0, 1)$ ,  
 97 ensuring the almost sure convergence of the estimate. It is inappropriate to start with small values  
 98 for step size  $\gamma_k$  and large values for the number of simulations  $M_k$ . Rather, it is recommended that  
 99 one decrease  $\gamma_k$  and keep a constant and small number of MC samples  $M_k$  which shows a great  
 100 advantage over the MC-step (5), which requires large  $M_k$  to converge.

101 This Robbins-Monro type of update represents the *first level* of our algorithm, needed to temper  
 102 the variance and noise implied by MC integration. In the next section, we derive variants of this  
 103 algorithm to adapt to the sheer size of data of today's applications and formalize the *second level* of  
 104 our class of Two-Time-Scale EM methods.

## 105 2.2 Incremental and Bi-Level Noisy EM Methods

106 Strategies to scale to large datasets include classical incremental and variance reduced variants. We  
 107 will explicit a general update that will cover those variants and that represents the *second level* of our  
 108 algorithm, namely the incremental update of the noisy statistics  $\hat{S}^{(k)}$  inside the RM type of update.

$$\text{Incremental-step : } \tilde{S}^{(k+1)} = \tilde{S}^{(k)} + \rho_{k+1}(\mathcal{S}^{(k+1)} - \tilde{S}^{(k)}), \quad (8)$$

109 Note  $\{\rho_k\}_{k>1} \in (0, 1)$  is a sequence of step sizes,  $\mathcal{S}^{(k)}$  is a proxy for  $\tilde{S}^{(k)}$ , If the stepsize is equal  
 110 to one and the proxy  $\mathcal{S}^{(k)} = \tilde{S}^{(k)}$ , i.e., computed in a full batch manner as in (6), then we recover  
 111 the SAEM algorithm. Also if  $\rho_k = 1$ ,  $\gamma_k = 1$  and  $\mathcal{S}^{(k)} = \tilde{S}^{(k)}$ , then we recover the MCEM [20].

112 We now introduce three variants of the SAEM update depending on different definitions of the  
 113 proxy  $\mathcal{S}^{(k)}$  and the choice of the stepsize  $\rho_k$ . Let  $i_k \in \llbracket 1, n \rrbracket$  be a random index drawn at iteration  
 114  $k$  and  $\tau_i^k = \max\{k' : i_{k'} = i, k' < k\}$  be the iteration index where  $i \in \llbracket 1, n \rrbracket$  is last drawn  
 115 prior to iteration  $k$ . For iteration  $k \geq 0$ , the fITTSEM method draws *two* indices *independently* and  
 116 uniformly as  $i_k, j_k \in \llbracket 1, n \rrbracket$ . In addition to  $\tau_i^k$  which was defined w.r.t.  $i_k$ , we define  $t_j^k = \{k' :$

117  $j_{k'} = j, k' < k\}$  to be the iteration index where the sample  $j \in \llbracket 1, n \rrbracket$  is last drawn as  $j_k$  prior to  
 118 iteration  $k$ . With the initialization  $\bar{\mathcal{S}}^{(0)} = \bar{\mathbf{s}}^{(0)}$ , we use a slightly different update rule from SAGA  
 119 inspired by [18]. Then, we obtain:

$$(iSAEM [11]) \quad \mathcal{S}^{(k+1)} = \mathcal{S}^{(k)} + \frac{1}{n} (\tilde{S}_{i_k}^{(k)} - \tilde{S}_{i_k}^{(\tau_{i_k}^k)}) \quad (9)$$

$$(vrTTSEM) \quad \mathcal{S}^{(k+1)} = \tilde{S}^{(\ell(k))} + (\tilde{S}_{i_k}^{(k)} - \tilde{S}_{i_k}^{(\ell(k))}) \quad (10)$$

$$(fiTTSEM) \quad \mathcal{S}^{(k+1)} = \bar{\mathcal{S}}^{(k)} + (\tilde{S}_{i_k}^{(k)} - \tilde{S}_{i_k}^{(t_{i_k}^k)}) \quad (11)$$

$$\bar{\mathcal{S}}^{(k+1)} = \bar{\mathcal{S}}^{(k)} + n^{-1} (\tilde{S}_{j_k}^{(k)} - \tilde{S}_{j_k}^{(t_{j_k}^k)}). \quad (12)$$

120 where  $\tilde{S}_{i_k}^{(k)}$  is the MC approximation of the expectation  $\bar{\mathbf{s}}_{i_k}(\theta^{(k)})$ :

$$\tilde{S}_{i_k}^{(k)} = \frac{1}{M_k} \sum_{m=1}^{M_k} S(z_{i_k, m}^{(k)}, y_{i_k}) \quad \text{with} \quad z_{i_k, m}^{(k)} \sim p(z_{i_k} | y_{i_k}; \theta^{(k)}) \quad (13)$$

121 The stepsize is set to  $\rho_{k+1} = 1$  for the iSAEM method and we initialize with  $\mathcal{S}^{(0)} = \tilde{S}^{(0)}$ ;  $\rho_{k+1} = \gamma$   
 122 is constant for the vrTTSEM and fiTTSEM methods. Moreover, for vrTTSEM we set an epoch size  
 123 of  $m$  and define  $\ell(k) := m \lfloor k/m \rfloor$  as the first iteration number in the epoch that iteration  $k$  is in.

124 **Two-Time-Scale Noisy EM methods:** We now introduce the general method derived using the two  
 125 variance reduction techniques described above. Algorithm 1 leverages both levels (7) and (8) in  
 126 order to output a vector of fitted parameters  $\hat{\theta}^{(K)}$  where  $K$  is a randomly chosen termination point.

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**Algorithm 1** Two-Time-Scale Noisy EM methods.

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- 1: **Input:** initializations  $\hat{\theta}^{(0)} \leftarrow 0, \hat{\mathbf{s}}^{(0)} \leftarrow \hat{S}^{(0)}, K_{\max} \leftarrow \text{max. iteration number}$ .
- 2: Set the terminating iteration number,  $K \in \{0, \dots, K_{\max} - 1\}$ , as a discrete r.v. with:

$$P(K = k) = \frac{\gamma_k}{\sum_{\ell=0}^{K_{\max}-1} \gamma_{\ell}} = \frac{\gamma_k}{P_{\max}}. \quad (14)$$

- 3: **for**  $k = 0, 1, 2, \dots, K$  **do**
- 4: Draw index  $i_k \in \llbracket 1, n \rrbracket$  uniformly (and  $j_k \in \llbracket 1, n \rrbracket$  for fiTTSEM).
- 5: Compute  $\hat{S}_{i_k}^{(k)}$  using the MC-step (5), for the drawn indices.
- 6: Compute the surrogate sufficient statistics  $\mathcal{S}^{(k+1)}$  using (9) or (10) or (11).
- 7: Compute  $\hat{S}^{(k+1)}$  and  $\hat{\mathbf{s}}^{(k+1)}$  using respectively (8) and (7):

$$\begin{aligned} \tilde{S}^{(k+1)} &= \tilde{S}^{(k)} + \rho_{k+1} (\mathcal{S}^{(k+1)} - \tilde{S}^{(k)}) \\ \hat{\mathbf{s}}^{(k+1)} &= \hat{\mathbf{s}}^{(k)} + \gamma_{k+1} (\tilde{S}^{(k+1)} - \hat{\mathbf{s}}^{(k)}) \end{aligned} \quad (15)$$

- 8: Compute  $\hat{\theta}^{(k+1)} = \bar{\theta}(\hat{\mathbf{s}}^{(k+1)})$  via the M-step (4).
  - 9: **end for**
  - 10: **Return:**  $\hat{\theta}^{(K)}$ .
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127 The update in (15) is said to have two-time-scales as the step sizes satisfy  $\lim_{k \rightarrow \infty} \gamma_k / \rho_k < 1$  such that  
 128  $\tilde{S}^{(k+1)}$  is updated at a faster time-scale, determined by  $\rho_k$ , than  $\hat{\mathbf{s}}^{(k+1)}$ , determined by  $\gamma_k$ . The next  
 129 section presents the main results of this paper and establishes global and finite-time bounds for the  
 130 three different updates of our two-time-scale scheme.

### 131 3 Finite Time Analysis of the Two-Time-Scale Scheme

132 Following [4], it can be shown that stationary points of the objective function (1) corresponds to the  
 133 stationary points of the following *nonconvex* Lyapunov function:

$$\min_{\mathbf{s} \in \mathcal{S}} V(\mathbf{s}) := \bar{\mathbf{L}}(\bar{\theta}(\mathbf{s})) = \mathbf{r}(\bar{\theta}(\mathbf{s})) + \frac{1}{n} \sum_{i=1}^n \mathcal{L}_i(\bar{\theta}(\mathbf{s})) \quad (16)$$

that we propose to study in this article. Several critical assumptions required to derive convergence guarantees read as follows:

**H1.** The sets  $Z, S$  are compact. There exists constants  $C_S, C_Z$  such that:

$$C_S := \max_{\mathbf{s}, \mathbf{s}' \in S} \|\mathbf{s} - \mathbf{s}'\| < \infty, \quad C_Z := \max_{i \in \llbracket 1, n \rrbracket} \int_Z |S(z, y_i)| \mu(dz) < \infty. \quad (17)$$

**H2.** The conditional distribution is smooth on  $\text{int}(\Theta)$ . For any  $i \in \llbracket 1, n \rrbracket$ ,  $z \in Z$ ,  $\boldsymbol{\theta}, \boldsymbol{\theta}' \in \text{int}(\Theta)^2$ , we have  $|p(z|y_i; \boldsymbol{\theta}) - p(z|y_i; \boldsymbol{\theta}')| \leq L_p \|\boldsymbol{\theta} - \boldsymbol{\theta}'\|$ .

We also recall from the introduction that we consider curved exponential family models, besides:

**H3.** For any  $\mathbf{s} \in S$ , the function  $\boldsymbol{\theta} \mapsto L(\mathbf{s}, \boldsymbol{\theta}) := r(\boldsymbol{\theta}) + \psi(\boldsymbol{\theta}) - \langle \mathbf{s} | \phi(\boldsymbol{\theta}) \rangle$  admits a unique global minimum  $\bar{\boldsymbol{\theta}}(\mathbf{s}) \in \text{int}(\Theta)$ . In addition,  $J_\phi^\theta(\bar{\boldsymbol{\theta}}(\mathbf{s}))$  is full rank,  $L_\phi$ -Lipschitz and  $\bar{\boldsymbol{\theta}}(\mathbf{s})$  is  $L_\theta$ -Lipschitz.

We denote by  $H_L^\theta(\mathbf{s}, \boldsymbol{\theta})$  the Hessian (w.r.t to  $\boldsymbol{\theta}$  for a given value of  $\mathbf{s}$ ) of the function  $\boldsymbol{\theta} \mapsto L(\mathbf{s}, \boldsymbol{\theta}) = r(\boldsymbol{\theta}) + \psi(\boldsymbol{\theta}) - \langle \mathbf{s} | \phi(\boldsymbol{\theta}) \rangle$ , and define

$$B(\mathbf{s}) := J_\phi^\theta(\bar{\boldsymbol{\theta}}(\mathbf{s})) \left( H_L^\theta(\mathbf{s}, \bar{\boldsymbol{\theta}}(\mathbf{s})) \right)^{-1} J_\phi^\theta(\bar{\boldsymbol{\theta}}(\mathbf{s}))^\top. \quad (18)$$

**H4.** It holds that  $v_{\max} := \sup_{\mathbf{s} \in S} \|B(\mathbf{s})\| < \infty$  and  $0 < v_{\min} := \inf_{\mathbf{s} \in S} \lambda_{\min}(B(\mathbf{s}))$ . There exists a constant  $L_B$  such that for all  $\mathbf{s}, \mathbf{s}' \in S^2$ , we have  $\|B(\mathbf{s}) - B(\mathbf{s}')\| \leq L_B \|\mathbf{s} - \mathbf{s}'\|$ .

The class of algorithms we develop in this paper are two-time-scale where the first stage corresponds to the variance reduction trick used in [9] in order to accelerate incremental methods and reduce the variance induced by the index sampling. The second stage is the Robbins-Monro type of update that aims to reduce the variance induced by the MC approximations

Indeed the expectations (3) are never available and requires Monte Carlo approximation. Thus, at iteration  $k + 1$ , we introduce the errors when approximating the quantity  $\bar{s}_i(\hat{\boldsymbol{\theta}}(\hat{\mathbf{s}}^{(k-1)}))$ . Define:

$$\eta_i^{(r)} := \tilde{S}_i^{(r)} - \bar{s}_i(\vartheta^{(r)}) \quad \text{for all } i \in \llbracket 1, n \rrbracket, r > 0 \quad \text{and} \quad \vartheta \in \Theta \quad (19)$$

For instance, we consider that the MC approximation is unbiased if for all  $i \in \llbracket 1, n \rrbracket$  and  $m \in \llbracket 1, M \rrbracket$ , the samples  $z_{i,m} \sim p(z_i|y_i; \boldsymbol{\theta})$  are i.i.d. under the posterior distribution, i.e.,  $\mathbb{E}[\eta_i^{(r)} | \mathcal{F}_r] = 0$  where  $\mathcal{F}_r$  is the filtration up to iteration  $r$ . The following results are derived under the assumption of control of the fluctuations implied by the approximation stated as follows:

**H5.** There exist a positive sequence of MC batch size  $\{M_r\}_{r>0}$  and constants  $(C, C_\eta)$  such that for all  $k > 0$ ,  $i \in \llbracket 1, n \rrbracket$  and  $\vartheta \in \Theta$ :

$$\mathbb{E} \left[ \left\| \eta_i^{(r)} \right\|^2 \right] \leq \frac{C_\eta}{M_r} \quad \text{and} \quad \mathbb{E} \left[ \left\| \mathbb{E}[\eta_i^{(r)} | \mathcal{F}_r] \right\|^2 \right] \leq \frac{C}{M_r} \quad (20)$$

We can prove two important results on the Lyapunov function. The first one suggests smoothness:

**Lemma 1.** [9] Assume H1-H4. For all  $\mathbf{s}, \mathbf{s}' \in S$  and  $i \in \llbracket 1, n \rrbracket$ , we have

$$\|\bar{s}_i(\bar{\boldsymbol{\theta}}(\mathbf{s})) - \bar{s}_i(\bar{\boldsymbol{\theta}}(\mathbf{s}'))\| \leq L_s \|\mathbf{s} - \mathbf{s}'\|, \quad \|\nabla V(\mathbf{s}) - \nabla V(\mathbf{s}')\| \leq L_V \|\mathbf{s} - \mathbf{s}'\|, \quad (21)$$

where  $L_s := C_Z L_p L_\theta$  and  $L_V := v_{\max}(1 + L_s) + L_B C_S$ .

and the second one suggests a growth condition on the gradient of  $V$  depending on the mean field of the algorithm:

**Lemma 2.** Assume H3, H4. For all  $\mathbf{s} \in S$ ,

$$v_{\min}^{-1} \langle \nabla V(\mathbf{s}) | \mathbf{s} - \bar{\mathbf{s}}(\bar{\boldsymbol{\theta}}(\mathbf{s})) \rangle \geq \|\mathbf{s} - \bar{\mathbf{s}}(\bar{\boldsymbol{\theta}}(\mathbf{s}))\|^2 \geq v_{\max}^{-2} \|\nabla V(\mathbf{s})\|^2, \quad (22)$$

Proof of this Lemma can be found in Appendix A.

### 3.1 Global Convergence of Incremental Noisy EM Algorithms

We present in this section a finite-time analysis of the incremental variant of the Stochastic Approximation of the EM algorithm. We want to draw the attention of the readers that the word "global" here does not mean for a global optimum of the nonconvex function, but of the independence of our analysis on the initialization and the iteration  $k$  (finite time).

The first intermediate result, see proof in Appendix B, is the computation of the quantity  $\hat{S}^{(k+1)} - \hat{S}^{(k)}$ , which corresponds to the drift term of (7) and reads as follows:

**Lemma 3.** *The update (9) is equivalent to the following update on the resulting statistics*

$$\hat{S}^{(k+1)} = \hat{S}^{(k)} + \gamma_{k+1} (\tilde{S}^{(k+1)} - \hat{S}^{(k)}) \quad \text{where} \quad \tilde{S}^{(k+1)} = \frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^{k+1})} \quad (23)$$

Also:

$$\mathbb{E} [\tilde{S}^{(k+1)} - \hat{S}^{(k)}] = \mathbb{E} [\bar{S}^{(k)} - \hat{S}^{(k)}] + \left(1 - \frac{1}{n}\right) \mathbb{E} \left[ \frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^k)} - \bar{S}^{(k)} \right] + \frac{1}{n} \mathbb{E} [\eta_{i_k}^{(k+1)}] \quad (24)$$

where  $\bar{S}^{(k)}$  is defined by (3) and  $\tau_i^k = \max\{k' : i_{k'} = i, k' < k\}$ .

The following main result for the iSAEM algorithm, which proof can be found in Appendix C, is derived under a control of the Monte Carlo fluctuations as described by assumption H 5. Typically, the controls exhibited above are of interest when the number of MC samples  $M_k$  increase with  $k$ .

**Theorem 1.** *Assume H1-H5. Let  $K_{\max}$  be a positive integer. Let  $\{\gamma_k, k \in \mathbb{N}\}$  be a sequence of positive step sizes and consider the iSAEM sequence  $\{\hat{S}^{(k)}, k \in \mathbb{N}\}$  obtained with  $\rho_{k+1} = 1$  for any  $k > 0$ . We also set  $c_1 = v_{\min}^{-1}$ ,  $\alpha = \max\{8, 1 + 6v_{\min}\}$ ,  $\bar{L} = \max\{L_s, L_V\}$ ,  $\gamma_{k+1} = \frac{1}{k^\alpha \alpha c_1 \bar{L}}$  where  $a \in (0, 1)$ ,  $\beta = \frac{c_1 \bar{L}}{n}$ . Assume that  $\hat{S}^{(k)} \in \mathcal{S}$  for any  $k \leq K_{\max}$ .*

$$v_{\max}^{-2} \sum_{k=0}^{K_{\max}} \tilde{\alpha}_k \mathbb{E} [\|\nabla V(\hat{S}^{(k)})\|^2] \leq \mathbb{E} [V(\hat{S}^{(0)}) - V(\hat{S}^{(K)})] + \sum_{k=0}^{K_{\max}-1} \tilde{\Gamma}_k \mathbb{E} [\|\eta_{i_k}^{(k)}\|^2] \quad (25)$$

### 3.2 Global Convergence of Two-Time-Scale Noisy EM Algorithms

We now proceed by giving our main result regarding the global convergence of the fTTSEM algorithm. Two important auxiliary Lemmas, which proofs are given in Appendix D.1, are need in order to derive our finite-time bound. The first one derives an identity for the quantity  $\mathbb{E} [\|\hat{S}^{(k)} - \tilde{S}^{(k+1)}\|^2]$  using the vrTTSEM update:

**Lemma 4.** *For any  $k \geq 0$  and consider the vrTTSEM update in (10) with  $\rho_k = \rho$ , it holds for all  $k > 0$*

$$\begin{aligned} \mathbb{E} [\|\hat{S}^{(k)} - \tilde{S}^{(k+1)}\|^2] &\leq 2\rho^2 \mathbb{E} [\|\hat{S}^{(k)} - \bar{S}^{(k)}\|^2] + 2\rho^2 L_s^2 \mathbb{E} [\|\hat{S}^{(k)} - \hat{S}^{(\ell(k))}\|^2] \\ &\quad + 2(1 - \rho)^2 \mathbb{E} [\|\hat{S}^{(\ell(k))} - \tilde{S}^{(k)}\|^2] + 2\rho^2 \mathbb{E} [\|\eta_{i_k}^{(k+1)}\|^2] \end{aligned} \quad (26)$$

where we recall that  $\ell(k)$  is the first iteration number in the epoch that iteration  $k$  is in.

The second one derives an identity for the quantity  $\mathbb{E} [\|\hat{S}^{(k)} - \tilde{S}^{(k+1)}\|^2]$  using the fTTSEM update:

**Lemma 5.** *For any  $k \geq 0$  and consider the fTTSEM update in (11) with  $\rho_k = \rho$ , it holds for all  $k > 0$*

$$\begin{aligned} \mathbb{E} [\|\hat{S}^{(k)} - \tilde{S}^{(k+1)}\|^2] &\leq 2\rho^2 \mathbb{E} [\|\hat{S}^{(k)} - \bar{S}^{(k)}\|^2] + 2\rho^2 \frac{L_s^2}{n} \sum_{i=1}^n \mathbb{E} [\|\hat{S}^{(k)} - \hat{S}^{(\tau_i^k)}\|^2] \\ &\quad + 2(1 - \rho)^2 \mathbb{E} [\|\hat{S}^{(\ell(k))} - \tilde{S}^{(k)}\|^2] + 2\rho^2 \mathbb{E} [\|\eta_{i_k}^{(k+1)}\|^2] \end{aligned} \quad (27)$$

Recalling that  $K$  is an independent discrete r.v. drawn from  $\{1, \dots, K_{\max}\}$  with distribution  $\{\gamma_k/P_{\max}, 0 \leq k \leq K_{\max} - 1\}$ , as in (14), we have

$$\mathbb{E}[\|\nabla V(\hat{\mathbf{s}}^{(K)})\|^2] = \frac{1}{P_{\max}} \sum_{k=0}^{K_{\max}-1} \gamma_{k+1} \mathbb{E}[\|\nabla V(\hat{\mathbf{s}}^{(k)})\|^2] \quad (28)$$

195

We now state the main result regarding the vrTTSEM method, see proof in Appendix E:

**Theorem 2.** Assume H1-H5. Let  $K_{\max}$  be a positive integer. Let  $\{\gamma_k, k \in \mathbb{N}\}$  be a sequence of positive step sizes and consider the vrTTSEM sequence  $\{\hat{\mathbf{s}}^{(k)}, k \in \mathbb{N}\}$  obtained with  $\rho_{k+1} = \rho$  for any  $k > 0$ . Assume that  $\hat{\mathbf{s}}^{(k)} \in \mathcal{S}$  for any  $k \leq K_{\max}$ . Setting  $\bar{L} = \max\{L_{\mathbf{s}}, L_V\}$ ,  $\rho = \frac{\mu}{c_1 \bar{L} n^{2/3}}$ ,  $m = \frac{nc_1^2}{2\mu^2 + \mu c_1^2}$ , a constant  $\mu \in (0, 1)$ ,  $\gamma_{k+1} = \frac{1}{k^a \bar{L}}$  where  $a \in (0, 1)$ , we have the following bound:

$$\begin{aligned} \mathbb{E}[\|\nabla V(\hat{\mathbf{s}}^{(K)})\|^2] &\leq \frac{2n^{2/3} \bar{L}}{\mu P_{\max} v_{\min}^2 v_{\max}^2} \mathbb{E}[V(\hat{\mathbf{s}}^{(0)}) - V(\hat{\mathbf{s}}^{(K_{\max})})] \\ &\quad + \frac{2n^{2/3} \bar{L}}{\mu P_{\max} v_{\min}^2 v_{\max}^2} \sum_{k=0}^{K_{\max}-1} \left[ \tilde{\eta}^{(k+1)} + \chi^{(k+1)} \mathbb{E} \left[ \left\| \hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)} \right\|^2 \right] \right] \end{aligned} \quad (29)$$

We now state the main result regarding the fiTTSEM method.

**Theorem 3.** Assume H1-H5. Let  $K_{\max}$  be a positive integer. Let  $\{\gamma_k, k \in \mathbb{N}\}$  be a sequence of positive step sizes and consider the fiTTSEM sequence  $\{\hat{\mathbf{s}}^{(k)}, k \in \mathbb{N}\}$  obtained with  $\rho_{k+1} = \rho$  for any  $k > 0$ . Assume that  $\hat{\mathbf{s}}^{(k)} \in \mathcal{S}$  for any  $k \leq K_{\max}$ . By setting  $\alpha = \max\{2, 1 + 2v_{\min}\}$ ,  $\bar{L} = \max\{L_{\mathbf{s}}, L_V\}$ ,  $\beta = \frac{1}{\alpha n}$ ,  $\rho = \frac{1}{\alpha c_1 \bar{L} n^{2/3}}$ ,  $c_1(k\alpha - 1) \geq c_1(\alpha - 1) \geq 2$ ,  $\alpha \geq 2$  and  $\gamma_{k+1} = \frac{1}{k^a \alpha c_1 \bar{L}}$  where  $a \in (0, 1)$ , we have the following bound:

$$\begin{aligned} \mathbb{E}[\|\nabla V(\hat{\mathbf{s}}^{(K)})\|^2] &\leq \frac{4\alpha \bar{L} n^{2/3}}{P_{\max} v_{\min}^2 v_{\max}^2} [V(\hat{\mathbf{s}}^{(0)}) - V(\hat{\mathbf{s}}^{(K_{\max})})] \\ &\quad + \frac{4\alpha \bar{L} n^{2/3}}{P_{\max} v_{\min}^2 v_{\max}^2} \sum_{k=0}^{K_{\max}-1} \left[ \Xi^{(k+1)} + \Gamma_{k+1} \mathbb{E} \left[ \left\| \hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)} \right\|^2 \right] \right] \end{aligned} \quad (30)$$

Proof of this Theorem can be found in Appendix F. Note that in those two bounds, the quantities

$\tilde{\eta}^{(k+1)}$  and  $\Xi^{(k+1)}$  depends only on the MC fluctuations  $\mathbb{E} \left[ \left\| \eta_{i_k}^{(k)} \right\|^2 \right]$  and some constants.

**Remarks:** The following remarks are worth noting on the quantity  $\mathbb{E} \left[ \left\| \hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)} \right\|^2 \right]$ :

- This term is the price we pay for the two-time-scale dynamics and corresponds to the gap between the two asynchronous updates (one is on  $\hat{\mathbf{s}}^{(k)}$  and the other on  $\tilde{S}^{(k)}$ ).
- It is trivial to see that if  $\rho = 1$ , i.e., there is no variance reduction, then for any  $k > 0$

$$\mathbb{E} \left[ \left\| \hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)} \right\|^2 \right] = \mathbb{E} \left[ \left\| \mathcal{S}^{(k+1)} - \tilde{S}^{(k+1)} \right\|^2 \right] = 0 \quad \text{with} \quad \hat{\mathbf{s}}^{(0)} = \tilde{S}^{(0)} = 0$$

which strengthen the fact that this quantity characterizes the impact of the variance reduction technique introduced in our two stages class of methods.

The following lemma, which proof can be found in Appendix D.2, characterizes this gap:

**Lemma 6.** Consider a decreasing stepsize  $\gamma_k \in (0, 1)$  and a constant  $\rho \in (0, 1)$ , then the following inequality holds:

$$\mathbb{E} \left[ \left\| \hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)} \right\|^2 \right] \leq \frac{\rho}{1 - \rho} \sum_{\ell=0}^k (1 - \gamma_{\ell})^2 (\mathcal{S}^{(\ell)} - \tilde{S}^{(\ell)}) \quad (31)$$

where  $\mathcal{S}^{(k)}$  is defined either by (10) (vrTTSEM) or (11) (fiTTSEM).

In the next section, we illustrate the benefits of our two-time-scale class of algorithms on several numerical applications.



## 4 Numerical Examples

### 4.1 Gaussian Mixture Models

We begin by a simple and illustrative example. The authors acknowledge that the following model can be trained using deterministic EM-type of algorithms but propose to apply stochastic methods, including theirs, and to compare their performances. Given  $n$  observations  $\{y_i\}_{i=1}^n$ , we want to fit a Gaussian Mixture Model (GMM) whose distribution is modeled as a Gaussian mixture of  $M$  components, each with a unit variance. Let  $z_i \in \llbracket M \rrbracket$  be the latent labels of each component, the complete log-likelihood is defined as:

$$\log f(z_i, y_i; \theta) = \sum_{m=1}^M \mathbb{1}_{\{m\}}(z_i) [\log(\omega_m) - \mu_m^2/2] + \sum_{m=1}^M \mathbb{1}_{\{m\}}(z_i) \mu_m y_i + \text{constant} . \quad (32)$$

where  $\theta := (\omega, \mu)$  with  $\omega = \{\omega_m\}_{m=1}^{M-1}$  are the mixing weights with the convention  $\omega_M = 1 - \sum_{m=1}^{M-1} \omega_m$  and  $\mu = \{\mu_m\}_{m=1}^M$  are the means. We use the penalization  $r(\theta) = \frac{\delta}{2} \sum_{m=1}^M \mu_m^2 - \log \text{Dir}(\omega; M, \epsilon)$  where  $\delta > 0$  and  $\text{Dir}(\cdot; M, \epsilon)$  is the  $M$  dimensional symmetric Dirichlet distribution with concentration parameter  $\epsilon > 0$ . The constraint set on  $\theta$  is given by

$$\Theta = \{\omega_m, m = 1, \dots, M-1 : \omega_m \geq 0, \sum_{m=1}^{M-1} \omega_m \leq 1\} \times \{\mu_m \in \mathbb{R}, m = 1, \dots, M\}. \quad (33)$$

Exact two-time-scale updates are given in Appendix G.1.

In the following experiments on synthetic data, we generate samples from a GMM model with  $M = 2$  components with two mixtures with means  $\mu_1 = -\mu_2 = 0.5$ . We use  $n = 10^5$  synthetic samples and run the bEM method until convergence (to double precision) to obtain the ML estimate  $\mu^*$  averaged on 50 datasets. We compare the bEM, iEM (incremental EM), SAEM, iSAEM, vrTTSEM and fiTTSEM methods in terms of their precision measured by  $|\mu - \mu^*|^2$ . We set the stepsize of the SA-step of all method as  $\gamma_k = 1/k^\alpha$  with  $\alpha = 0.5$ , and the stepsizes of the Incremental-step for vrTTSEM and the fiTTSEM to a constant stepsize equal to  $1/n^{2/3}$ .

The number of MC samples is fixed to  $M = 10$  chains. Figure 1 shows the convergence of the precision  $|\mu - \mu^*|^2$  for the different methods against the epoch(s) elapsed (one epoch equals  $n$  iterations). We observe that the vrTTSEM and fiTTSEM methods outperform the other stochastic methods, supporting the benefits of our newly introduced scheme.

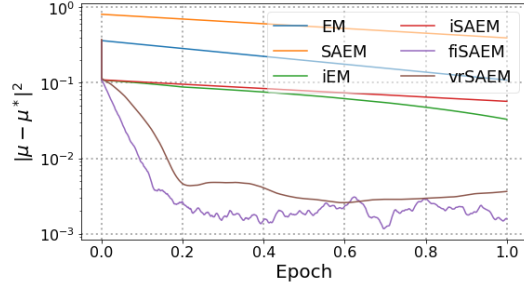


Figure 1: TO COMPLETE

### 4.2 Deformable Template Model for Image Analysis

Let  $(y_i, i \in \llbracket 1, n \rrbracket)$  be observed gray level images defined on a grid of pixels. Let  $u \in \mathcal{U} \subset \mathbb{R}^2$  denotes the pixel index on the image and  $x_u \in \mathcal{D} \subset \mathbb{R}^2$  its location. The model used in this experiment suggests that each image  $y_i$  is a deformation of a template, noted  $I : \mathcal{D} \rightarrow \mathbb{R}$ , common to all images of the dataset:

$$y_i(u) = I(x_u - \Phi_i(x_u, z_i)) + \varepsilon_i(u) \quad (34)$$

where  $\phi_i : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  is a deformation function,  $z_i$  some latent variable parameterizing this deformation and  $\varepsilon_i \sim \mathcal{N}(0, \sigma^2)$  is an observation error.

The template model, given  $(p_k, k \in \llbracket 1, k_p \rrbracket)$  landmarks on the template, a fixed known kernel  $\mathbf{K}_p$  and a vector of parameters  $\beta \in \mathbb{R}^{k_p}$  is defined as follows:

$$I_\xi = \mathbf{K}_p \beta, \quad \text{where} \quad (\mathbf{K}_p \beta)(x) = \sum_{k=1}^{k_p} \mathbf{K}_p(x, p_k) \beta_k \quad (35)$$

Besides, we parameterize the deformation model given some landmarks  $(g_k, k \in \llbracket 1, k_g \rrbracket)$  and a fixed kernel  $\mathbf{K}_g$  as:

$$\Phi_i = \mathbf{K}_g z_i \quad \text{where} \quad (\mathbf{K}_g z_i)(x) = \sum_{k=1}^{k_g} \mathbf{K}_g(x, g_k) \left( z_i^{(1)}(k), z_i^{(2)}(k) \right) \quad (36)$$



where we put a Gaussian prior on the latent variables,  $z_i \sim \mathcal{N}(0, \Gamma)$  and  $z_i \in (\mathbb{R}^{k_g})^2$ . The vector of parameters we ought to estimate is thus  $\theta = (\beta, \Gamma, \sigma)$ . The complete model belongs to the curved exponential family, see [1], which vector of sufficient statistics  $S = (S_1(z), S_2(z), S_3(z))$  read:

$$\begin{aligned} S_1(z) &= \frac{1}{n} \sum_{i=1}^n S_1(y_i, z_i) = \frac{1}{n} \sum_{i=1}^n (\mathbf{K}_p^{z_i})^\top y_i \\ S_2(z) &= \frac{1}{n} \sum_{i=1}^n S_2(y_i, z_i) = \frac{1}{n} \sum_{i=1}^n (\mathbf{K}_p^{z_i})^\top (\mathbf{K}_p^{z_i}) \\ S_3(z) &= \frac{1}{n} \sum_{i=1}^n S_3(y_i, z_i) = \frac{1}{n} \sum_{i=1}^n z_i^t z_i \end{aligned} \quad (37)$$

where for any pixel  $u \in \mathbb{R}^2$  and  $j \in \llbracket 1, k_g \rrbracket$  we noted:

$$\mathbf{K}_p^{z_i}(x_u, j) = \mathbf{K}_p^{z_i}(x_u - \phi_i(x_u, z_i), p_j) \quad (38)$$

Finally, the Two-Time-Scale M-step yields the following parameter updates:

$$\bar{\theta}(\hat{s}) = \begin{pmatrix} \beta(\hat{s}) = \hat{s}_2^{-1}(z) \hat{s}_1(z) \\ \Gamma(\hat{s}) = \frac{1}{n} \hat{s}_3(z) \\ \sigma(\hat{s}) = \beta(\hat{s})^\top \hat{s}_2(z) \beta(\hat{s}) - 2\beta(\hat{s}) \hat{s}_1(z) \end{pmatrix} \quad (39)$$

where  $\hat{s} = (\hat{s}_1(z), \hat{s}_2(z), \hat{s}_3(z))$  is the vector of statistics obtained via the SA-step (7) and using the MC approximation of the sufficient statistics  $(S_1(z), S_2(z), S_3(z))$  defined in (142).

**Comparison using epochs credit**

**Comparison using number of training samples credit**

### 4.3 PK Model with Absorption Lag Time

This numerical example was conducted in order to characterize the pharmacokinetics (PK) of orally administered drug to simulated patients, using a population pharmacokinetic approach.  $M = 50$  synthetic datasets were generated for  $n = 500$  patients with 10 observations (concentration measures) per patient. The goal is to model the evolution of the concentration of the absorbed drug using a nonlinear and latent data model. The fitting of that model is done using our two-time-scale class of algorithms.

**The model:** We consider a one-compartment PK model for oral administration with an absorption lag-time ( $T^{\text{lag}}$ ), assuming first-order absorption and linear elimination processes. The final model includes the following variables:  $ka$  the absorption rate constant,  $V$  the volume of distribution,  $k$  the elimination rate constant and  $T^{\text{lag}}$  the absorption lag-time. We also add several covariates to our model such as  $D$  the dose of drug administered,  $t$  the time at which measures are taken and the weight of the patient influencing the volume  $V$ . More precisely, the log-volume  $\log(V)$  is a linear function of the log-weight  $lw70 = \log(wt/70)$ . The final model reads:

$$f(t, ka, V, k) = \frac{D ka}{V(ka - k)} (e^{-ka(t - T^{\text{lag}})} - e^{-k(t - T^{\text{lag}})}) , \quad (40)$$

Here,  $T^{\text{lag}}$ ,  $ka$ ,  $V$  and  $k$  are PK parameters that can change from one individual to another.

Let  $z_i = (T_i^{\text{lag}}, ka_i, V_i, k_i)$  be the vector of individual PK parameters for individual  $i$ . The model for the  $j$ -th measured concentration, noted  $y_{ij}$ , for individual  $i$  reads:

$$y_{ij} = f(t_{ij}, z_i) + \varepsilon_{ij} \quad (41)$$

where  $y_{ij}$  is the  $j$ -th concentration measurement of the drug of dosage  $D$  injected at time  $t_{ij}$  for patient  $i$ . We assume in this example that the residual errors  $\varepsilon_{ij}$  are independent and normally distributed with mean 0 and variance  $\sigma^2$ . Lognormal distributions are used for the three PK parameters:

$$\log(T_i^{\text{lag}}) \sim \mathcal{N}(\log(T_{\text{pop}}^{\text{lag}}), \omega_{T^{\text{lag}}}^2), \log(ka_i) \sim \mathcal{N}(\log(ka_{\text{pop}}), \omega_{ka}^2) , \quad (42)$$

$$\log(V_i) \sim \mathcal{N}(\log(V_{\text{pop}}), \omega_V^2), \log(k_i) \sim \mathcal{N}(\log(k_{\text{pop}}), \omega_k^2) . \quad (43)$$

290 The complete model belongs to the curved exponential family, which vector of sufficient statistics  
 291  $S = (S_1(z), S_2(z), S_3(z))$  read:

$$S_1(z) = \frac{1}{n} \sum_{i=1}^n z_i, \quad S_2(z) = \frac{1}{n} \sum_{i=1}^n z_i^\top z_i, \quad S_3(z) = \frac{1}{n} \sum_{i=1}^n (y_i - f(t_i, z_i))^2 \quad (44)$$

292 where we have noted  $y_i$  and  $t_i$  the vector of observations and time for each patient  $i$ .

293 **Monte Carlo study:** We conduct a Monte  
 294 Carlo study to showcase the benefits of our  
 295 scheme.

296  $M = 50$  datasets have been simulated using  
 297 the following PK parameters values:  $T_{\text{pop}}^{\text{lag}} =$   
 298  $1$ ,  $ka_{\text{pop}} = 1$ ,  $V_{\text{pop}} = 8$ ,  $k_{\text{pop}} = 0.1$ ,  
 299  $\omega_{T^{\text{lag}}} = 0.4$ ,  $\omega_{ka} = 0.5$ ,  $\omega_V = 0.2$ ,  $\omega_k =$   
 300  $0.3$  and  $\sigma^2 = 0.5$ . We define the mean  
 301 square distance over the  $M$  replicates  $E_k(\ell) =$

302  $\frac{1}{M} \sum_{m=1}^M \left( \theta_k^{(m)}(\ell) - \theta^* \right)^2$  and plot it against

303 the epochs (passes over the data) Figure 2. Note that the MC-step (5) is performed using a Metropo-  
 304 lis Hastings procedure since the posterior distribution under the model  $\theta$  noted  $p(z_i|y_i, \theta)$  is in-  
 305 tractable due to the nonlinearity of the model (40) (see Appendix G.2 for implementation details).  
 306 Figure 2 shows clear advantage of variance reduced methods (vrTTSEM and fittSEM ) avoiding  
 307 the twists and turns displayed by the incremental and the batch methods.

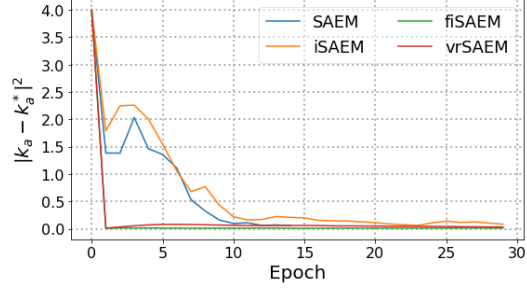


Figure 2: TO COMPLETE

## 308 5 Conclusion

## References

- [1] S. Allasonnière, Y. Amit, and A. Trouvé. Towards a coherent statistical framework for dense deformable template estimation. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 69(1):3–29, 2007.
- [2] C. Baey, S. Trevezas, and P.-H. Cournède. A non linear mixed effects model of plant growth and estimation via stochastic variants of the em algorithm. *Communications in Statistics-Theory and Methods*, 45(6):1643–1669, 2016.
- [3] O. Cappé. Online em algorithm for hidden markov models. *Journal of Computational and Graphical Statistics*, 20(3):728–749, 2011.
- [4] O. Cappé and E. Moulines. On-line expectation–maximization algorithm for latent data models. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 71(3):593–613, 2009.
- [5] A. Chakraborty and K. Das. Inferences for joint modelling of repeated ordinal scores and time to event data. *Computational and mathematical methods in medicine*, 11(3):281–295, 2010.
- [6] B. Delyon, M. Lavielle, and E. Moulines. Convergence of a stochastic approximation version of the em algorithm. *Ann. Statist.*, 27(1):94–128, 03 1999. doi: 10.1214/aos/1018031103. URL <https://doi.org/10.1214/aos/1018031103>.
- [7] A. P. Dempster, N. M. Laird, and D. B. Rubin. Maximum likelihood from incomplete data via the EM algorithm. *Journal of the royal statistical society. Series B (methodological)*, pages 1–38, 1977.
- [8] J. P. Hughes. Mixed effects models with censored data with application to hiv rna levels. *Biometrics*, 55(2):625–629, 1999.
- [9] B. Karimi, H.-T. Wai, É. Moulines, and M. Lavielle. On the global convergence of (fast) incremental expectation maximization methods. In *Advances in Neural Information Processing Systems*, pages 2833–2843, 2019.
- [10] E. Kuhn and M. Lavielle. Coupling a stochastic approximation version of em with an mcmc procedure. *ESAIM: Probability and Statistics*, 8:115–131, 2004.
- [11] E. Kuhn, C. Matias, and T. Rebafka. Properties of the stochastic approximation em algorithm with mini-batch sampling. *arXiv preprint arXiv:1907.09164*, 2019.
- [12] P. Liang and D. Klein. Online em for unsupervised models. In *Proceedings of human language technologies: The 2009 annual conference of the North American chapter of the association for computational linguistics*, pages 611–619, 2009.
- [13] C. E. McCulloch. Maximum likelihood algorithms for generalized linear mixed models. *Journal of the American statistical Association*, 92(437):162–170, 1997.
- [14] G. McLachlan and T. Krishnan. *The EM algorithm and extensions*, volume 382. John Wiley & Sons, 2007.
- [15] S. P. Meyn and R. L. Tweedie. *Markov chains and stochastic stability*. Springer Science & Business Media, 2012.
- [16] R. M. Neal and G. E. Hinton. A view of the EM algorithm that justifies incremental, sparse, and other variants. In *Learning in graphical models*, pages 355–368. Springer, 1998.
- [17] H. D. Nguyen, F. Forbes, and G. J. McLachlan. Mini-batch learning of exponential family finite mixture models. *Statistics and Computing*, pages 1–18, 2020.

- 351 [18] S. J. Reddi, S. Sra, B. Póczos, and A. Smola. Fast incremental method for nonconvex opti-  
352 mization. *arXiv preprint arXiv:1603.06159*, 2016.
- 353 [19] H. Robbins and S. Monro. A stochastic approximation method. *The annals of mathematical*  
354 *statistics*, pages 400–407, 1951.
- 355 [20] G. C. Wei and M. A. Tanner. A monte carlo implementation of the em algorithm and the poor  
356 man’s data augmentation algorithms. *Journal of the American statistical Association*, 85(411):  
357 699–704, 1990.
- 358 [21] R. Zhu, L. Wang, C. Zhai, and Q. Gu. High-dimensional variance-reduced stochastic gradient  
359 expectation-maximization algorithm. In *Proceedings of the 34th International Conference on*  
360 *Machine Learning-Volume 70*, pages 4180–4188. JMLR. org, 2017.

## 361 A Proof of Lemma 2

362 **Lemma.** Assume H3, H4. For all  $\mathbf{s} \in \mathcal{S}$ ,

$$v_{\min}^{-1} \langle \nabla V(\mathbf{s}) | \mathbf{s} - \bar{\mathbf{s}}(\bar{\boldsymbol{\theta}}(\mathbf{s})) \rangle \geq \|\mathbf{s} - \bar{\mathbf{s}}(\bar{\boldsymbol{\theta}}(\mathbf{s}))\|^2 \geq v_{\max}^{-2} \|\nabla V(\mathbf{s})\|^2, \quad (45)$$

363 **Proof** Using H3 and the fact that we can exchange integration with differentiation and the Fisher's  
364 identity, we obtain

$$\begin{aligned} \nabla_{\mathbf{s}} V(\mathbf{s}) &= \mathbf{J}_{\bar{\boldsymbol{\theta}}}^{\mathbf{s}}(\mathbf{s})^\top \left( \nabla_{\boldsymbol{\theta}} \mathbf{r}(\bar{\boldsymbol{\theta}}(\mathbf{s})) + \nabla_{\boldsymbol{\theta}} \mathbf{L}(\bar{\boldsymbol{\theta}}(\mathbf{s})) \right) \\ &= \mathbf{J}_{\bar{\boldsymbol{\theta}}}^{\mathbf{s}}(\mathbf{s})^\top \left( \nabla_{\boldsymbol{\theta}} \psi(\bar{\boldsymbol{\theta}}(\mathbf{s})) + \nabla_{\boldsymbol{\theta}} \mathbf{r}(\bar{\boldsymbol{\theta}}(\mathbf{s})) - \mathbf{J}_{\phi}^{\boldsymbol{\theta}}(\bar{\boldsymbol{\theta}}(\mathbf{s}))^\top \bar{\mathbf{s}}(\bar{\boldsymbol{\theta}}(\mathbf{s})) \right) \\ &= \mathbf{J}_{\bar{\boldsymbol{\theta}}}^{\mathbf{s}}(\mathbf{s})^\top \mathbf{J}_{\phi}^{\boldsymbol{\theta}}(\bar{\boldsymbol{\theta}}(\mathbf{s}))^\top (\mathbf{s} - \bar{\mathbf{s}}(\bar{\boldsymbol{\theta}}(\mathbf{s}))), \end{aligned} \quad (46)$$

365 Consider the following vector map:

$$\mathbf{s} \rightarrow \nabla_{\boldsymbol{\theta}} L(\mathbf{s}, \boldsymbol{\theta})|_{\boldsymbol{\theta}=\bar{\boldsymbol{\theta}}(\mathbf{s})} = \nabla_{\boldsymbol{\theta}} \psi(\bar{\boldsymbol{\theta}}(\mathbf{s})) + \nabla_{\boldsymbol{\theta}} \mathbf{r}(\bar{\boldsymbol{\theta}}(\mathbf{s})) - \mathbf{J}_{\phi}^{\boldsymbol{\theta}}(\bar{\boldsymbol{\theta}}(\mathbf{s}))^\top \mathbf{s}. \quad (47)$$

366 Taking the gradient of the above map w.r.t.  $\mathbf{s}$  and using assumption H3, we show that:

$$\mathbf{0} = -\mathbf{J}_{\phi}^{\boldsymbol{\theta}}(\bar{\boldsymbol{\theta}}(\mathbf{s})) + \underbrace{\left( \nabla_{\boldsymbol{\theta}}^2 (\psi(\boldsymbol{\theta}) + \mathbf{r}(\boldsymbol{\theta}) - \langle \phi(\boldsymbol{\theta}) | \mathbf{s} \rangle) \right)|_{\boldsymbol{\theta}=\bar{\boldsymbol{\theta}}(\mathbf{s})}}_{=\mathbf{H}_L^{\boldsymbol{\theta}}(\mathbf{s}; \boldsymbol{\theta})} \mathbf{J}_{\bar{\boldsymbol{\theta}}}^{\mathbf{s}}(\mathbf{s}). \quad (48)$$

367 The above yields

$$\nabla_{\mathbf{s}} V(\mathbf{s}) = \mathbf{B}(\mathbf{s})(\mathbf{s} - \bar{\mathbf{s}}(\bar{\boldsymbol{\theta}}(\mathbf{s}))) \quad (49)$$

368 where we recall  $\mathbf{B}(\mathbf{s}) = \mathbf{J}_{\phi}^{\boldsymbol{\theta}}(\bar{\boldsymbol{\theta}}(\mathbf{s})) \left( \mathbf{H}_L^{\boldsymbol{\theta}}(\mathbf{s}; \bar{\boldsymbol{\theta}}(\mathbf{s})) \right)^{-1} \mathbf{J}_{\phi}^{\boldsymbol{\theta}}(\bar{\boldsymbol{\theta}}(\mathbf{s}))^\top$ . The proof of (45) follows directly  
369 from the assumption H4.  $\square$

## 370 B Proof of Lemma 3

371 **Lemma.** Assume H??. The update (9) is equivalent to the following update on the resulting statistics

$$\hat{\mathbf{s}}^{(k+1)} = \hat{\mathbf{s}}^{(k)} + \gamma_{k+1} (\tilde{\mathbf{S}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}) \quad (50)$$

373 Also:

$$\mathbb{E} [\tilde{\mathbf{S}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}] = \mathbb{E} [\bar{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(k)}] + \left(1 - \frac{1}{n}\right) \mathbb{E} \left[ \frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^k)} - \bar{\mathbf{s}}^{(k)} \right] + \frac{1}{n} \mathbb{E} [\eta_{i_k}^{(k+1)}] \quad (51)$$

374 where  $\bar{\mathbf{s}}^{(k)}$  is defined by (3) and  $\tau_i^k = \max\{k' : i_{k'} = i, k' < k\}$ .

375 **Proof** From update (9), we have:

$$\begin{aligned} \tilde{\mathbf{S}}^{(k+1)} - \hat{\mathbf{s}}^{(k)} &= \tilde{\mathbf{S}}^{(k)} - \hat{\mathbf{s}}^{(k)} + \frac{1}{n} \left( \tilde{S}_{i_k}^{(k+1)} - \tilde{S}_{i_k}^{(\tau_{i_k}^k)} \right) \\ &= \bar{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(k)} + \tilde{\mathbf{S}}^{(k)} - \bar{\mathbf{s}}^{(k)} - \frac{1}{n} \left( \tilde{S}_{i_k}^{(\tau_{i_k}^k)} - \tilde{S}_{i_k}^{(k+1)} \right) \end{aligned} \quad (52)$$

376 Since  $\tilde{S}_{i_k}^{(k+1)} = \bar{s}_{i_k}(\boldsymbol{\theta}^{(k)}) + \eta_{i_k}^{(k+1)}$  we have

$$\tilde{\mathbf{S}}^{(k+1)} - \hat{\mathbf{s}}^{(k)} = \bar{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(k)} + \tilde{\mathbf{S}}^{(k)} - \bar{\mathbf{s}}^{(k)} - \frac{1}{n} \left( \tilde{S}_{i_k}^{(\tau_{i_k}^k)} - \bar{s}_{i_k}(\boldsymbol{\theta}^{(k)}) \right) + \frac{1}{n} \eta_{i_k}^{(k+1)} \quad (53)$$

377 Taking the full expectation of both side of the equation leads to:

$$\begin{aligned} \mathbb{E} [\tilde{\mathbf{S}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}] &= \mathbb{E} [\bar{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(k)}] + \mathbb{E} \left[ \frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^k)} - \bar{\mathbf{s}}^{(k)} \right] \\ &\quad - \frac{1}{n} \mathbb{E} \left[ \mathbb{E} [\tilde{S}_{i_k}^{(\tau_{i_k}^k)} - \bar{s}_{i_k}(\boldsymbol{\theta}^{(k)}) | \mathcal{F}_k] \right] + \frac{1}{n} \mathbb{E} [\eta_{i_k}^{(k+1)}] \end{aligned} \quad (54)$$

378 The following equalities:

$$\mathbb{E} [\tilde{S}_i^{(\tau_i^k)} | \mathcal{F}_k] = \frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^k)} \quad \text{and} \quad \mathbb{E} [\bar{s}_{i_k}(\boldsymbol{\theta}^{(k)}) | \mathcal{F}_k] = \bar{\mathbf{s}}^{(k)} \quad (55)$$

379 concludes the proof of the Lemma.  $\square$

## 380 C Proof of Theorem 1

381 **Theorem.** Assume H1-H5. Let  $K_{\max}$  be a positive integer. Let  $\{\gamma_k, k \in \mathbb{N}\}$  be a sequence of  
 382 positive step sizes and consider the iSAEM sequence  $\{\hat{\mathbf{s}}^{(k)}, k \in \mathbb{N}\}$  obtained with  $\rho_{k+1} = 1$  for any  
 383  $k > 0$ . We also set  $c_1 = v_{\min}^{-1}$ ,  $\alpha = \max\{8, 1 + 6v_{\min}\}$ ,  $\bar{L} = \max\{L_{\mathbf{s}}, L_V\}$ ,  $\gamma_{k+1} = \frac{1}{k^\alpha \alpha c_1 \bar{L}}$  where  
 384  $a \in (0, 1)$ ,  $\beta = \frac{c_1 \bar{L}}{n}$ . Assume that  $\hat{\mathbf{s}}^{(k)} \in \mathcal{S}$  for any  $k \leq K_{\max}$ .

$$v_{\max}^{-2} \sum_{k=0}^{K_{\max}} \tilde{\alpha}_k \mathbb{E} \left[ \left\| \nabla V(\hat{\mathbf{s}}^{(k)}) \right\|^2 \right] \leq \mathbb{E} \left[ V(\hat{\mathbf{s}}^{(0)}) - V(\hat{\mathbf{s}}^{(K)}) \right] + \sum_{k=0}^{K_{\max}-1} \tilde{\Gamma}_k \mathbb{E} \left[ \left\| \eta_{i_k}^{(k)} \right\|^2 \right] \quad (56)$$

385 **Proof** We begin our proof by giving this auxiliary Lemma setting an upper bound for the quantity  
 386  $\mathbb{E} \left[ \left\| \tilde{S}^{(k+1)} - \hat{\mathbf{s}}^{(k)} \right\|^2 \right]$

387 **Lemma 7.** For any  $k \geq 0$  and consider the iSAEM update in (9), it holds that

$$\begin{aligned} \mathbb{E} \left[ \left\| \tilde{S}^{(k+1)} - \hat{\mathbf{s}}^{(k)} \right\|^2 \right] &\leq 4\mathbb{E} \left[ \left\| \bar{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(k)} \right\|^2 \right] + \frac{2L_{\mathbf{s}}^2}{n^3} \sum_{i=1}^n \mathbb{E} \left[ \left\| \hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_i^k)} \right\|^2 \right] \\ &\quad + 2\frac{C_\eta}{M_k} + 4\mathbb{E} \left[ \left\| \frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^k)} - \bar{\mathbf{s}}^{(k)} \right\|^2 \right] \end{aligned} \quad (57)$$

388 **Proof** Applying the iSAEM update yields:

$$\begin{aligned} \mathbb{E} \left[ \left\| \tilde{S}^{(k+1)} - \hat{\mathbf{s}}^{(k)} \right\|^2 \right] &= \mathbb{E} \left[ \left\| \tilde{S}^{(k)} - \hat{\mathbf{s}}^{(k)} - \frac{1}{n} (\tilde{S}_{i_k}^{(\tau_i^k)} - \tilde{S}_{i_k}^{(k)}) \right\|^2 \right] \\ &\leq 4\mathbb{E} \left[ \left\| \frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^k)} - \bar{\mathbf{s}}^{(k)} \right\|^2 \right] + 4\mathbb{E} \left[ \left\| \bar{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(k)} \right\|^2 \right] \\ &\quad + \frac{2}{n^2} \mathbb{E} \left[ \left\| \bar{\mathbf{s}}_{i_k}^{(k)} - \bar{\mathbf{s}}_{i_k}^{(t_{i_k}^k)} \right\|^2 \right] + 2\frac{C_\eta}{M_k} \end{aligned} \quad (58)$$

389 The last expectation can be further bounded by

$$\frac{2}{n^2} \mathbb{E} \left[ \left\| \bar{\mathbf{s}}_{i_k}^{(k)} - \bar{\mathbf{s}}_{i_k}^{(t_{i_k}^k)} \right\|^2 \right] = \frac{2}{n^3} \sum_{i=1}^n \mathbb{E} \left[ \left\| \bar{\mathbf{s}}_i^{(k)} - \bar{\mathbf{s}}_i^{(t_i^k)} \right\|^2 \right] \stackrel{(a)}{\leq} \frac{2L_{\mathbf{s}}^2}{n^3} \sum_{i=1}^n \mathbb{E} \left[ \left\| \hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_i^k)} \right\|^2 \right], \quad (59)$$

390 where (a) is due to Lemma 1 and which concludes the proof of the Lemma.

391 □

392 Under the smoothness of the Lyapunov function  $V$  (cf. Lemma 1), we can write:

$$V(\hat{\mathbf{s}}^{(k+1)}) \leq V(\hat{\mathbf{s}}^{(k)}) + \gamma_{k+1} \langle \tilde{S}^{(k+1)} - \hat{\mathbf{s}}^{(k)} | \nabla V(\hat{\mathbf{s}}^{(k)}) \rangle + \frac{\gamma_{k+1}^2 L_V}{2} \left\| \tilde{S}^{(k+1)} - \hat{\mathbf{s}}^{(k)} \right\|^2 \quad (60)$$

393 Taking the expectation on both sides yields:

$$\mathbb{E} \left[ V(\hat{\mathbf{s}}^{(k+1)}) \right] \leq \mathbb{E} \left[ V(\hat{\mathbf{s}}^{(k)}) \right] + \gamma_{k+1} \mathbb{E} \left[ \langle \tilde{S}^{(k+1)} - \hat{\mathbf{s}}^{(k)} | \nabla V(\hat{\mathbf{s}}^{(k)}) \rangle \right] + \frac{\gamma_{k+1}^2 L_V}{2} \mathbb{E} \left[ \left\| \tilde{S}^{(k+1)} - \hat{\mathbf{s}}^{(k)} \right\|^2 \right] \quad (61)$$



394 Using Lemma 3, we obtain:

$$\begin{aligned}
& \mathbb{E} \left[ \langle \tilde{S}^{(k+1)} - \hat{s}^{(k)} \mid \nabla V(\hat{s}^{(k)}) \rangle \right] = \\
& \mathbb{E} \left[ \langle \bar{s}^{(k)} - \hat{s}^{(k)} \mid \nabla V(\hat{s}^{(k)}) \rangle \right] + \left( 1 - \frac{1}{n} \right) \mathbb{E} \left[ \left\langle \frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^k)} - \bar{s}^{(k)} \mid \nabla V(\hat{s}^{(k)}) \right\rangle \right] + \frac{1}{n} \mathbb{E} \left[ \langle \eta_{i_k}^{(k)} \mid \nabla V(\hat{s}^{(k)}) \rangle \right] \\
& \stackrel{(a)}{\leq} -v_{\min} \mathbb{E} \left[ \left\| \bar{s}^{(k)} - \hat{s}^{(k)} \right\|^2 \right] + \left( 1 - \frac{1}{n} \right) \mathbb{E} \left[ \left\langle \frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^k)} - \bar{s}^{(k)} \mid \nabla V(\hat{s}^{(k)}) \right\rangle \right] + \frac{1}{n} \mathbb{E} \left[ \langle \eta_{i_k}^{(k)} \mid \nabla V(\hat{s}^{(k)}) \rangle \right] \\
& \stackrel{(b)}{\leq} -v_{\min} \mathbb{E} \left[ \left\| \bar{s}^{(k)} - \hat{s}^{(k)} \right\|^2 \right] + \frac{1 - \frac{1}{n}}{2\beta} \mathbb{E} \left[ \left\| \frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^k)} - \bar{s}^{(k)} \right\|^2 \right] \\
& + \frac{\beta(n-1)+1}{2n} \mathbb{E} \left[ \left\| \nabla V(\hat{s}^{(k)}) \right\|^2 \right] + \frac{1}{2n} \mathbb{E} \left[ \left\| \eta_{i_k}^{(k)} \right\|^2 \right] \\
& \stackrel{(a)}{\leq} \left( v_{\max}^2 \frac{\beta(n-1)+1}{2n} - v_{\min} \right) \mathbb{E} \left[ \left\| \bar{s}^{(k)} - \hat{s}^{(k)} \right\|^2 \right] + \frac{1 - \frac{1}{n}}{2\beta} \mathbb{E} \left[ \left\| \frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^k)} - \bar{s}^{(k)} \right\|^2 \right] + \frac{1}{2n} \mathbb{E} \left[ \left\| \eta_{i_k}^{(k)} \right\|^2 \right]
\end{aligned} \tag{62}$$

395 where (a) is due to the growth condition (2) and (b) is due to Young's inequality (with  $\beta \rightarrow 1$ ). Note

396  $a_k = \gamma_{k+1} \left( v_{\min} - v_{\max}^2 \frac{\beta(n-1)+1}{2n} \right)$  and

$$\begin{aligned}
a_k \mathbb{E} \left[ \left\| \bar{s}^{(k)} - \hat{s}^{(k)} \right\|^2 \right] & \leq \mathbb{E} \left[ V(\hat{s}^{(k)}) - V(\hat{s}^{(k+1)}) \right] + \frac{\gamma_{k+1}^2 L_V}{2} \mathbb{E} \left[ \left\| \tilde{S}^{(k+1)} - \hat{s}^{(k)} \right\|^2 \right] \\
& + \frac{\gamma_{k+1}(1 - \frac{1}{n})}{2\beta} \mathbb{E} \left[ \left\| \frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^k)} - \bar{s}^{(k)} \right\|^2 \right] + \frac{\gamma_{k+1}}{2n} \mathbb{E} \left[ \left\| \eta_{i_k}^{(k)} \right\|^2 \right]
\end{aligned} \tag{63}$$

397 We now give an upper bound of  $\mathbb{E} \left[ \left\| \tilde{S}^{(k+1)} - \hat{s}^{(k)} \right\|^2 \right]$  using Lemma 7 and plug it into (63):

$$\begin{aligned}
(a_k - 2\gamma_{k+1}^2 L_V) \mathbb{E} \left[ \left\| \bar{s}^{(k)} - \hat{s}^{(k)} \right\|^2 \right] & \leq \mathbb{E} \left[ V(\hat{s}^{(k)}) - V(\hat{s}^{(k+1)}) \right] \\
& + \gamma_{k+1} \left( \frac{1}{2\beta} (1 - \frac{1}{n}) + 2\gamma_{k+1} L_V \right) \mathbb{E} \left[ \left\| \frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^k)} - \bar{s}^{(k)} \right\|^2 \right] \\
& + \gamma_{k+1} \left( \gamma_{k+1} L_V + \frac{1}{2n} \right) \mathbb{E} \left[ \left\| \eta_{i_k}^{(k)} \right\|^2 \right] \\
& + \frac{\gamma_{k+1}^2 L_V L_s^2}{n^3} \sum_{i=1}^n \mathbb{E} \left[ \left\| \hat{s}^{(k)} - \hat{s}^{(\tau_i^k)} \right\|^2 \right]
\end{aligned} \tag{64}$$

398 Next, we observe that

$$\frac{1}{n} \sum_{i=1}^n \mathbb{E} \left[ \left\| \hat{s}^{(k+1)} - \hat{s}^{(\tau_i^{k+1})} \right\|^2 \right] = \frac{1}{n} \sum_{i=1}^n \left( \frac{1}{n} \mathbb{E} \left[ \left\| \hat{s}^{(k+1)} - \hat{s}^{(k)} \right\|^2 \right] + \frac{n-1}{n} \mathbb{E} \left[ \left\| \hat{s}^{(k+1)} - \hat{s}^{(\tau_i^k)} \right\|^2 \right] \right) \tag{65}$$

399 where the equality holds as  $i_k$  and  $j_k$  are drawn independently. For any  $\beta > 0$ , it holds

$$\begin{aligned}
& \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(t_i^k)}\|^2] \\
&= \mathbb{E}\left[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}\|^2 + \|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\tau_i^k)}\|^2 + 2\langle \hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)} \mid \hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\tau_i^k)} \rangle\right] \\
&= \mathbb{E}\left[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}\|^2 + \|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\tau_i^k)}\|^2 - 2\gamma_{k+1}\langle \hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k+1)} \mid \hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\tau_i^k)} \rangle\right] \\
&\leq \mathbb{E}\left[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}\|^2 + \|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\tau_i^k)}\|^2 + \frac{\gamma_{k+1}}{\beta}\|\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k+1)}\|^2 + \gamma_{k+1}\beta\|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\tau_i^k)}\|^2\right]
\end{aligned} \tag{66}$$

400 where the last inequality is due to the Young's inequality. Subsequently, we have

$$\begin{aligned}
& \frac{1}{n} \sum_{i=1}^n \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(\tau_i^{k+1})}\|^2] \\
&\leq \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}\|^2] + \frac{n-1}{n^2} \sum_{i=1}^n \mathbb{E}\left[\left(1 + \gamma_{k+1}\beta\right)\|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\tau_i^k)}\|^2 + \frac{\gamma_{k+1}}{\beta}\|\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k+1)}\|^2\right]
\end{aligned} \tag{67}$$

401 Observe that  $\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)} = -\gamma_{k+1}(\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k+1)})$ . Applying Lemma 7 yields

$$\begin{aligned}
& \frac{1}{n} \sum_{i=1}^n \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(\tau_i^{k+1})}\|^2] \\
&\leq \left(\gamma_{k+1}^2 + \frac{n-1}{n} \frac{\gamma_{k+1}}{\beta}\right) \mathbb{E}[\|\tilde{\mathbf{S}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}\|^2] + \sum_{i=1}^n \mathbb{E}\left[\frac{1 - \frac{1}{n} + \gamma_{k+1}\beta}{n} \|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\tau_i^k)}\|^2\right] \\
&\leq 4\left(\gamma_{k+1}^2 + \frac{\gamma_{k+1}}{\beta}\right) \mathbb{E}[\|\bar{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(k)}\|^2] + 2\left(\gamma_{k+1}^2 + \frac{\gamma_{k+1}}{\beta}\right) \mathbb{E}\left[\left\|\eta_{i_k}^{(k)}\right\|^2\right] \\
&\quad + 4\left(\gamma_{k+1}^2 + \frac{\gamma_{k+1}}{\beta}\right) \mathbb{E}\left[\left\|\frac{1}{n} \sum_{i=1}^n \tilde{\mathbf{S}}_i^{(\tau_i^k)} - \bar{\mathbf{s}}^{(k)}\right\|^2\right] \\
&\quad + \sum_{i=1}^n \mathbb{E}\left[\frac{1 - \frac{1}{n} + \gamma_{k+1}\beta + \frac{2\gamma_{k+1}L_{\mathbf{s}}^2}{n^2}(\gamma_{k+1} + \frac{1}{\beta})}{n} \|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_i^k)}\|^2\right]
\end{aligned} \tag{68}$$

402 Let us define

$$\Delta^{(k)} := \frac{1}{n} \sum_{i=1}^n \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\tau_i^k)}\|^2] \tag{69}$$

403 From the above, we get

$$\begin{aligned}
\Delta^{(k+1)} &\leq \left(1 - \frac{1}{n} + \gamma_{k+1}\beta + \frac{2\gamma_{k+1}L_{\mathbf{s}}^2}{n^2}(\gamma_{k+1} + \frac{1}{\beta})\right) \Delta^{(k)} + 4\left(\gamma_{k+1}^2 + \frac{\gamma_{k+1}}{\beta}\right) \mathbb{E}[\|\bar{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(k)}\|^2] \\
&\quad + 2\left(\gamma_{k+1}^2 + \frac{\gamma_{k+1}}{\beta}\right) \mathbb{E}\left[\left\|\eta_{i_k}^{(k)}\right\|^2\right] + 4\left(\gamma_{k+1}^2 + \frac{\gamma_{k+1}}{\beta}\right) \mathbb{E}\left[\left\|\frac{1}{n} \sum_{i=1}^n \tilde{\mathbf{S}}_i^{(\tau_i^k)} - \bar{\mathbf{s}}^{(k)}\right\|^2\right]
\end{aligned} \tag{70}$$

404 Setting  $c_1 = v_{\min}^{-1}$ ,  $\alpha = \max\{8, 1 + 6v_{\min}\}$ ,  $\bar{L} = \max\{L_{\mathbf{s}}, L_V\}$ ,  $\gamma_{k+1} = \frac{1}{k\alpha c_1 \bar{L}}$ ,  $\beta = \frac{c_1 \bar{L}}{n}$ ,

405  $c_1(k\alpha - 1) \geq c_1(\alpha - 1) \geq 6$ ,  $\alpha \geq 8$ , we observe that

$$1 - \frac{1}{n} + \gamma_{k+1}\beta + \frac{2\gamma_{k+1}L_{\mathbf{s}}^2}{n^2}(\gamma_{k+1} + \frac{1}{\beta}) \leq 1 - \frac{c_1(k\alpha - 1) - 4}{k\alpha n c_1} \leq 1 - \frac{2}{k\alpha n c_1} \tag{71}$$

406 which shows that  $1 - \frac{1}{n} + \gamma_{k+1}\beta + \frac{2\gamma_{k+1}L_s^2}{n^2}(\gamma_{k+1} + \frac{1}{\beta}) \in (0, 1)$  for any  $k > 0$ . Denote  $\Lambda_{(k+1)} =$   
 407  $\frac{1}{n} - \gamma_{k+1}\beta - \frac{2\gamma_{k+1}L_s^2}{n^2}(\gamma_{k+1} + \frac{1}{\beta})$  and note that  $\Delta^{(0)} = 0$ , thus the telescoping sum yields:

$$\begin{aligned} \Delta^{(k+1)} \leq & 4 \sum_{\ell=0}^k \prod_{j=\ell+1}^k \left(1 - \Lambda_{(j)}\right) (\gamma_{\ell+1}^2 + \frac{\gamma_{\ell+1}}{\beta}) \mathbb{E}[\|\bar{\mathbf{s}}^{(\ell)} - \hat{\mathbf{s}}^{(\ell)}\|^2] + 2 \sum_{\ell=0}^k \prod_{j=\ell+1}^k \left(1 - \Lambda_{(j)}\right) (\gamma_{\ell+1}^2 + \frac{\gamma_{\ell+1}}{\beta}) \mathbb{E}[\|\eta_{i_\ell}^{(\ell)}\|^2] \\ & + 4 \sum_{\ell=0}^k \prod_{j=\ell+1}^k \left(1 - \Lambda_{(j)}\right) (\gamma_{\ell+1}^2 + \frac{\gamma_{\ell+1}}{\beta}) \mathbb{E}\left[\left\|\frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^\ell)} - \bar{\mathbf{s}}^{(\ell)}\right\|^2\right] \end{aligned} \quad (72)$$

408 Note  $\omega_{k,\ell} = \prod_{j=\ell+1}^k (1 - \Lambda_{(j)})$  Summing on both sides over  $k = 0$  to  $k = K_{\max} - 1$  yields:

$$\begin{aligned} & \sum_{k=0}^{K_{\max}-1} \Delta^{(k+1)} \\ &= 4 \sum_{k=0}^{K_{\max}-1} (\gamma_{k+1}^2 + \frac{\gamma_{k+1}}{\beta}) \omega_{k,1} \mathbb{E}[\|\bar{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(k)}\|^2] + 2 \sum_{k=0}^{K_{\max}-1} (\gamma_{k+1}^2 + \frac{\gamma_{k+1}}{\beta}) \omega_{k,1} \mathbb{E}[\|\eta_{i_\ell}^{(k)}\|^2] \\ &+ \sum_{k=0}^{K_{\max}-1} 4(\gamma_{k+1}^2 + \frac{\gamma_{k+1}}{\beta}) \omega_{k,1} \mathbb{E}\left[\left\|\frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^k)} - \bar{\mathbf{s}}^{(k)}\right\|^2\right] \\ &\leq \sum_{k=0}^{K_{\max}-1} \frac{4(\gamma_{k+1}^2 + \frac{\gamma_{k+1}}{\beta})}{\Lambda_{(k+1)}} \mathbb{E}[\|\bar{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(k)}\|^2] + \sum_{k=0}^{K_{\max}-1} \frac{2(\gamma_{k+1}^2 + \frac{\gamma_{k+1}}{\beta})}{\Lambda_{(k+1)}} \mathbb{E}[\|\eta_{i_\ell}^{(k)}\|^2] \\ &+ \sum_{k=0}^{K_{\max}-1} \frac{4(\gamma_{k+1}^2 + \frac{\gamma_{k+1}}{\beta})}{\Lambda_{(k+1)}} \mathbb{E}\left[\left\|\frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^k)} - \bar{\mathbf{s}}^{(k)}\right\|^2\right] \end{aligned} \quad (73)$$

409 We recall (64) where we have summed on both sides from  $k = 0$  to  $k = K_{\max} - 1$ :

$$\begin{aligned} & \sum_{k=0}^{K_{\max}-1} (a_k - 2\gamma_{k+1}^2 L_V) \mathbb{E}[\|\bar{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(k)}\|^2] \leq \mathbb{E}[V(\hat{\mathbf{s}}^{(0)}) - V(\hat{\mathbf{s}}^{(K)})] \\ &+ \sum_{k=0}^{K_{\max}-1} \gamma_{k+1} \left(\frac{1}{2\beta}(1 - \frac{1}{n}) + 2\gamma_{k+1} L_V\right) \mathbb{E}\left[\left\|\frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^k)} - \bar{\mathbf{s}}^{(k)}\right\|^2\right] \\ &+ \sum_{k=0}^{K_{\max}-1} \gamma_{k+1} \left(\gamma_{k+1} L_V + \frac{1}{2n}\right) \mathbb{E}[\|\eta_{i_k}^{(k)}\|^2] \\ &+ \sum_{k=0}^{K_{\max}-1} \frac{\gamma_{k+1}^2 L_V L_s^2}{n^2} \Delta^{(k)} \end{aligned} \quad (74)$$

410 Plugging (73) into (74) results in:

$$\begin{aligned} & \sum_{k=0}^{K_{\max}-1} \tilde{\alpha}_k \mathbb{E}[\|\bar{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(k)}\|^2] + \sum_{k=0}^{K_{\max}-1} \tilde{\beta}_k \mathbb{E}\left[\left\|\frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(\tau_i^k)} - \bar{\mathbf{s}}^{(k)}\right\|^2\right] \leq \mathbb{E}[V(\hat{\mathbf{s}}^{(0)}) - V(\hat{\mathbf{s}}^{(K)})] \\ &+ \sum_{k=0}^{K_{\max}-1} \tilde{\Gamma}_k \mathbb{E}[\|\eta_{i_k}^{(k)}\|^2] \end{aligned} \quad (75)$$

411 where:

$$\begin{aligned}\tilde{\alpha}_k &= a_k - 2\gamma_{k+1}^2 L_V - \frac{\gamma_{k+1}^2 L_V L_{\mathbf{s}}^2}{n^2} \frac{4(\gamma_{k+1}^2 + \frac{\gamma_{k+1}}{\beta})}{\Lambda_{(k+1)}} \\ \tilde{\beta}_k &= \gamma_{k+1} \left( \frac{1}{2\beta} (1 - \frac{1}{n}) + 2\gamma_{k+1} L_V \right) - \frac{\gamma_{k+1}^2 L_V L_{\mathbf{s}}^2}{n^2} \frac{4(\gamma_{k+1}^2 + \frac{\gamma_{k+1}}{\beta})}{\Lambda_{(k+1)}} \\ \tilde{\Gamma}_k &= \gamma_{k+1} \left( \gamma_{k+1} L_V + \frac{1}{2n} \right) + \frac{\gamma_{k+1}^2 L_V L_{\mathbf{s}}^2}{n^2} \frac{2(\gamma_{k+1}^2 + \frac{\gamma_{k+1}}{\beta})}{\Lambda_{(k+1)}}\end{aligned}$$

412 and

$$\begin{aligned}a_k &= \gamma_{k+1} \left( v_{\min} - v_{\max}^2 \frac{\beta(n-1) + 1}{2n} \right) \\ \Lambda_{(k+1)} &= \frac{1}{n} - \gamma_{k+1}\beta - \frac{2\gamma_{k+1} L_{\mathbf{s}}^2}{n^2} (\gamma_{k+1} + \frac{1}{\beta}) \\ c_1 &= v_{\min}^{-1}, \alpha = \max\{8, 1 + 6v_{\min}\}, \bar{L} = \max\{L_{\mathbf{s}}, L_V\}, \gamma_{k+1} = \frac{1}{k\alpha c_1 \bar{L}}, \beta = \frac{c_1 \bar{L}}{n}\end{aligned}$$

413 When, for any  $k > 0$ ,  $\tilde{\alpha}_k \geq 0$ , we have by Lemma 2 that:

$$\sum_{k=0}^{K_{\max}} \tilde{\alpha}_k \mathbb{E} \left[ \left\| \nabla V(\hat{\mathbf{s}}^{(k)}) \right\|^2 \right] \leq v_{\max}^2 \sum_{k=0}^{K_{\max}} \tilde{\alpha}_k \mathbb{E} \left[ \left\| \bar{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(k)} \right\|^2 \right] \quad (76)$$

414 which yields an upper bound of the gradient of the Lyapunov function  $V$  along the path of the  
415 iSAEM update and concludes the proof of the Theorem.  $\square$

## 416 D Proofs of Auxiliary Lemmas

### 417 D.1 Proof of Lemma 4 and Lemma 5

418 **Lemma.** For any  $k \geq 0$  and consider the vrTTSEM update in (10) with  $\rho_k = \rho$ , it holds for all  
419  $k > 0$

$$\begin{aligned} \mathbb{E} \left[ \left\| \hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k+1)} \right\|^2 \right] &\leq 2\rho^2 \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \bar{\mathbf{s}}^{(k)}\|^2] + 2\rho^2 L_s^2 \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\ell(k))}\|^2] \\ &\quad + 2(1-\rho)^2 \mathbb{E}[\|\hat{\mathbf{s}}^{((k))} - \tilde{S}^{(k)}\|^2] + 2\rho^2 \mathbb{E}[\|\eta_{i_k}^{(k+1)}\|^2] \end{aligned} \quad (77)$$

420 where we recall that  $\ell(k)$  is the first iteration number in the epoch that iteration  $k$  is in.

421 **Proof** Beforehand, we provide a rewriting of the quantity  $\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}$  that will be useful through-  
422 out this proof:

$$\begin{aligned} \hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)} &= -\gamma_{k+1}(\hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k+1)}) = -\gamma_{k+1}(\hat{\mathbf{s}}^{(k)} - (1-\rho)\tilde{S}^{(k)} - \rho\mathbf{S}^{(k+1)}) \\ &= -\gamma_{k+1} \left( (1-\rho) \left[ \hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)} \right] + \rho \left[ \hat{\mathbf{s}}^{(k)} - \mathbf{S}^{(k+1)} \right] \right) \end{aligned} \quad (78)$$

423 We observe, using the identity (78), that

$$\mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k+1)}\|^2] \leq 2\rho^2 \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \bar{\mathbf{s}}^{(k)}\|^2] + 2\rho^2 \mathbb{E}[\|\bar{\mathbf{s}}^{(k)} - \mathbf{S}^{(k+1)}\|^2] + 2(1-\rho)^2 \mathbb{E}[\|\hat{\mathbf{s}}^{((k))} - \tilde{S}^{(k)}\|^2] \quad (79)$$

424 For the latter term, we obtain its upper bound as

$$\begin{aligned} \mathbb{E}[\|\bar{\mathbf{s}}^{(k)} - \mathbf{S}^{(k+1)}\|^2] &= \mathbb{E} \left[ \left\| \frac{1}{n} \sum_{i=1}^n (\bar{\mathbf{s}}_i^{(k)} - \tilde{S}_i^{\ell(k)}) - (\bar{\mathbf{s}}_{i_k}^{(k)} - \tilde{S}_{i_k}^{\ell(k)}) \right\|^2 \right] \\ &\stackrel{(a)}{\leq} \mathbb{E}[\|\bar{\mathbf{s}}_{i_k}^{(k)} - \bar{\mathbf{s}}_{i_k}^{\ell(k)}\|^2] + \mathbb{E}[\|\eta_{i_k}^{(k+1)}\|^2] \stackrel{(b)}{\leq} L_s^2 \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{\ell(k)}\|^2] + \mathbb{E}[\|\eta_{i_k}^{(k+1)}\|^2] \end{aligned} \quad (80)$$

425 where (a) uses the variance inequality and (b) uses Lemma 1. Substituting into (79) proves the  
426 lemma.  $\square$

427 **Lemma.** For any  $k \geq 0$  and consider the fiTTSEM update in (11) with  $\rho_k = \rho$ , it holds for all  $k > 0$   
428

$$\begin{aligned} \mathbb{E} \left[ \left\| \hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k+1)} \right\|^2 \right] &\leq 2\rho^2 \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \bar{\mathbf{s}}^{(k)}\|^2] + 2\rho^2 \frac{L_s^2}{n} \sum_{i=1}^n \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_k)}\|^2] \\ &\quad + 2(1-\rho)^2 \mathbb{E}[\|\hat{\mathbf{s}}^{((k))} - \tilde{S}^{(k)}\|^2] + 2\rho^2 \mathbb{E}[\|\eta_{i_k}^{(k+1)}\|^2] \end{aligned} \quad (81)$$

429 **Proof** Beforehand, we provide a rewriting of the quantity  $\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}$  that will be useful through-  
430 out this proof:

$$\begin{aligned} \hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)} &= -\gamma_{k+1}(\hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k+1)}) \\ &= -\gamma_{k+1}(\hat{\mathbf{s}}^{(k)} - (1-\rho)\tilde{S}^{(k)} - \rho\mathbf{S}^{(k+1)}) \\ &= -\gamma_{k+1} \left( (1-\rho) \left[ \hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)} \right] + \rho \left[ \hat{\mathbf{s}}^{(k)} - \mathbf{S}^{(k+1)} \right] \right) \\ &= -\gamma_{k+1} \left( (1-\rho) \left[ \hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)} \right] + \rho \left[ \hat{\mathbf{s}}^{(k)} - \bar{\mathbf{s}}^{(k)} - (\tilde{S}_{i_k}^{(k)} - \tilde{S}_{i_k}^{(t_k)}) \right] \right) \end{aligned} \quad (82)$$

431 We observe, using the identity (82), that

$$\mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k+1)}\|^2] \leq 2\rho^2 \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \bar{\mathbf{s}}^{(k)}\|^2] + 2\rho^2 \mathbb{E}[\|\bar{\mathbf{s}}^{(k)} - \mathbf{S}^{(k+1)}\|^2] + 2(1-\rho)^2 \mathbb{E}[\|\hat{\mathbf{s}}^{((k))} - \tilde{S}^{(k)}\|^2] \quad (83)$$

432 For the latter term, we obtain its upper bound as

$$\begin{aligned}\mathbb{E}[\|\bar{\mathbf{s}}^{(k)} - \mathbf{S}^{(k+1)}\|^2] &= \mathbb{E}\left[\left\|\frac{1}{n} \sum_{i=1}^n (\bar{\mathbf{s}}_i^{(k)} - \bar{\mathbf{S}}_i^{(k)}) - (\tilde{\mathbf{S}}_{i_k}^{(k)} - \tilde{\mathbf{S}}_{i_k}^{(t_{i_k}^k)})\right\|^2\right] \\ &\stackrel{(a)}{\leq} \mathbb{E}[\|\bar{\mathbf{s}}_{i_k}^{(k)} - \bar{\mathbf{s}}_{i_k}^{(\ell(k))}\|^2] + \mathbb{E}[\|\eta_{i_k}^{(k+1)}\|^2]\end{aligned}\quad (84)$$

433 where (a) uses the variance inequality. We can further bound the last expectation using Lemma 1:

$$\mathbb{E}[\|\bar{\mathbf{s}}_{i_k}^{(k)} - \bar{\mathbf{s}}_{i_k}^{(t_{i_k}^k)}\|^2] = \frac{1}{n} \sum_{i=1}^n \mathbb{E}[\|\bar{\mathbf{s}}_i^{(k)} - \bar{\mathbf{s}}_i^{(t_i^k)}\|^2] \stackrel{(a)}{\leq} \frac{L_s^2}{n} \sum_{i=1}^n \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_i^k)}\|^2] \quad (85)$$

434 Substituting into (83) proves the lemma.  $\square$

## 435 D.2 Proof of Lemma 6

436 **Lemma.** Consider a decreasing stepsize  $\gamma_k \in (0, 1)$  and a constant  $\rho$ , then the following inequality  
437 holds:

$$\mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k)}\|^2] \leq \frac{\rho}{1-\rho} \sum_{\ell=0}^k (1-\gamma_\ell)^2 (\mathbf{S}^{(\ell)} - \tilde{\mathbf{S}}^{(\ell)}) \quad (86)$$

438 where  $\mathbf{S}^{(k)}$  is defined either by (11) (fTTSEM) or (10) (vrTTSEM)

439 **Proof** We begin by writing the two-time-scale update:

$$\begin{aligned}\tilde{\mathbf{S}}^{(k+1)} &= \tilde{\mathbf{S}}^{(k)} + \rho(\mathbf{S}^{(k+1)} - \tilde{\mathbf{S}}^{(k)}) \\ \hat{\mathbf{s}}^{(k+1)} &= \hat{\mathbf{s}}^{(k)} + \gamma_{k+1}(\tilde{\mathbf{S}}^{(k+1)} - \hat{\mathbf{s}}^{(k)})\end{aligned}\quad (87)$$

440 where  $\mathbf{S}^{(k+1)} = \frac{1}{n} \sum_{i=1}^n \tilde{\mathbf{S}}_i^{(t_i^k)} + (\tilde{\mathbf{S}}_{i_k}^{(k)} - \tilde{\mathbf{S}}_{i_k}^{(t_{i_k}^k)})$  according to (11). Denote  $\delta^{(k+1)} = \hat{\mathbf{s}}^{(k+1)} -$   
441  $\tilde{\mathbf{S}}^{(k+1)}$ . Then from (87), doing the subtraction of both equations yields:

$$\delta^{(k+1)} = (1 - \gamma_{k+1})\delta^{(k)} + \frac{\rho}{1-\rho} (1 - \gamma_{k+1})(\mathbf{S}^{(k+1)} - \tilde{\mathbf{S}}^{(k+1)}) \quad (88)$$

442 Using the telescoping sum and noting that  $\delta^{(0)} = 0$ , we have

$$\delta^{(k+1)} \leq \frac{\rho}{1-\rho} \sum_{\ell=0}^k (1 - \gamma_{\ell+1})^2 (\mathbf{S}^{(\ell+1)} - \tilde{\mathbf{S}}^{(\ell+1)}) \quad (89)$$

443  $\square$

## 444 D.3 Additional Intermediary Result

445 **Lemma 8.** At iteration  $k + 1$ , the drift term of update (11), with  $\rho_{k+1} = \rho$ , is equivalent to the  
446 following :

$$\begin{aligned}\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k+1)} &= \rho(\hat{\mathbf{s}}^{(k)} - \bar{\mathbf{s}}^{(k)}) + \rho\eta_{i_k}^{(k+1)} + \rho \left[ (\bar{\mathbf{s}}_{i_k}^{(k)} - \tilde{\mathbf{S}}_{i_k}^{(t_{i_k}^k)}) - \mathbb{E}[\bar{\mathbf{s}}_{i_k}^{(k)} - \tilde{\mathbf{S}}_{i_k}^{(t_{i_k}^k)}] \right] \\ &\quad + (1 - \rho) (\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k)})\end{aligned}\quad (90)$$

447 where we recall that  $\eta_{i_k}^{(k+1)}$ , defined in (20), which is the gap between the MC approximation and  
448 the expected statistics.



449 **Proof** Using the fTTSEM update  $\tilde{S}^{(k+1)} = (1-\rho)\tilde{S}^{(k)} + \rho\mathcal{S}^{(k+1)}$  where  $\mathcal{S}^{(k+1)} = \overline{\mathcal{S}}^{(k)} + (\tilde{S}_{i_k}^{(k)} - \tilde{S}_{i_k}^{(t_{i_k}^k)})$  leads to the following decomposition:

$$\begin{aligned}
& \tilde{S}^{(k+1)} - \hat{s}^{(k)} \\
&= (1-\rho)\tilde{S}^{(k)} + \rho\left(\overline{\mathcal{S}}^{(k)} + (\tilde{S}_{i_k}^{(k)} - \tilde{S}_{i_k}^{(t_{i_k}^k)})\right) - \hat{s}^{(k)} + \rho\overline{\mathcal{S}}^{(k)} - \rho\overline{\mathcal{S}}^{(k)} \\
&= \rho(\overline{\mathcal{S}}^{(k)} - \hat{s}^{(k)}) + \rho(\tilde{S}_{i_k}^{(k)} - \overline{\mathcal{S}}_{i_k}^{(k)}) + (1-\rho)\left(\tilde{S}^{(k)} - \hat{s}^{(k)}\right) + \rho\left(\overline{\mathcal{S}}^{(k)} - \overline{\mathcal{S}}^{(k)} + (\overline{\mathcal{S}}_{i_k}^{(k)} - \tilde{S}_{i_k}^{(t_{i_k}^k)})\right) \\
&= \rho(\overline{\mathcal{S}}^{(k)} - \hat{s}^{(k)}) + \rho\eta_{i_k}^{(k+1)} - \rho\left[(\overline{\mathcal{S}}_{i_k}^{(k)} - \tilde{S}_{i_k}^{(t_{i_k}^k)}) - \mathbb{E}[\overline{\mathcal{S}}_{i_k}^{(k)} - \tilde{S}_{i_k}^{(t_{i_k}^k)}]\right] \\
&+ (1-\rho)\left(\tilde{S}^{(k)} - \hat{s}^{(k)}\right)
\end{aligned}$$

451 where we observe that  $\mathbb{E}[\overline{\mathcal{S}}_{i_k}^{(k)} - \tilde{S}_{i_k}^{(t_{i_k}^k)}] = \overline{\mathcal{S}}^{(k)} - \overline{\mathcal{S}}^{(k)}$  and which concludes the proof.

452 *Important Note:* Note that  $\overline{\mathcal{S}}_{i_k}^{(k)} - \tilde{S}_{i_k}^{(t_{i_k}^k)}$  is not equal to  $\eta_{i_k}^{(k+1)}$ , defined in (20), which is the gap  
453 between the MC approximation and the expected statistics. Indeed  $\tilde{S}_{i_k}^{(t_{i_k}^k)}$  is not computed under the  
454 same model as  $\overline{\mathcal{S}}_{i_k}^{(k)}$ .  $\square$

## 455 E Proof of Theorem 2

456 **Theorem.** Assume H1-H5. Let  $K_{\max}$  be a positive integer. Let  $\{\gamma_k, k \in \mathbb{N}\}$  be a sequence of  
 457 positive step sizes and consider the vrTTSEM sequence  $\{\hat{\mathbf{s}}^{(k)}, k \in \mathbb{N}\}$  obtained with  $\rho_{k+1} = \rho$  for  
 458 any  $k > 0$ .

459 Assume that  $\hat{\mathbf{s}}^{(k)} \in \mathcal{S}$  for any  $k \leq K_{\max}$ . By setting  $\bar{L} = \max\{L_{\mathbf{s}}, L_V\}$ ,  $\rho = \frac{\mu}{c_1 \bar{L} n^{2/3}}$ ,  $m = \frac{nc_1^2}{2\mu^2 + \mu c_1^2}$   
 460 and a constant  $\mu \in (0, 1)$  and  $\gamma_{k+1} = \frac{1}{k^a \bar{L}}$  where  $a \in (0, 1)$ , we have the following bound:

$$\begin{aligned} \sum_{k=0}^{K_{\max}-1} \gamma_{k+1} \mathbb{E}[\|\nabla V(\hat{\mathbf{s}}^{(k)})\|^2] &\leq \frac{2n^{2/3}\bar{L}}{\mu v_{\min}^2 v_{\max}^2} \mathbb{E}[V(\hat{\mathbf{s}}^{(0)}) - V(\hat{\mathbf{s}}^{(K_{\max})})] \\ &\quad + \frac{2n^{2/3}\bar{L}}{\mu v_{\min}^2 v_{\max}^2} \sum_{k=0}^{K_{\max}-1} \left[ \tilde{\eta}^{(k+1)} + \chi^{(k+1)} \mathbb{E} \left[ \left\| \hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k)} \right\|^2 \right] \right] \end{aligned} \quad (91)$$

461 **Proof** Using the smoothness of  $V$  and update (10), we obtain:

$$\begin{aligned} V(\hat{\mathbf{s}}^{(k+1)}) &\leq V(\hat{\mathbf{s}}^{(k)}) + \langle \hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)} | \nabla V(\hat{\mathbf{s}}^{(k)}) \rangle + \frac{L_V}{2} \|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}\|^2 \\ &\leq V(\hat{\mathbf{s}}^{(k)}) - \gamma_{k+1} \langle \hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k+1)} | \nabla V(\hat{\mathbf{s}}^{(k)}) \rangle + \frac{\gamma_{k+1}^2 L_V}{2} \|\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k+1)}\|^2 \end{aligned} \quad (92)$$

462 Denote  $\mathbf{H}_{k+1} := \hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k+1)}$  the drift term of the fiTTSEM update in (7) and  $\mathbf{h}_k = \hat{\mathbf{s}}^{(k)} - \bar{\mathbf{s}}^{(k)}$ .  
 463 Taking expectations on both sides show that

$$\begin{aligned} &\mathbb{E}[V(\hat{\mathbf{s}}^{(k+1)})] \\ &\stackrel{(a)}{\leq} \mathbb{E}[V(\hat{\mathbf{s}}^{(k)})] - \gamma_{k+1}(1 - \rho) \mathbb{E}[\langle \hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k)} | \nabla V(\hat{\mathbf{s}}^{(k)}) \rangle] - \gamma_{k+1} \rho \mathbb{E}[\langle \hat{\mathbf{s}}^{(k)} - \mathbf{S}^{(k+1)} | \nabla V(\hat{\mathbf{s}}^{(k)}) \rangle] \\ &\quad + \frac{\gamma_{k+1}^2 L_V}{2} \mathbb{E}[\|\mathbf{H}_{k+1}\|^2] \\ &\stackrel{(b)}{\leq} \mathbb{E}[V(\hat{\mathbf{s}}^{(k)})] - \gamma_{k+1} \rho \mathbb{E}[\langle \mathbf{h}_k | \nabla V(\hat{\mathbf{s}}^{(k)}) \rangle] - \gamma_{k+1}(1 - \rho) \mathbb{E}[\langle \hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k)} | \nabla V(\hat{\mathbf{s}}^{(k)}) \rangle] \\ &\quad - \gamma_{k+1} \rho \mathbb{E}[\langle \eta_{i_k}^{(k+1)} | \nabla V(\hat{\mathbf{s}}^{(k)}) \rangle] + \frac{\gamma_{k+1}^2 L_V}{2} \mathbb{E}[\|\mathbf{H}_{k+1}\|^2] \\ &\stackrel{(c)}{\leq} \mathbb{E}[V(\hat{\mathbf{s}}^{(k)})] - (\gamma_{k+1} \rho v_{\min} + \gamma_{k+1} v_{\max}^2) \mathbb{E}[\|\mathbf{h}_k\|^2] + \frac{\gamma_{k+1}^2 L_V}{2} \mathbb{E}[\|\mathbf{H}_{k+1}\|^2] \\ &\quad - \gamma_{k+1} \rho \mathbb{E}[\|\eta_{i_k}^{(k+1)}\|^2] - \gamma_{k+1}(1 - \rho) \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k)}\|^2] \end{aligned} \quad (93)$$

464 where we have used (78) in (a) and  $\mathbb{E}[\mathbf{S}^{(k+1)}] = \bar{\mathbf{s}}^{(k)} + \mathbb{E}[\eta_{i_k}^{(k+1)}]$  in (b), the growth condition in  
 465 Lemma 2 and the Young's inequality with the constant equal to 1 in (c).

466 Furthermore, for  $k+1 \leq \ell(k) + m$  (i.e.,  $k+1$  is in the same epoch as  $k$ ), we have

$$\begin{aligned} \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(\ell(k))}\|^2] &= \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)} + \hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\ell(k))}\|^2] \\ &= \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\ell(k))}\|^2 + \|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}\|^2 + 2\langle \hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\ell(k))} | \hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)} \rangle] \\ &= \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\ell(k))}\|^2 + \gamma_{k+1}^2 \|\mathbf{H}_{k+1}\|^2 \\ &\quad - 2\gamma_{k+1} \langle \hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\ell(k))} | \rho(\mathbf{h}_k - \eta_{i_k}^{(k+1)}) + (1 - \rho)(\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k)}) \rangle] \\ &\leq \mathbb{E}[(1 + \gamma_{k+1}\beta) \|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\ell(k))}\|^2 + \gamma_{k+1}^2 \|\mathbf{H}_{k+1}\|^2 + \frac{\gamma_{k+1}\rho}{\beta} \|\mathbf{h}_k\|^2 \\ &\quad + \frac{\gamma_{k+1}\rho}{\beta} \|\eta_{i_k}^{(k+1)}\|^2 + \frac{\gamma_{k+1}(1 - \rho)}{\beta} \|\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k)}\|^2], \end{aligned} \quad (94)$$

467 where we first used (78) and the last inequality is due to the Young's inequality.

468 Consider the following sequence

$$R_k := \mathbb{E}[V(\hat{\mathbf{s}}^{(k)}) + b_k \|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\ell(k))}\|^2] \quad (95)$$

469 where  $b_k := \bar{b}_{k \bmod m}$  is a periodic sequence where:

$$\bar{b}_i = \bar{b}_{i+1}(1 + \gamma_{k+1}\beta + 2\gamma_{k+1}^2\rho^2 L_{\mathbf{s}}^2) + \gamma_{k+1}^2\rho^2 L_V L_{\mathbf{s}}^2, \quad i = 0, 1, \dots, m-1 \quad \text{with } \bar{b}_m = 0. \quad (96)$$

470 Note that  $\bar{b}_i$  is decreasing with  $i$  and this implies

$$\bar{b}_i \leq \bar{b}_0 = \gamma_{k+1}^2\rho^2 L_V L_{\mathbf{s}}^2 \frac{(1 + \gamma_{k+1}\beta + 2\gamma_{k+1}^2\rho^2 L_{\mathbf{s}}^2)^m - 1}{\gamma_{k+1}\beta + 2\gamma_{k+1}^2\rho^2 L_{\mathbf{s}}^2}, \quad i = 1, 2, \dots, m. \quad (97)$$

471 For  $k+1 \leq \ell(k) + m$ , we have the following inequality

$$\begin{aligned} R_{k+1} &\leq \mathbb{E}\left[V(\hat{\mathbf{s}}^{(k)}) - (\gamma_{k+1}\rho v_{\min} + \gamma_{k+1}v_{\max}^2) \|\mathbf{h}_k\|^2 + \frac{\gamma_{k+1}^2 L_V}{2} \|\mathbf{H}_{k+1}\|^2\right] \\ &\quad + \gamma_{k+1} \mathbb{E}\left[\rho \left\|\eta_{i_k}^{(k+1)}\right\|^2 - (1-\rho) \left\|\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k)}\right\|^2\right] \\ &\quad + b_{k+1} \mathbb{E}\left[(1 + \gamma_{k+1}\beta) \|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\ell(k))}\|^2 + \gamma_{k+1}^2 \|\mathbf{H}_{k+1}\|^2 + \frac{\gamma_{k+1}\rho}{\beta} \|\mathbf{h}_k\|^2\right] \\ &\quad + b_{k+1} \mathbb{E}\left[\frac{\gamma_{k+1}\rho}{\beta} \left\|\eta_{i_k}^{(k+1)}\right\|^2 + \frac{\gamma_{k+1}(1-\rho)}{\beta} \|\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k)}\|^2\right] \end{aligned} \quad (98)$$

472 And using Lemma 4 we obtain:

$$\begin{aligned} R_{k+1} &\leq \mathbb{E}\left[V(\hat{\mathbf{s}}^{(k)}) - (\gamma_{k+1}\rho v_{\min} + \gamma_{k+1}v_{\max}^2 - \gamma_{k+1}^2\rho^2 L_V) \|\mathbf{h}_k\|^2 + \gamma_{k+1}^2\rho^2 L_V L_{\mathbf{s}}^2 \|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\ell(k))}\|^2\right] \\ &\quad + b_{k+1} \mathbb{E}\left[(1 + \gamma_{k+1}\beta + 2\gamma_{k+1}^2\rho^2 L_{\mathbf{s}}^2) \|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\ell(k))}\|^2 + \left(\frac{\gamma_{k+1}\rho}{\beta} + 2\gamma_{k+1}^2\rho^2\right) \|\mathbf{h}_k\|^2\right] \\ &\quad + \gamma_{k+1} \mathbb{E}\left[(\rho + \rho^2\gamma_{k+1} L_V) \left\|\eta_{i_k}^{(k+1)}\right\|^2 - (1-\rho - (1-\rho)^2\gamma_{k+1} L_V) \|\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k)}\|^2\right] \\ &\quad + b_{k+1} \mathbb{E}\left[\left(\frac{\gamma_{k+1}\rho}{\beta} + 2\gamma_{k+1}^2\rho^2\right) \left\|\eta_{i_k}^{(k+1)}\right\|^2 + \left(\frac{\gamma_{k+1}(1-\rho)}{\beta} + 2\gamma_{k+1}^2(1-\rho)^2\right) \|\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k)}\|^2\right] \end{aligned} \quad (99)$$

473 Rearranging the terms yields:

$$\begin{aligned} R_{k+1} &\leq \mathbb{E}[V(\hat{\mathbf{s}}^{(k)})] - \gamma_{k+1}(\rho v_{\min} + v_{\max}^2 - \gamma_{k+1}\rho^2 L_V - b_{k+1}(\frac{\rho}{\beta} + 2\gamma_{k+1}\rho^2)) \mathbb{E}[\|\mathbf{h}_k\|^2] \\ &\quad + \underbrace{\left(b_{k+1}(1 + \gamma\beta + 2\gamma^2\rho^2 L_{\mathbf{s}}^2) + \gamma^2\rho^2 L_V L_{\mathbf{s}}^2\right)}_{=b_k \text{ since } k+1 \leq \ell(k) + m} \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(\ell(k))}\|^2] + \tilde{\eta}^{(k+1)} + \tilde{\chi}^{(k+1)} \end{aligned} \quad (100)$$

474 where

$$\begin{aligned} \tilde{\eta}^{(k+1)} &= \left(\gamma_{k+1}(\rho + \rho^2\gamma_{k+1} L_V) + b_{k+1}(\frac{\gamma_{k+1}\rho}{\beta} + 2\gamma_{k+1}^2\rho^2)\right) \mathbb{E}\left[\left\|\eta_{i_k}^{(k+1)}\right\|^2\right] \\ \chi^{(k+1)} &= \left(b_{k+1}(\frac{\gamma_{k+1}(1-\rho)}{\beta} + 2\gamma_{k+1}^2(1-\rho)^2) - \gamma_{k+1}(1-\rho - (1-\rho)^2\gamma_{k+1} L_V)\right) \quad (101) \\ \tilde{\chi}^{(k+1)} &= \chi^{(k+1)} \mathbb{E}\left[\|\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k)}\|^2\right] \end{aligned}$$

475 This leads, using Lemma 2, that for any  $\gamma_{k+1}$ ,  $\rho$  and  $\beta$  such that  $\rho v_{\min} + v_{\max}^2 -$   
476  $\gamma_{k+1}\rho^2 L_V - b_{k+1}(\frac{\rho}{\beta} + 2\gamma_{k+1}\rho^2) > 0$ ,

$$\begin{aligned} v_{\max}^2 \mathbb{E}[\|\nabla V(\hat{\mathbf{s}}^{(k)})\|^2] &\leq \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \bar{\mathbf{s}}^{(k)}\|^2] \leq \frac{R_k - R_{k+1}}{\gamma_{k+1}(\rho v_{\min} + v_{\max}^2 - \gamma_{k+1}\rho^2 L_V - b_{k+1}(\frac{\rho}{\beta} + 2\gamma_{k+1}\rho^2))} \\ &\quad + \frac{\tilde{\eta}^{(k+1)} + \tilde{\chi}^{(k+1)}}{\gamma_{k+1}(\rho v_{\min} + v_{\max}^2 - \gamma_{k+1}\rho^2 L_V - b_{k+1}(\frac{\rho}{\beta} + 2\gamma_{k+1}\rho^2))} \end{aligned} \quad (102)$$

477 We first remark that

$$\begin{aligned} & \gamma_{k+1}(\rho v_{\min} + v_{\max}^2 - \gamma_{k+1}\rho^2 L_V - b_{k+1}(\frac{\rho}{\beta} + 2\gamma_{k+1}\rho^2)) \\ & \geq \frac{\gamma_{k+1}\rho}{c_1}(1 - \gamma_{k+1}c_1\rho L_V - b_{k+1}(\frac{c_1}{\beta} + 2\gamma_{k+1}\rho c_1)) \end{aligned} \quad (103)$$

478 where  $c_1 = v_{\min}^{-1}$ . By setting  $\bar{L} = \max\{L_s, L_V\}$ ,  $\beta = \frac{c_1\bar{L}}{n^{1/3}}$ ,  $\rho = \frac{\mu}{c_1\bar{L}n^{2/3}}$ ,  $m = \frac{nc_1^2}{2\mu^2 + \mu c_1^2}$  and  
479  $\{\gamma_{k+1}\}$  any sequence of decreasing stepsizes in  $(0, 1)$ , it can be shown that there exists  $\mu \in (0, 1)$ ,  
480 such that the following lower bound holds

$$\begin{aligned} & 1 - \gamma_{k+1}c_1\rho L_V - b_{k+1}(\frac{c_1}{\beta} + 2\gamma_{k+1}\rho c_1) \geq 1 - \frac{\mu}{n^{\frac{2}{3}}} - \bar{b}_0(\frac{n^{\frac{1}{3}}}{\bar{L}} + \frac{2\mu}{\bar{L}n^{\frac{2}{3}}}) \\ & \geq 1 - \frac{\mu}{n^{\frac{2}{3}}} - \frac{L_V\mu^2}{c_1^2n^{\frac{4}{3}}}\frac{(1 + \gamma\beta + 2\gamma^2L_s^2)^m - 1}{\gamma\beta + 2\gamma^2L_s^2}(\frac{n^{\frac{1}{3}}}{\bar{L}} + \frac{2\mu}{\bar{L}n^{\frac{2}{3}}}) \\ & \stackrel{(a)}{\geq} 1 - \frac{\mu}{n^{\frac{2}{3}}} - \frac{\mu}{c_1^2}(e - 1)(1 + \frac{2\mu}{n}) \geq 1 - \mu - \mu(1 + 2\mu)\frac{e - 1}{c_1^2} \stackrel{(b)}{\geq} \frac{1}{2} \end{aligned} \quad (104)$$

481 where the simplification in (a) is due to

$$\frac{\mu}{n} \leq \gamma\beta + 2\gamma^2L_s^2 \leq \frac{\mu}{n} + \frac{2\mu^2}{c_1^2n^{\frac{4}{3}}} \leq \frac{\mu c_1^2 + 2\mu^2}{c_1^2} \frac{1}{n} \text{ and } (1 + \gamma\beta + 2\gamma^2L_s^2)^m \leq e - 1. \quad (105)$$

482 and the required  $\mu$  in (b) can be found by solving the quadratic equation.

483 Finally, these results yield:

$$v_{\max}^2 \sum_{k=0}^{K_{\max}-1} \gamma_{k+1} \mathbb{E}[\|\nabla V(\hat{s}^{(k)})\|^2] \leq \frac{2(R_0 - R_{K_{\max}})}{v_{\min}\rho} + 2 \sum_{k=0}^{K_{\max}-1} \frac{\tilde{\eta}^{(k+1)} + \tilde{\chi}^{(k+1)}}{v_{\min}\rho} \quad (106)$$

484 Note that  $R_0 = \mathbb{E}[V(\hat{s}^{(0)})]$  and if  $K_{\max}$  is a multiple of  $m$ , then  $R_{\max} = \mathbb{E}[V(\hat{s}^{(K_{\max})})]$ . Under the  
485 latter condition, we have

$$\sum_{k=0}^{K_{\max}-1} \gamma_{k+1} \mathbb{E}[\|\nabla V(\hat{s}^{(k)})\|^2] \leq \frac{2n^{2/3}\bar{L}}{\mu v_{\min}^2 v_{\max}^2} \mathbb{E}[V(\hat{s}^{(0)}) - V(\hat{s}^{(K_{\max})})] + \frac{2n^{2/3}\bar{L}}{\mu v_{\min}^2 v_{\max}^2} \sum_{k=0}^{K_{\max}-1} [\tilde{\eta}^{(k+1)} + \tilde{\chi}^{(k+1)}] \quad (107)$$

486 This concludes our proof.

487 □

## 488 **F Proof of Theorem 3**

489 **Theorem.** Assume H1-H5. Let  $K_{\max}$  be a positive integer. Let  $\{\gamma_k, k \in \mathbb{N}\}$  be a sequence of  
 490 positive step sizes and consider the fTTSEM sequence  $\{\hat{\mathbf{s}}^{(k)}, k \in \mathbb{N}\}$  obtained with  $\rho_{k+1} = \rho$  for  
 491 any  $k > 0$ .

492 Assume that  $\hat{\mathbf{s}}^{(k)} \in \mathcal{S}$  for any  $k \leq K_{\max}$ . By setting  $\alpha = \max\{2, 1 + 2v_{\min}\}$ ,  $\bar{L} = \max\{L_s, L_V\}$ ,  
 493  $\beta = \frac{c_1 \bar{L}}{n}$ ,  $\rho = \frac{1}{n^{2/3}}$ ,  $c_1(k\alpha - 1) \geq c_1(\alpha - 1) \geq 2$ ,  $\alpha \geq 2$  and  $\gamma_{k+1} = \frac{1}{k^a \alpha c_1 \bar{L}}$  where  $a \in (0, 1)$ , we  
 494 have the following bound:

$$\begin{aligned} \sum_{k=0}^{K_{\max}-1} \gamma_{k+1} \mathbb{E}[\|\nabla V(\hat{\mathbf{s}}^{(k)})\|^2] &\leq \frac{\alpha \bar{L} n^{2/3}}{v_{\min} v_{\max}^2} [V(\hat{\mathbf{s}}^{(0)}) - V(\hat{\mathbf{s}}^{(K_{\max})})] \\ &\quad + \frac{\alpha \bar{L} n^{2/3}}{v_{\min} v_{\max}^2} \sum_{k=0}^{K_{\max}-1} \left[ \Xi^{(k+1)} + \Gamma_{k+1} \mathbb{E} \left[ \left\| \hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)} \right\|^2 \right] \right] \end{aligned} \quad (108)$$

495 **Proof** Using the smoothness of  $V$  and update (11), we obtain:

$$\begin{aligned} V(\hat{\mathbf{s}}^{(k+1)}) &\leq V(\hat{\mathbf{s}}^{(k)}) + \langle \hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)} | \nabla V(\hat{\mathbf{s}}^{(k)}) \rangle + \frac{L_V}{2} \|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}\|^2 \\ &\leq V(\hat{\mathbf{s}}^{(k)}) - \gamma_{k+1} \langle \hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k+1)} | \nabla V(\hat{\mathbf{s}}^{(k)}) \rangle + \frac{\gamma_{k+1}^2 L_V}{2} \|\hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k+1)}\|^2 \end{aligned} \quad (109)$$

496 Denote  $\mathbf{H}_{k+1} := \hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k+1)}$  the drift term of the fTTSEM update in (7) and  $\mathbf{h}_k = \hat{\mathbf{s}}^{(k)} - \bar{\mathbf{s}}^{(k)}$ .  
 497 Using Lemma 8 and the additional following identity:

$$\mathbb{E} \left[ (\bar{\mathbf{s}}_{i_k}^{(k)} - \tilde{S}_{i_k}^{(t_{i_k}^k)}) - \mathbb{E}[\bar{\mathbf{s}}_{i_k}^{(k)} - \tilde{S}_{i_k}^{(t_{i_k}^k)}] \right] = 0 \quad (110)$$

498 we have:

$$\begin{aligned} &\mathbb{E}[V(\hat{\mathbf{s}}^{(k+1)})] \\ &\leq \mathbb{E}[V(\hat{\mathbf{s}}^{(k)})] - \gamma_{k+1} \rho \mathbb{E}[\langle \mathbf{h}_k | \nabla V(\hat{\mathbf{s}}^{(k)}) \rangle] - \gamma_{k+1} \mathbb{E} \left[ \langle \rho \mathbb{E}[\eta_{i_k}^{(k+1)} | \mathcal{F}_k] + (1 - \rho) \mathbb{E}[\hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)}] | \nabla V(\hat{\mathbf{s}}^{(k)}) \rangle \right] \\ &\quad + \frac{\gamma_{k+1}^2 L_V}{2} \|\mathbf{H}_{k+1}\|^2 \\ &\stackrel{(a)}{\leq} -v_{\min} \gamma_{k+1} \rho \mathbb{E}[\|\mathbf{h}_k\|^2] - \gamma_{k+1} \mathbb{E} \left[ \|\nabla V(\hat{\mathbf{s}}^{(k)})\|^2 \right] - \frac{\gamma_{k+1} \rho^2}{2} \xi^{(k+1)} - \frac{\gamma_{k+1} (1 - \rho)^2}{2} \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)}\|^2] \\ &\quad + \frac{\gamma_{k+1}^2 L_V}{2} \|\mathbf{H}_{k+1}\|^2 \\ &\stackrel{(b)}{\leq} -(v_{\min} \gamma_{k+1} \rho + \gamma_{k+1} v_{\max}^2) \mathbb{E}[\|\mathbf{h}_k\|^2] - \frac{\gamma_{k+1} \rho^2}{2} \xi^{(k+1)} - \frac{\gamma_{k+1} (1 - \rho)^2}{2} \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)}\|^2] \\ &\quad + \frac{\gamma_{k+1}^2 L_V}{2} \|\mathbf{H}_{k+1}\|^2 \end{aligned} \quad (111)$$

499 where  $\xi^{(k+1)} = \mathbb{E} \left[ \left\| \mathbb{E}[\eta_{i_k}^{(k+1)} | \mathcal{F}_k] \right\|^2 \right]$ . **Bounding**  $\mathbb{E}[\|\mathbf{H}_{k+1}\|^2]$  Using Lemma 5, we obtain:

$$\begin{aligned} &\gamma_{k+1} (v_{\min} \rho + v_{\max}^2 - \gamma_{k+1} \rho^2 L_V) \mathbb{E}[\|\mathbf{h}_k\|^2] \\ &\leq \mathbb{E} [V(\hat{\mathbf{s}}^{(k)}) - V(\hat{\mathbf{s}}^{(k+1)})] + \tilde{\xi}^{(k+1)} + \left( (1 - \rho)^2 \gamma_{k+1}^2 L_V - \frac{\gamma_{k+1} (1 - \rho)^2}{2} \right) \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)}\|^2] \\ &\quad + \frac{\gamma_{k+1}^2 L_V \rho^2 L_s^2}{n} \sum_{i=1}^n \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_i^k)}\|^2] \end{aligned} \quad (112)$$

500 where  $\tilde{\xi}^{(k+1)} = \gamma_{k+1}^2 \rho^2 \mathbb{L}_V \mathbb{E}[\|\eta_{i_k}^{(k+1)}\|^2] - \frac{\gamma_{k+1}\rho^2}{2} \xi^{(k+1)}$ . Next, we observe that

$$\frac{1}{n} \sum_{i=1}^n \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(t_i^{k+1})}\|^2] = \frac{1}{n} \sum_{i=1}^n \left( \frac{1}{n} \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}\|^2] + \frac{n-1}{n} \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(t_i^k)}\|^2] \right) \quad (113)$$

501 where the equality holds as  $i_k$  and  $j_k$  are drawn independently. Next,

$$\begin{aligned} & \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(t_i^k)}\|^2] \\ &= \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}\|^2 + \|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_i^k)}\|^2 + 2\langle \hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)} \mid \hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_i^k)} \rangle] \end{aligned} \quad (114)$$

502 Note that  $\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)} = -\gamma_{k+1}(\hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k+1)}) = -\gamma_{k+1}\mathbf{H}_{k+1}$  and that in expectation we recall  
 503 that  $\mathbb{E}[\mathbf{H}_{k+1}|\mathcal{F}_k] = \rho\mathbf{h}_k + \rho\mathbb{E}[\eta_{i_k}^{(k+1)}|\mathcal{F}_k] + (1-\rho)\mathbb{E}[\tilde{S}^{(k)} - \hat{\mathbf{s}}^{(k)}]$  where  $\mathbf{h}_k = \hat{\mathbf{s}}^{(k)} - \bar{\mathbf{s}}^{(k)}$ . Thus,  
 504 for any  $\beta > 0$ , it holds

$$\begin{aligned} & \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(t_i^k)}\|^2] \\ &= \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}\|^2 + \|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_i^k)}\|^2 + 2\langle \hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)} \mid \hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_i^k)} \rangle] \\ &\leq \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}\|^2 + (1 + \gamma_{k+1}\beta)\|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_i^k)}\|^2 + \frac{\gamma_{k+1}\rho^2}{\beta}\|\mathbf{h}_k\|^2 + \frac{\gamma_{k+1}\rho^2}{\beta}\mathbb{E}[\|\eta_{i_k}^{(k+1)}\|^2] \\ &\quad + \frac{\gamma_{k+1}(1-\rho)^2}{\beta}\mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)}\|^2]] \end{aligned} \quad (115)$$

505 where the last inequality is due to the Young's inequality. Plugging this into (113) yields:

$$\begin{aligned} & \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(t_i^k)}\|^2] \\ &= \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}\|^2 + \|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_i^k)}\|^2 + 2\langle \hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)} \mid \hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_i^k)} \rangle] \\ &\leq \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}\|^2 + (1 + \gamma_{k+1}\beta)\|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_i^k)}\|^2 + \frac{\gamma_{k+1}\rho^2}{\beta}\|\mathbf{h}_k\|^2 + \frac{\gamma_{k+1}\rho^2}{\beta}\mathbb{E}[\|\eta_{i_k}^{(k+1)}\|^2] \\ &\quad + \frac{\gamma_{k+1}(1-\rho)^2}{\beta}\mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)}\|^2]] \end{aligned} \quad (116)$$

506 Subsequently, we have

$$\begin{aligned} & \frac{1}{n} \sum_{i=1}^n \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(t_i^{k+1})}\|^2] \\ &\leq \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}\|^2] + \frac{n-1}{n^2} \sum_{i=1}^n \mathbb{E}[(1 + \gamma_{k+1}\beta)\|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_i^k)}\|^2 + \frac{\gamma_{k+1}\rho^2}{\beta}\|\mathbf{h}_k\|^2] \\ &\quad + \frac{\gamma_{k+1}\rho^2}{\beta}\mathbb{E}[\|\eta_{i_k}^{(k+1)}\|^2] + \frac{\gamma_{k+1}(1-\rho)^2}{\beta}\mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)}\|^2]] \end{aligned} \quad (117)$$



507 We now use Lemma 5 on  $\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(k)}\|^2 = \gamma_{k+1}^2 \|\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k+1)}\|^2$  and obtain:

$$\begin{aligned}
& \frac{1}{n} \sum_{i=1}^n \mathbb{E}[\|\hat{\mathbf{s}}^{(k+1)} - \hat{\mathbf{s}}^{(t_i^{k+1})}\|^2] \\
& \leq \left(2\gamma_{k+1}^2 \rho^2 + \frac{\gamma_{k+1} \rho^2}{\beta}\right) \mathbb{E}[\|\bar{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(k)}\|^2] + \sum_{i=1}^n \left(\frac{\gamma_{k+1}^2 \rho^2 \mathbf{L}_s^2}{n} + \frac{(n-1)(1+\gamma_{k+1}\beta)}{n^2}\right) \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_i^k)}\|^2] \\
& + \gamma_{k+1}(1-\rho)^2 \left(2\gamma_{k+1} + \frac{1}{\beta}\right) \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k)}\|^2] + \left(2\gamma_{k+1}^2 + \frac{\gamma_{k+1} \rho^2}{\beta}\right) \mathbb{E}[\|\eta_{i_k}^{(k+1)}\|^2] \\
& \leq \left(2\gamma_{k+1}^2 \rho^2 + \frac{\gamma_{k+1} \rho^2}{\beta}\right) \mathbb{E}[\|\bar{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(k)}\|^2] + \sum_{i=1}^n \left(\frac{1 - \frac{1}{n} + \gamma_{k+1}\beta + \gamma_{k+1}^2 \rho^2 \mathbf{L}_s^2}{n}\right) \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_i^k)}\|^2] \\
& + \gamma_{k+1}(1-\rho)^2 \left(2\gamma_{k+1} + \frac{1}{\beta}\right) \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k)}\|^2] + \left(2\gamma_{k+1}^2 + \frac{\gamma_{k+1} \rho^2}{\beta}\right) \mathbb{E}[\|\eta_{i_k}^{(k+1)}\|^2]
\end{aligned} \tag{118}$$

508 Let us define

$$\Delta^{(k)} := \frac{1}{n} \sum_{i=1}^n \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(t_i^k)}\|^2] \tag{119}$$

509 From the above, we get

$$\begin{aligned}
\Delta^{(k+1)} & \leq \left(1 - \frac{1}{n} + \gamma_{k+1}\beta + \gamma_{k+1}^2 \rho^2 \mathbf{L}_s^2\right) \Delta^{(k)} + \left(2\gamma_{k+1}^2 \rho^2 + \frac{\gamma_{k+1} \rho^2}{\beta}\right) \mathbb{E}[\|\bar{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(k)}\|^2] \\
& + \gamma_{k+1}(1-\rho)^2 \left(2\gamma_{k+1} + \frac{1}{\beta}\right) \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k)}\|^2] + \gamma_{k+1} \left(2\gamma_{k+1} + \frac{\rho^2}{\beta}\right) \mathbb{E}[\|\eta_{i_k}^{(k+1)}\|^2]
\end{aligned} \tag{120}$$

510 Setting  $c_1 = v_{\min}^{-1}$ ,  $\alpha = \max\{2, 1+2v_{\min}\}$ ,  $\bar{L} = \max\{\mathbf{L}_s, \mathbf{L}_V\}$ ,  $\gamma_{k+1} = \frac{1}{k}$ ,  $\beta = \frac{1}{\alpha n}$ ,  $\rho = \frac{1}{\alpha c_1 \bar{L} n^{2/3}}$ ,  
511  $c_1(k\alpha - 1) \geq c_1(\alpha - 1) \geq 2$ ,  $\alpha \geq 2$ , we observe that

$$1 - \frac{1}{n} + \gamma_{k+1}\beta + \gamma_{k+1}^2 \rho^2 \mathbf{L}_s^2 \leq 1 - \frac{1}{n} + \frac{1}{\alpha k n} + \frac{1}{\alpha^2 c_1^2 k^2 n^{4/3}} \leq 1 - \frac{c_1(k\alpha - 1) - 1}{k\alpha n c_1} \leq 1 - \frac{1}{k\alpha n c_1} \tag{121}$$

512 which shows that  $1 - \frac{1}{n} + \gamma_{k+1}\beta + \gamma_{k+1}^2 \rho^2 \mathbf{L}_s^2 \in (0, 1)$  for any  $k > 0$ . Denote  $\Lambda_{(k+1)} = \frac{1}{n} -$   
513  $\gamma_{k+1}\beta - \gamma_{k+1}^2 \rho^2 \mathbf{L}_s^2$  and note that  $\Delta^{(0)} = 0$ , thus the telescoping sum yields:

$$\begin{aligned}
\Delta^{(k+1)} & \leq \sum_{\ell=0}^k \omega_{k,\ell} \left(2\gamma_{\ell+1}^2 \rho^2 + \frac{\gamma_{\ell+1}^2 \rho^2}{\beta}\right) \mathbb{E}[\|\bar{\mathbf{s}}^{(\ell)} - \hat{\mathbf{s}}^{(\ell)}\|^2] \\
& + \sum_{\ell=0}^k \omega_{k,\ell} \gamma_{\ell+1} (1-\rho)^2 \left(2\gamma_{\ell+1} + \frac{1}{\beta}\right) \mathbb{E}[\|\tilde{\mathbf{S}}^{(\ell)} - \hat{\mathbf{s}}^{(\ell)}\|^2] + \sum_{\ell=0}^k \omega_{k,\ell} \gamma_{\ell+1} \tilde{\epsilon}^{(\ell+1)}
\end{aligned} \tag{122}$$

514 where  $\omega_{k,\ell} = \prod_{j=\ell+1}^k (1 - \Lambda_{(j)})$  and  $\tilde{\epsilon}^{(\ell+1)} = \left(2\gamma_{k+1} + \frac{\rho^2}{\beta}\right) \mathbb{E}[\|\eta_{i_k}^{(k+1)}\|^2]$ .

515 Summing on both sides over  $k = 0$  to  $k = K_{\max} - 1$  yields:

$$\begin{aligned}
\sum_{k=0}^{K_{\max}-1} \Delta^{(k+1)} & \leq \sum_{k=0}^{K_{\max}-1} \frac{2\gamma_{k+1}^2 \rho^2 + \frac{\gamma_{k+1} \rho^2}{\beta}}{\Lambda_{(k+1)}} \mathbb{E}[\|\bar{\mathbf{s}}^{(k)} - \hat{\mathbf{s}}^{(k)}\|^2] \\
& + \sum_{k=0}^{K_{\max}-1} \frac{\gamma_{k+1}(1-\rho)^2 \left(2\gamma_{k+1} + \frac{1}{\beta}\right)}{\Lambda_{(k+1)}} \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \tilde{\mathbf{S}}^{(k)}\|^2] + \sum_{k=0}^{K_{\max}-1} \frac{\gamma_{k+1}}{\Lambda_{(k+1)}} \tilde{\epsilon}^{(k+1)}
\end{aligned} \tag{123}$$

516 We recall (112) where we have summed on both sides from  $k = 0$  to  $k = K_{\max} - 1$ :

$$\begin{aligned}
& \mathbb{E}[V(\hat{\mathbf{s}}^{(K_{\max})}) - V(\hat{\mathbf{s}}^{(0)})] \\
& \leq \sum_{k=0}^{K_{\max}-1} \left\{ \gamma_{k+1}(-v_{\min}\rho + v_{\max}^2) + \gamma_{k+1}\rho^2 L_V \mathbb{E}[\|\mathbf{h}_k\|^2] + \gamma^2 L_V \rho^2 L_{\mathbf{s}}^2 \Delta^{(k)} \right\} \\
& + \sum_{k=0}^{K_{\max}-1} \left\{ \tilde{\xi}^{(k+1)} + \left( (1-\rho)^2 \gamma_{k+1}^2 L_V - \frac{\gamma_{k+1}(1-\rho)^2}{2} \right) \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)}\|^2] \right\} \\
& \leq \sum_{k=0}^{K_{\max}-1} \left\{ -\gamma_{k+1}(v_{\min}\rho + v_{\max}^2) + \gamma_{k+1}^2 \rho^2 L_V + \frac{\rho^2 \gamma_{k+1}^2 L_V L_{\mathbf{s}}^2 \left( 2\gamma_{k+1}^2 \rho^2 + \frac{\gamma_{k+1}\rho^2}{\beta} \right)}{\Lambda_{(k+1)}} \right\} \mathbb{E}[\|\mathbf{h}_k\|^2] \\
& + \sum_{k=0}^{K_{\max}-1} \Xi^{(k+1)} + \sum_{k=0}^{K_{\max}-1} \Gamma_{k+1} \mathbb{E}[\|\hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)}\|^2]
\end{aligned} \tag{124}$$

where

$$\Xi^{(k+1)} = \tilde{\xi}^{(k+1)} + \frac{\gamma_{k+1}^3 L_V \rho^2 L_{\mathbf{s}}^2}{\Lambda_{(k+1)}} \tilde{\epsilon}^{(k+1)}$$

and

$$\Gamma_{k+1} = \left( (1-\rho)^2 \gamma_{k+1}^2 L_V - \frac{\gamma_{k+1}(1-\rho)^2}{2} \right) + \frac{\gamma_{k+1}^3 L_V \rho^2 L_{\mathbf{s}}^2 (1-\rho)^2 \left( 2\gamma_{k+1} + \frac{1}{\beta} \right)}{\Lambda_{(k+1)}}$$

517 We now analyse the following quantity

$$\begin{aligned}
& -\gamma_{k+1}(v_{\min}\rho + v_{\max}^2) + \gamma_{k+1}^2 \rho^2 L_V + \frac{\rho^2 \gamma_{k+1}^2 L_V L_{\mathbf{s}}^2 \left( 2\gamma_{k+1}^2 \rho^2 + \frac{\gamma_{k+1}\rho^2}{\beta} \right)}{\Lambda_{(k+1)}} \\
& = \gamma_{k+1} \left[ -(v_{\min}\rho + v_{\max}^2) + \gamma_{k+1} \rho^2 L_V + \frac{\rho^2 \gamma_{k+1} L_V L_{\mathbf{s}}^2 \left( 2\gamma_{k+1}^2 \rho^2 + \frac{\gamma_{k+1}\rho^2}{\beta} \right)}{\Lambda_{(k+1)}} \right]
\end{aligned} \tag{125}$$

518 Furthermore, we recall that  $c_1 = v_{\min}^{-1}$ ,  $\alpha = \max\{2, 1 + 2v_{\min}\}$ ,  $\bar{L} = \max\{L_{\mathbf{s}}, L_V\}$ ,  $\gamma_{k+1} = \frac{1}{k}$ ,

519  $\beta = \frac{1}{\alpha n}$ ,  $\rho = \frac{1}{\alpha c_1 \bar{L} n^{2/3}}$ ,  $c_1(k\alpha - 1) \geq c_1(\alpha - 1) \geq 2$ ,  $\alpha \geq 2$ . Then,

$$\begin{aligned}
& \gamma_{k+1} \rho^2 L_V + \frac{\rho^2 \gamma_{k+1} L_V L_{\mathbf{s}}^2 \left( 2\gamma_{k+1}^2 \rho^2 + \frac{\gamma_{k+1}\rho^2}{\beta} \right)}{\frac{1}{n} - \gamma_{k+1}\beta - \gamma_{k+1}^2 \rho^2 L_{\mathbf{s}}^2} \\
& \leq \frac{1}{k\alpha^2 c_1^2 \bar{L} n^{4/3}} + \frac{\bar{L}(k\alpha^2 c_1^2 n^{4/3})^{-1} \left( \frac{2}{k^2 \alpha^2 c_1^2 \bar{L}^2 n^{4/3}} + \frac{1}{k\alpha c_1^2 \bar{L} n^{1/3}} \right)}{\frac{1}{n} - \frac{1}{k\alpha n} - \frac{1}{k^2 \alpha^2 c_1^2 n^{4/3}}} \\
& = \frac{1}{k\alpha^2 c_1^2 \bar{L} n^{4/3}} + \frac{\bar{L} \left( \frac{2}{k^2 \alpha^2 c_1^2 \bar{L}^2 n^{4/3}} + \frac{1}{k\alpha c_1^2 \bar{L} n^{1/3}} \right)}{(k\alpha c_1 n^{1/3})(k\alpha - 1)c_1 - 1} \\
& \stackrel{(a)}{\leq} \frac{1}{k\alpha^2 c_1^2 \bar{L} n^{4/3}} + \frac{\frac{1}{k\alpha c_1^2 \bar{L} n^{1/3}} \left( \frac{2}{k\alpha n} + 1 \right)}{2(\alpha c_1 n^{1/3}) - 1} \\
& \leq \frac{1}{k^2 \alpha c_1^2 \bar{L} n^{4/3}} + \frac{1}{4k\alpha^2 c_1^3 \bar{L} n^{2/3}} \\
& \leq \frac{3/4}{\alpha c_1^2 \bar{L} n^{2/3}}
\end{aligned} \tag{126}$$

where (a) is due to  $c_1(k\alpha - 1) \geq c_1(\alpha - 1) \geq 2$  and  $k\alpha c_1 n^{1/3} \geq 1$ . Note also that

$$-(v_{\min}\rho + v_{\max}^2) \leq -\rho v_{\min} = -\frac{1}{\alpha c_1^2 \bar{L} n^{2/3}}$$

which yields that

$$\left[ -(v_{\min}\rho + v_{\max}^2) + \gamma_{k+1}\rho^2 L_V + \frac{\rho^2 \gamma_{k+1} L_V L_{\mathbf{s}}^2 \left( 2\gamma_{k+1}^2 \rho^2 + \frac{\gamma_{k+1}\rho^2}{\beta} \right)}{\Lambda_{(k+1)}} \right] \leq -\frac{1/4}{\alpha c_1^2 \bar{L} n^{2/3}}$$

520 Using the Lemma 2, we know that  $v_{\max}^2 \|\nabla V(\hat{\mathbf{s}}^{(k)})\|^2 \leq \|\hat{\mathbf{s}}^{(k)} - \bar{\mathbf{s}}^{(k)}\|^2$  and using (126) on (124)  
 521 yields:

$$\begin{aligned} v_{\max}^2 \sum_{k=0}^{K_{\max}-1} \gamma_{k+1} \mathbb{E}[\|\nabla V(\hat{\mathbf{s}}^{(k)})\|^2] &\leq \frac{4\alpha \bar{L} n^{2/3}}{v_{\min}^2} [V(\hat{\mathbf{s}}^{(0)}) - V(\hat{\mathbf{s}}^{(K_{\max})})] \\ &\quad + \frac{4\alpha \bar{L} n^{2/3}}{v_{\min}^2} \sum_{k=0}^{K_{\max}-1} \Xi^{(k+1)} + \sum_{k=0}^{K_{\max}-1} \Gamma_{k+1} \mathbb{E} \left[ \left\| \hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)} \right\|^2 \right] \end{aligned} \quad (127)$$

522 proving the final bound on the gradient of the Lyapunov function:

$$\begin{aligned} \sum_{k=0}^{K_{\max}-1} \gamma_{k+1} \mathbb{E}[\|\nabla V(\hat{\mathbf{s}}^{(k)})\|^2] &\leq \frac{4\alpha \bar{L} n^{2/3}}{v_{\min}^2 v_{\max}^2} [V(\hat{\mathbf{s}}^{(0)}) - V(\hat{\mathbf{s}}^{(K_{\max})})] \\ &\quad + \frac{4\alpha \bar{L} n^{2/3}}{v_{\min}^2 v_{\max}^2} \sum_{k=0}^{K_{\max}-1} \Xi^{(k+1)} + \sum_{k=0}^{K_{\max}-1} \Gamma_{k+1} \mathbb{E} \left[ \left\| \hat{\mathbf{s}}^{(k)} - \tilde{S}^{(k)} \right\|^2 \right] \end{aligned} \quad (128)$$

523

□

## 524 G Practical Implementations of Two-Time-Scale EM Methods

### 525 G.1 Application on GMM

#### 526 G.1.1 Explicit Updates

527 We first recognize that the constraint set for  $\theta$  is given by

$$\Theta = \Delta^M \times \mathbb{R}^M. \quad (129)$$

528 Using the partition of the sufficient statistics as  $S(y_i, z_i) =$   
 529  $(S^{(1)}(y_i, z_i)^\top, S^{(2)}(y_i, z_i)^\top, S^{(3)}(y_i, z_i)^\top)^\top \in \mathbb{R}^{M-1} \times \mathbb{R}^{M-1} \times \mathbb{R}$ , the partition  
 530  $\phi(\theta) = (\phi^{(1)}(\theta)^\top, \phi^{(2)}(\theta)^\top, \phi^{(3)}(\theta)^\top)^\top \in \mathbb{R}^{M-1} \times \mathbb{R}^{M-1} \times \mathbb{R}$  and the fact that  
 531  $\mathbb{1}_{\{M\}}(z_i) = 1 - \sum_{m=1}^{M-1} \mathbb{1}_{\{m\}}(z_i)$ , the complete data log-likelihood can be expressed as in  
 532 (2) with

$$\begin{aligned} s_{i,m}^{(1)} &= \mathbb{1}_{\{m\}}(z_i), \quad \phi_m^{(1)}(\theta) = \left\{ \log(\omega_m) - \frac{\mu_m^2}{2} \right\} - \left\{ \log(1 - \sum_{j=1}^{M-1} \omega_j) - \frac{\mu_M^2}{2} \right\}, \\ s_{i,m}^{(2)} &= \mathbb{1}_{\{m\}}(z_i) y_i, \quad \phi_m^{(2)}(\theta) = \mu_m, \quad s_i^{(3)} = y_i, \quad \phi^{(3)}(\theta) = \mu_M, \end{aligned} \quad (130)$$

533 and  $\psi(\theta) = -\left\{ \log(1 - \sum_{m=1}^{M-1} \omega_m) - \frac{\mu_M^2}{2\sigma^2} \right\}$ . We also define for each  $m \in \llbracket 1, M \rrbracket$ ,  $j \in \llbracket 1, 3 \rrbracket$ ,  
 534  $s_m^{(j)} = n^{-1} \sum_{i=1}^n s_{i,m}^{(j)}$ . Consider the following latent sample used to compute an approximation of  
 535 the conditional expected value  $\mathbb{E}_\theta[\mathbb{1}_{\{z_i=m\}} | y = y_i]$ :

$$z_{i,m} \sim \mathbb{P}(z_i = m | y_i; \theta) \quad (131)$$

536 where  $m \in \llbracket 1, M \rrbracket$ ,  $i \in \llbracket 1, n \rrbracket$  and  $\theta = (\mathbf{w}, \boldsymbol{\mu}) \in \Theta$ .

537 In particular, given iteration  $k + 1$ , the computation of the approximated quantity  $\tilde{S}_{i_k}^{(k)}$  during  
 538 Incremental-step updates, see (8) can be written as

$$\tilde{S}_{i_k}^{(k)} = \left( \underbrace{\mathbb{1}_{\{1\}}(z_{i_k,1}), \dots, \mathbb{1}_{\{M-1\}}(z_{i_k,M-1})}_{:=\tilde{s}_{i_k}^{(1)}}, \underbrace{\mathbb{1}_{\{1\}}(z_{i_k,1})y_{i_k}, \dots, \mathbb{1}_{\{M-1\}}(z_{i_k,M-1})y_{i_k}}_{:=\tilde{s}_{i_k}^{(2)}}, \underbrace{y_{i_k}}_{:=\tilde{s}_{i_k}^{(3)}(\theta^{(k)})} \right)^\top. \quad (132)$$

539 Recall that we have used the following regularizer:

$$\mathbf{r}(\theta) = \frac{\delta}{2} \sum_{m=1}^M \mu_m^2 - \epsilon \sum_{m=1}^M \log(\omega_m) - \epsilon \log(1 - \sum_{m=1}^{M-1} \omega_m), \quad (133)$$

540 It can be shown that the regularized M-step in (4) evaluates to

$$\bar{\theta}(\mathbf{s}) = \begin{pmatrix} (1 + \epsilon M)^{-1} (s_1^{(1)} + \epsilon, \dots, s_{M-1}^{(1)} + \epsilon)^\top \\ ((s_1^{(1)} + \delta)^{-1} s_1^{(2)}, \dots, (s_{M-1}^{(1)} + \delta)^{-1} s_{M-1}^{(2)})^\top \\ (1 - \sum_{m=1}^{M-1} s_m^{(1)} + \delta)^{-1} (s^{(3)} - \sum_{m=1}^{M-1} s_m^{(2)}) \end{pmatrix} = \begin{pmatrix} \bar{\omega}(\mathbf{s}) \\ \bar{\boldsymbol{\mu}}(\mathbf{s}) \\ \bar{\mu}_M(\mathbf{s}) \end{pmatrix}. \quad (134)$$

541 where we have defined for all  $m \in \llbracket 1, M \rrbracket$  and  $j \in \llbracket 1, 3 \rrbracket$ ,  $s_m^{(j)} = n^{-1} \sum_{i=1}^n s_{i,m}^{(j)}$ .

#### 542 G.1.2 Model Assumptions (GMM example)

543 We use the GMM example to illustrate the required assumptions.

544 Many practical models can satisfy the compactness of the sets as in Assumption H1 For instance,  
 545 the GMM example satisfies (17) as the sufficient statistics are composed of indicator functions and  
 546 observations as defined Section G.1 Equation (130).

Assumptions H2 and H3 are standard for the curved exponential family models. For GMM, the following (strongly convex) regularization  $\mathbf{r}(\theta)$  ensures H3:

$$\mathbf{r}(\theta) = \frac{\delta}{2} \sum_{m=1}^M \mu_m^2 - \epsilon \sum_{m=1}^M \log(\omega_m) - \epsilon \log(1 - \sum_{m=1}^{M-1} \omega_m)$$

547 since it ensures  $\theta^{(k)}$  is unique and lies in  $\text{int}(\Delta^M) \times \mathbb{R}^M$ . We remark that for H2, it is possible to  
 548 define the Lipschitz constant  $L_p$  independently for each data  $y_i$  to yield a refined characterization.

549 Again, H4 is satisfied by practical models. For GMM, it can be verified by deriving the closed form  
 550 expression for  $B(s)$  and using H1.

551 Under H1 and H3, we have  $\|\hat{s}^{(k)}\| < \infty$  since  $S$  is compact and  $\hat{\theta}^{(k)} \in \text{int}(\Theta)$  for any  $k \geq 0$  which  
 552 thus ensure that the EM methods operate in a closed set throughout the optimization process.

### 553 G.1.3 Algorithms updates

554 In the sequel, recall that, for all  $i \in \llbracket n \rrbracket$  and iteration  $k$ , the computed statistic  $\tilde{S}_{i_k}^{(k)}$  is defined by  
 555 (132). At iteration  $k$ , the several E-steps defined by (9) or (10) and (11) leads to the definition of the  
 556 quantity  $\hat{s}^{(k+1)}$ . For the GMM example, after the initialization of the quantity  $\hat{s}^{(0)} = n^{-1} \sum_{i=1}^n \bar{s}_i^{(0)}$ ,  
 557 those E-steps break down as follows:

558 **Batch EM (EM):** for all  $i \in \llbracket 1, n \rrbracket$ , compute  $\bar{s}_i^{(k)}$  and set

$$\hat{s}^{(k+1)} = n^{-1} \sum_{i=1}^n \bar{s}_i^{(k)}. \quad (135)$$

559 where  $\bar{s}_i^{(k)}$  are computed using the exact conditional expected balue  $\mathbb{E}_{\theta}[\mathbb{1}_{\{z_i=m\}} | y = y_i]$ :

$$\tilde{\omega}_m(y_i; \theta) := \mathbb{E}_{\theta}[\mathbb{1}_{\{z_i=m\}} | y = y_i] = \frac{\omega_m \exp(-\frac{1}{2}(y_i - \mu_i)^2)}{\sum_{j=1}^M \omega_j \exp(-\frac{1}{2}(y_i - \mu_j)^2)}, \quad (136)$$

560 **Incremental EM (iEM):** draw an index  $i_k$  uniformly at random on  $\llbracket n \rrbracket$ , compute  $\bar{s}_{i_k}^{(k)}$  and set

$$\hat{s}^{(k+1)} = \hat{s}^{(k)} + \frac{1}{n} (\bar{s}_{i_k}^{(k)} - \bar{s}_{i_k}^{(\tau_k)}) = n^{-1} \sum_{i=1}^n \bar{s}_i^{(\tau_k)}. \quad (137)$$

561 **batch SAEM (SAEM):** draw an index  $i_k$  uniformly at random on  $\llbracket n \rrbracket$ , compute  $\bar{s}_{i_k}^{(k)}$  and set

$$\hat{s}^{(k+1)} = \hat{s}^{(k)} (1 - \gamma_{k+1}) + \gamma_{k+1} \tilde{S}^{(k)}. \quad (138)$$

562 where  $= \frac{1}{n} \sum_{i=1}^n \tilde{S}_i^{(k)}$  with  $\tilde{S}_i^{(k)}$  defined in (132).

563 **Incremental SAEM (iSAEM):** draw an index  $i_k$  uniformly at random on  $\llbracket n \rrbracket$ , compute  $\bar{s}_{i_k}^{(k)}$  and set

$$\hat{s}^{(k+1)} = \hat{s}^{(k)} (1 - \gamma_{k+1}) + \gamma_{k+1} (\tilde{S}^{(k)} + \frac{1}{n} (\tilde{S}_{i_k}^{(k)} - \tilde{S}_{i_k}^{(\tau_k)})). \quad (139)$$

565 **Variance Reduced Two-Time-Scale EM (vrTTSEM):** draw an index  $i_k$  uniformly at random on  
 566  $\llbracket n \rrbracket$ , compute  $\bar{s}_{i_k}^{(k)}$  and set

$$\hat{s}^{(k+1)} = \hat{s}^{(k)} (1 - \gamma_{k+1}) + \gamma_{k+1} (\tilde{S}^{(k)} (1 - \rho) + \rho (\tilde{S}^{(\ell(k))} + (\tilde{S}_{i_k}^{(k)} - \tilde{S}_{i_k}^{(\ell(k))}))). \quad (140)$$

567 **Fast Incremental Two-Time-Scale EM (fiTTSEM):** draw an index  $i_k$  uniformly at random on  $\llbracket n \rrbracket$ ,  
 568 compute  $\bar{s}_{i_k}^{(k)}$  and set

$$\hat{s}^{(k+1)} = \hat{s}^{(k)} (1 - \gamma_{k+1}) + \gamma_{k+1} (\tilde{S}^{(k)} (1 - \rho) + \rho (\bar{\mathcal{S}}^{(k)} + (\tilde{S}_{i_k}^{(k)} - \tilde{S}_{i_k}^{(t_k)}))). \quad (141)$$

569 Finally, the  $k$ -th update reads  $\hat{\theta}^{(k+1)} = \bar{\theta}(\hat{s}^{(k+1)})$  where the function  $s \rightarrow \bar{\theta}(s)$  is defined by (134).

## 570 G.2 Application on PK Model

### 571 G.2.1 Explicit Updates

572 We recall that the complete model  $(y, z)$  defined by (40) and (41) belongs to the curved exponential  
 573 family, which vector of sufficient statistics  $S = (S_1(z), S_2(z), S_3(z))$  read:

$$S_1(z) = \frac{1}{n} \sum_{i=1}^n z_i, \quad S_2(z) = \frac{1}{n} \sum_{i=1}^n z_i^\top z_i, \quad S_3(z) = \frac{1}{n} \sum_{i=1}^n (y_i - f(t_i, z_i))^2 \quad (142)$$

574 where we have noted  $y_i$  and  $t_i$  the vector of observations and time for each patient  $i$ . At iter-  
575 ation  $k$ , and setting the number of MC samples to 1 for the sake of clarity, the MC sampling  
576  $z_i^{(k)} \sim p(z_i|y_i, \theta^{(k)})$  is performed using a Metropolis-Hastings procedure detailed in algorithm 2.  
577 The quantities  $\tilde{S}^{(k+1)}$  and  $\hat{s}^{(k+1)}$  are then updated according to the different methods. Finally the  
578 maximization step yields:

$$\bar{\theta}(s) = \begin{pmatrix} \hat{s}_1^{(k+1)} \\ \hat{s}_2^{(k+1)} - \hat{s}_1^{(k+1)} \left( \hat{s}_1^{(k+1)} \right)^\top \\ \hat{s}_3^{(k+1)} \end{pmatrix} = \begin{pmatrix} \overline{z_{\text{pop}}}(\hat{s}^{(k+1)}) \\ \overline{\omega_z}(\hat{s}^{(k+1)}) \\ \overline{\sigma}(\hat{s}^{(k+1)}) \end{pmatrix}. \quad (143)$$

## 579 G.2.2 Metropolis Hastings algorithm

580 During the simulation step of the MISSO method, the sampling from the target distribution  
581  $\pi(z_i, \theta) := p(z_i|y_i, \theta)$  is performed using a Metropolis Hastings (MH) algorithm [15] with pro-  
582 posal distribution  $q(z_i, \delta)$  where  $\theta = (z_{\text{pop}}, \omega_z)$  and  $\delta$  is the vector of parameters of the proposal  
583 distribution. Commonly they parameterize a Gaussian proposal. The MH algorithm is summarized  
584 in 2.

---

### Algorithm 2 MH algorithm

---

```

1: Input: initialization  $z_{i,0} \sim q(z_i; \delta)$ 
2: for  $m = 1, \dots, M$  do
3:   Sample  $z_{i,m} \sim q(z_i; \delta)$ 
4:   Sample  $u \sim \mathcal{U}([0, 1])$ 
5:   Calculate the ratio  $r = \frac{\pi(z_{i,m}; \theta) / q(z_{i,m}; \delta)}{\pi(z_{i,m-1}; \theta) / q(z_{i,m-1}; \delta)}$ 
6:   if  $u < r$  then
7:     Accept  $z_{i,m}$ 
8:   else
9:      $z_{i,m} \leftarrow z_{i,m-1}$ 
10:  end if
11: end for
12: Output:  $z_{i,M}$ 

```

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