

## SEQUENTIAL MAXIMUM LIKELIHOOD ESTIMATION IN NONLINEAR NONMARKOV DIFFUSION TYPE PROCESSES

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**ABSTRACT:** We obtain the strong consistency, uniform asymptotic normality and local asymptotic minimaxity (in the Hajek-LeCam sense) of the two stage sequential maximum likelihood estimator of a parameter appearing nonlinearly in the drift coefficient of a stochastic differential equation when the corresponding non-Markov diffusion type process is observed until the observed Fisher information of the process exceeds a predetermined level of precision and the level becomes large. Main results are illustrated by the exponential memory non-Markovian Ornstein-Uhlenbeck process.

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### 1. INTRODUCTION

For recent results on higher order likelihood asymptotics and Bayesian asymptotics for drift estimation of finite and infinite dimensional Markovian stochastic differential equations, see the monograph [3]. The long time asymptotics of the maximum likelihood estimator (MLE) and the Bayes estimators (BEs) of the drift parameter in the nonlinear nonhomogeneous Markov diffusion processes was studied by [4] and [34]. Here we study sequential estimation of the drift parameter of nonlinear nonhomogeneous non-Markovian diffusion type processes. For such processes Kutoyants [26] showed the asymptotic properties of MLE and regular BEs as the intensity of noise

$\epsilon \rightarrow 0$  when the model satisfies the LAN condition. Linkov [35] obtained the LAMN property of such models as observation time  $T \rightarrow \infty$ . Dietz [6] studied asymptotic properties of MLE as the intensity of noise  $\epsilon \rightarrow 0$  or the observation time  $T \rightarrow \infty$  when the model satisfies the LAMN condition. Dietz [7] studied the properties of MLE in a concrete example of diffusion type process which is an exponential memory nonhomogeneous process, a non-Markovian alternative to the Ornstein-Uhlenbeck process as the observation time  $T \rightarrow \infty$ . For a linear stochastic differential equation with time delay, the MLE shows eleven different behaviors for eleven parts of the parameter space [16].

However, in addition to asymptotic theory which certainly play a predominant role in statistical theory sequential asymptotics has certain advantages. Here we study the asymptotic properties of a sequential estimate of the parameter appearing in the drift coefficient of nonlinear nonhomogeneous diffusion type process, a non-Markovian process, when the solution process is observed continuously up to a random stopping time. In particular, we study the properties of sequential maximum likelihood estimate (SMLE), i.e., the maximum likelihood estimate based on observation of the process on the random time interval  $[0, \tau]$  where  $\tau$  is the stopping time which is the first passage time until the observed (stochastic) Fisher information of the process reaches a preassigned level of precision  $H$ . Under some regularity conditions, the SMLE is shown to be strongly consistent, asymptotically normal and locally asymptotically minimax in the Hajek-LeCam sense as  $H \rightarrow \infty$ .

For the linear diffusion model where the drift coefficient is  $b(\theta, t, x) = \theta a(t, x)$  and the diffusion coefficient is  $\sigma(t, x) = 1$ , Novikov [42] (see also [32]) proved that the SMLE of  $\theta$  is unbiased and exactly normally distributed for all values of the parameter in the parameter space  $\Theta \subset \mathbb{R}$ . Further, he showed that SMLE is optimal in the mean square sense and is more efficient in the sense of having less mean square error than the ordinary MLE based on fixed time observation, under the assumption that the mean durations of observation time in both the sampling plans are the same. Tikhov [47] proved that for the case  $b(\theta, t, x) = \theta a(t)$  and  $\sigma(t, x) = 1$ , the SMLE is optimal relative to the power loss function  $L_\alpha(|\delta(x) - \theta|) = |\delta(x) - \theta|^\alpha$ ,  $\alpha \geq 1$ . Tikhov [48] generalised this to the case  $b(\theta, t, x) = \theta b_1(t, x) + b_0(t, x)$ . Sørensen [45] gave a review of sequential maximum likelihood estimation in linearly parametrized diffusion type processes. Sørensen [46] (see also [24]) studied similar properties of SMLE for exponential families of stochastic processes. Musiela [40, 41] studied sequential ML estimation in a linear diffusion model. Le Breton and Musiela [31] studied similar properties of SMLE in linear homogeneous multidimensional SDE. Rozanskii [44] extended the work of Novikov [42] to a linear homogeneous diffusion field. Brown and Hewitt [5] studied the properties of sequential maximum likelihood estimator for diffusion branching process using a different type of stopping rule.

**2. MODEL, ASSUMPTIONS AND THE SEQUENTIAL PLAN**

Let  $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t \geq 0}, P)$  be a stochastic basis satisfying the usual hypotheses on which we have a real valued non-Markovian diffusion type process  $\{X_t, t \geq 0\}$  satisfying the functional stochastic differential equation (SDE)

$$\begin{aligned} dX_t &= f(\theta, t, X)dt + dW_t, \quad t \geq 0, \\ X_0 &= \xi \end{aligned} \tag{2.1}$$

where  $\{W_t, t \geq 0\}$  is a standard Wiener process,  $\xi$  is a  $\mathcal{F}_0$ -measurable random variable with  $P\{|\xi| < \infty\} = 1$ ,  $\theta \in \Theta$  a compact subset of  $\mathbb{R}$  is the unknown parameter to be estimated on the basis of observation of the process  $\{X_t, t \geq 0\}$ . The measurable function  $f(\theta, t, x)$ ,  $t \geq 0$ ,  $\theta \in \Theta$  and  $x \in C$  are assumed to be (for each fixed  $\theta$ ) nonanticipative, that is  $\mathcal{B}_t$ -measurable for each  $t \geq 0$ . Here  $(C, \mathcal{B})$  is the space of continuous functions  $\{x_t, t \geq 0\}$  with  $x_0 = \xi$  with the associated Borel  $\sigma$ -algebra  $\mathcal{B}$  and  $\mathcal{B}_t = \sigma(X_s, s \geq t)$  are  $\sigma$ -algebras in the measurable space  $(C, \mathcal{B})$ .

Prime denotes derivative with respect to  $\theta$  throughout the paper. We assume the following conditions.

$$(A1) \int_0^T f^2(\theta, t, x)dt < \infty, \quad T < \infty, \quad x \in C, \quad \theta \in \mathbb{R},$$

$$(A2) P\left(\int_0^\infty f'^2(\theta, t, X)dt = \infty\right) = 1, \quad \theta \in \mathbb{R},$$

$$(A3) |f(\theta, t, x) - f(\theta, t, y)| \leq M_1 \int_0^t |x_s - y_s|ds + M_2|x_t - y_t|,$$

$$f^2(\theta, t, x) \leq M_1 \int_0^t (1 + |x_s|)ds + M_2(1 + |x_t|),$$

where  $x_s, y_s \in C, \theta \in \mathbb{R}, M_1$  and  $M_2$  are constants.

Under the condition (A3), it is well known that equation (2.1) has a unique solution (see [24]).

We estimate the unknown parameter  $\theta$  from the observation of the process  $\{X_t, t \geq 0\}$  until the observed Fisher information exceeds a predetermined level of precision. This idea of using observed Fisher information to define a stopping rule dates back to [1] (see also [11, 12]). This type of stopping rule was used for autoregressive parameter estimation in [8, 9, 29, 38, 43] among others.

Let  $\tau = \tau(X)$  be a Markov stopping time with respect to the system  $\{\mathcal{B}_t\}_{t \geq 0}$  and  $\delta(t, X)$  be a progressively measurable real process defined on  $(C, \mathcal{B})$ . The pair of functions  $D = D(\tau, \delta)$ , where  $\tau(X)$  is a Markov time and  $\delta = \delta(\tau(X), X)$  is an estimate of  $\theta$  resulting from the observation of the trajectory of  $X$  on the time interval  $[0, \tau(X)]$  yields a sequential sampling plan.

Let  $P_\theta^T$  be the measure generated by the process  $\{X_t, 0 \leq t \leq T\}$  on the space  $(C_T, \mathcal{B}_T)$  of continuous functions from  $[0, T] \rightarrow \mathbb{R}$  with the associated Borel  $\sigma$ -algebra

$\mathcal{B}_T$  under the supremum norm and  $P_W^T$  be the measure generated by  $\xi + W_t$  on the space  $(C_T, \mathcal{B}_T)$ . Let  $E_\theta^T$  denote the expectation w.r.t. measure  $P_\theta^T$ . Under the assumption (A1),  $P_\theta^T \ll P_W^T$  and the Radon-Nikodym derivative (likelihood function based on sample path  $X_0^T := (X_s, 0 \leq s \leq T)$ ) is given by

$$L_T(\theta) = \frac{dP_\theta^T}{dP_W^T}(X_0^T) = \exp \left\{ \int_0^T f(\theta, t, X) dX_t - \frac{1}{2} \int_0^T f^2(\theta, t, X) dt \right\}. \quad (2.2)$$

Maximization of the likelihood  $L_T(\theta)$  provides the maximum likelihood estimate (MLE)  $\theta_T$ . Dietz [6] proved the consistency and asymptotic mixed normality of  $\theta_T$  as  $T \rightarrow \infty$ . Kutoyants [25, 27] also studied the asymptotic properties of MLE as the diffusion coefficient  $\epsilon \rightarrow 0$  (for fixed  $T$ ).

Let  $l_T(\theta) := \log L_T(\theta)$ . We assume that differentiation under the stochastic and ordinary integral sign is valid (see [23]).

Note that  $\theta_t$  is the MLE based on the sample path  $X_0^t := (X_s, 0 \leq s \leq t)$ . The MLE process satisfies the following evolution equation (see [34]) when  $X = X_t$  in the drift coefficient in equation (2.1):

$$\begin{aligned} d\theta_t &= -l_t''^{-1}(\theta_t) \{ f'(\theta_t, t, X_t) [dX_t - f(\theta_t, t, X_t) dt] \\ &\quad + [\frac{1}{2} l_t'''(\theta_t) l_t''^{-2}(\theta_t) f'^2(\theta_t, t, X_t) - l_t''^{-1}(\theta_t) f'(\theta_t, t, X_t) f''(\theta_t, t, X_t)] dt \}, \end{aligned} \quad (2.3)$$

with initial conditions:  $\theta_{t_0} < \infty$ ,  $l_t'(\theta_{t_0}) = 0$ ,  $l_t''(\theta_{t_0}) < 0$  where the initial time  $t_0 > 0$  is fixed. This shows that in this case the MLE process itself is a continuous semimartingale.

We have

$$\begin{aligned} l_T'(\theta) &= \int_0^T f'(\theta, t, X) dX_t - \int_0^T f(\theta, t, X) f'(\theta, t, X) dt \\ &= \int_0^T f'(\theta, t, X) [dX_t - f(\theta, t, X) dt] \\ &= \int_0^T f'(\theta, t, X) dW_t \end{aligned} \quad (2.4)$$

when  $\theta$  is the true parameter.

We shall use the Fisher information to define a stopping rule. The a priori Fisher information is

$$I(\theta) = \text{var}[l_T'(\theta)] = E_\theta^T [l_T'(\theta)]^2 = E_\theta^T \int_0^T f'^2(\theta, t, X) dt. \quad (2.5)$$

But  $I(\theta)$  can not be observed since it depends on the unknown parameter. The a posteriori observed Fisher information or stochastic Fisher information is given by

$$I_T = \int_0^T f'^2(\theta_t, t, X) dt \quad (2.6)$$

where  $\theta_t$  is the MLE based on the observation  $\{X_s, 0 \leq s \leq t\}$ .

Note that in the linear case the a priori Fisher information does not contain the unknown parameter. We are now ready to define the sequential sampling plan  $(\tau, \theta_\tau)$  as follows :

The stopping time  $\tau$  is defined as

$$\tau \equiv \tau_H := \inf\{t \geq 0 : \int_0^t f'^2(\theta_s, s, X)ds \geq H\} \tag{2.7}$$

where  $H > 0$  specifies the desired precision which is predetermined and  $\theta_s$  is the MLE based on the observation of  $X$  in the time interval  $[0, s]$ . Note that by Sudakov's lemma, the likelihood based on  $[0, \tau]$  is given by

$$L_\tau(\theta) = \frac{dP_\theta^\tau}{dP_W^\tau}(X_0^\tau) = \exp\left\{\int_0^\tau f(\theta, t, X)dX_t - \frac{1}{2}\int_0^\tau f^2(\theta, t, X)dt\right\}. \tag{2.8}$$

(see [32]). The sequential maximum likelihood estimate (SMLE) is defined as

$$\theta_\tau := \arg \max_{\theta \in \Theta} L_\tau(\theta).$$

We call the procedure here a two stage estimation procedure since we use an estimated stopping time to define the sequential estimate. One can show that there exists a  $\mathcal{F}_\tau$  measurable SMLM since  $L_\tau(\theta)$  is continuous in  $\theta$  and  $\Theta$  is compact. Hereafter we assume the existence of such a measurable SMLM.

### 3. CONSISTENCY AND ASYMPTOTIC NORMALITY

We assume the following conditions to prove the main results of this section.

(B1)  $P_{\theta_1}^\tau \neq P_{\theta_2}^\tau$  for  $\theta_1 \neq \theta_2$  in  $\Theta$ .

(B2)  $l_\tau(\theta)$  is twice continuously differentiable in a neighborhood  $U_\theta$  of  $\theta$  for every  $\theta \in \Theta$ .

(B3)  $\lim_{H \rightarrow \infty} \frac{1}{H} \int_0^\tau f''(\theta, t, X)dW_t = 0$  in  $P_\theta$ -probability.

**Remark 3.1.** Condition (B1) is the identifiability condition. Due to the consistency of the MLE  $\theta_t$  and by the definition of  $\theta_\tau$  this condition can be verified. Condition (B2) is provided for regularity. Condition (B3) is related to the law of large numbers for stochastic integrals.

**Lemma 3.1.** *Let  $A_t^\theta := f(\theta \pm \delta, t, X) - f(\theta, t, X)$  for some  $\delta > 0$ . Then under (A1)–(A3), we have*

$$\frac{\int_0^\tau (A_t^\theta)^2 dt}{\int_0^\tau (A_t^{\theta_t})^2 dt} \rightarrow 1 \quad \text{a.s. } [P_\theta^\tau] \text{ as } H \rightarrow \infty.$$

**Proof.** We have

$$\begin{aligned} A_t^\theta &= f(\theta \pm \delta, t, X) - f(\theta, t, X), \\ A_t^{\theta_t} &= f(\theta_t \pm \delta, t, X) - f(\theta_t, t, X). \end{aligned}$$

Thus

$$(A_t^\theta)^2 - (A_t^{\theta_t})^2 = [f(\theta \pm \delta, t, X) - f(\theta, t, X)]^2 - [f(\theta_t \pm \delta, t, X) - f(\theta_t, t, X)]^2.$$

Since  $\theta_t$  is a strongly consistent estimator of  $\theta$ ,  $\theta_t \rightarrow \theta$  a.s. as  $t \rightarrow \infty$ . Since  $f$  is continuous,  $(A_t^\theta)^2 - (A_t^{\theta_t})^2 \rightarrow 0$  a.s. as  $t \rightarrow \infty$ .

Further

$$\int_0^\tau (A_t^{\theta_t})^2 dt \rightarrow c(\theta) \text{ a.s. as } H \rightarrow \infty \text{ and } \delta \rightarrow 0$$

where  $c(\theta)$  is a positive constant and

$$\int_0^\tau [(A_t^\theta)^2 - (A_t^{\theta_t})^2] dt \rightarrow 0 \text{ a.s. as } H \rightarrow \infty.$$

Thus

$$\frac{\int_0^\tau [(A_t^\theta)^2 - (A_t^{\theta_t})^2] dt}{\int_0^\tau (A_t^{\theta_t})^2 dt} \rightarrow 0 \text{ a.s. } [P_\theta^\tau] \text{ as } H \rightarrow \infty.$$

This completes the proof of the lemma.  $\square$

The definition of first order efficiency (in the sense of C.R. Rao) of estimators for stochastic processes (cf. [17]) may be generalized to sequential sampling case as follows:

**Definition 3.1.** An estimator  $V_{\tau_H}$  of  $\theta$  is said to be *first order efficient* (FOE) if

$$\sqrt{H} \left[ V_{\tau_H} - \theta - \gamma(\theta) H^{-1} \frac{\partial l_\tau(\theta)}{\partial \theta} \right] \xrightarrow{P_\theta} 0 \text{ as } H \rightarrow \infty$$

where  $\gamma(\theta)$  is a nonrandom function.

We establish following properties of the SMLE.

**Theorem 3.1.** (a) Under the assumption (A1) – (A3), the sampling plan is closed, i.e.,  $\tau_H < \infty$   $P_\theta$ -a.s.

Under the assumptions (A1) – (A3) and (B1) – (B3), we have

(b) There exists a root of the likelihood equation which is strongly consistent, i.e.,  $\lim_{H \rightarrow \infty} \theta_\tau = \theta$  a.s.  $[P_\theta]$

(c)  $\sqrt{H}(\theta_\tau - \theta) \xrightarrow{D[P_\theta]} \mathcal{N}(0, 1)$  as  $H \rightarrow \infty$  uniformly in  $\theta \in \Theta$ .

(d)  $\theta_\tau$  is first order efficient as  $H \rightarrow \infty$ .

**Proof.** (a) From assumption (A2) it is obvious that  $\tau_H < \infty$  a.s.  $[P_\theta]$ .

(b) Observe that, for  $\delta > 0$ ,

$$\begin{aligned}
 & l_\tau(\theta \pm \delta) - l_\tau(\theta) \\
 = & \log \frac{dP_{\theta \pm \delta}^\tau}{dP_\theta^\tau} \\
 = & \int_0^\tau [f(\theta \pm \delta, t, X) - f(\theta, t, X)]dX_t - \frac{1}{2} \int_0^\tau [f^2(\theta \pm \delta, t, X) - f^2(\theta, t, X)]dt \\
 = & \int_0^\tau [f(\theta \pm \delta, t, X) - f(\theta, t, X)]dW_t - \frac{1}{2} \int_0^\tau [f(\theta \pm \delta, t, X) - f(\theta, t, X)]^2 dt \\
 = & \int_0^\tau A_t^\theta dW_t - \frac{1}{2} \int_0^\tau (A_t^\theta)^2 dt.
 \end{aligned}$$

Let

$$K_\tau := \int_0^\tau (A_t^\theta)^2 dt.$$

Then

$$\begin{aligned}
 \frac{l_\tau(\theta \pm \delta) - l_\tau(\theta)}{K_\tau} &= \frac{\int_0^\tau A_t^\theta dW_t}{\int_0^\tau (A_t^\theta)^2 dt} - \frac{1}{2} \\
 &= \frac{W^*(\int_0^\tau (A_t^\theta)^2 dt)}{\int_0^\tau (A_t^\theta)^2 dt} - \frac{1}{2} \\
 &= \frac{W^*(K_\tau)}{K_\tau} - \frac{1}{2}
 \end{aligned} \tag{3.1}$$

by the Skorohod embedding of the martingale  $\int_0^\tau A_t^\theta dW_t$  where  $W^*$  is some other Brownian motion with independent of  $K_\tau$ .

Using the assumption (A2) and Lemma 3.1, and the strong law of large numbers for Brownian motion (see [32]) the first term on the r.h.s. of (3.1) converges to zero a.s. as  $H \rightarrow \infty$ . Hence,

$$\frac{l_\tau(\theta \pm \delta) - l_\tau(\theta)}{K_\tau} \rightarrow -\frac{1}{2} \text{ a.s. } [P_\theta] \text{ as } H \rightarrow \infty.$$

Furthermore,  $K_\tau > 0$  a.s.  $[P_\theta]$  by (B1). Therefore, for almost every  $w \in \Omega, \delta$  and  $\theta$ , there exist some  $H_0$  such that for  $H \geq H_0$

$$l_\tau(\theta \pm \delta) < l_\tau(\theta). \tag{3.2}$$

Since  $l_\tau(\theta)$  is continuous on the compact set  $[\theta - \delta, \theta + \delta]$ , it has a local maximum and it is attained at a measurable  $\theta_\tau$  in  $[\theta - \delta, \theta + \delta]$ . In view of (3.2),  $\theta_\tau \in (\theta - \delta, \theta + \delta)$  for  $H > H_0$ . Since  $l_\tau(\theta)$  is differentiable with respect to  $\theta$ , it follows that  $l'_\tau(\theta_\tau) = 0$  for  $H \geq H_0$  and  $\theta_\tau \rightarrow \theta$  a.s. as  $H \rightarrow \infty$ .

(c) In view of the assumption (B3), we can apply Taylor's expansion, for  $l'_\tau(\theta)$  around  $\theta_\tau$  and write

$$0 = l'_\tau(\theta_\tau) = l'_\tau(\theta) + (\theta_\tau - \theta)l''_\tau(\theta + \beta_\tau(\theta_\tau - \theta)) \tag{3.3}$$

where  $|\beta_\tau| \leq 1$  a.s. for sufficiently large  $H$ .

Since  $\theta_\tau \rightarrow \theta$  a.s. as  $H \rightarrow \infty$  by (b) and since  $l''_\tau(\theta)$  is continuous by (B3), it follows that  $l''_\tau(\theta + \beta_\tau(\theta_\tau - \theta)) - l''_\tau(\theta) \rightarrow 0$  in  $P_\theta^\tau$ -probability as  $H \rightarrow \infty$ .

Hence as  $H \rightarrow \infty$

$$l'_\tau(\theta) + (\theta_\tau - \theta)l''_\tau(\theta) \rightarrow 0 \text{ in } P_\theta^\tau\text{-probability.} \quad (3.4)$$

We have  $l'_\tau(\theta) = \int_0^\tau f'(\theta, t, X)dW_t$ . Hence using the C.L.T. for stochastic integral (see [2]) and Lemma 3.1, we obtain

$$\frac{l'_\tau(\theta)}{\sqrt{H}} \xrightarrow{\mathcal{D}[P_\theta]} \mathcal{N}(0, 1) \text{ as } H \rightarrow \infty \quad (3.5)$$

Note that when  $\theta$  is the true parameter

$$\begin{aligned} l''_\tau(\theta) &= \int_0^\tau f''(\theta, t, X)dX_t - \int_0^\tau [f(\theta, t, X)f''(\theta, t, X) + f'^2(\theta, t, X)]dt \\ &= \int_0^\tau f''(\theta, t, X)dW_t - \int_0^\tau f'^2(\theta, t, X)dt. \end{aligned}$$

By Lemma 3.1 and (B3) it follows that

$$\frac{l''_\tau(\theta)}{H} \rightarrow -1 \text{ in } P_\theta\text{-probability as } H \rightarrow \infty. \quad (3.6)$$

From (3.5) and (3.6) it follows that

$$\sqrt{H}(\theta_\tau - \theta) \xrightarrow{\mathcal{D}[P_\theta]} \mathcal{N}(0, 1) \text{ as } H \rightarrow \infty.$$

(d) From (3.5) and (3.6) and the definition of first order efficiency with  $\gamma(\theta) = 1$ , SMLE  $\theta_\tau$  is first order efficient as  $H \rightarrow \infty$ .  $\square$

#### 4. LOCAL ASYMPTOTIC MINIMAXITY

In this section we prove the local asymptotic minimaxity of the SMLE  $\theta_\tau$  in the Hajek-Le Cam sense. Roughly speaking an estimator is said to be locally asymptotically minimax if it attains the lower bound in Hajek-Le Cam minimax theorem (see [21, 33]), i.e. if it attains the lower bound to the local asymptotic minimax risk of the normalized error an estimator. The minimum requirement for Hajek's minimax theorem is that the model should satisfy the LAN (locally asymptotically normal) or LAMN (locally asymptotically mixed normal) condition. When these conditions are satisfied the lower bound is attained only if the estimator is *asymptotically centering* (AC) (see [21]). But there are situations where either of the above two conditions may not be attained. Consider, for example, the Ornstein-Uhlenbeck process with



drift coefficient  $\theta X_t$ . This process exhibits qualitatively different behavior for different values of the parameter  $\theta$ . For  $\theta < 0$ , the model satisfies the LAN condition and for  $\theta > 0$  the model satisfies the LAMN condition. The point  $\theta = 0$  is critical. At  $\theta = 0$ , it satisfies neither the LAN condition nor the LAMN condition, but it satisfies the LABF (locally asymptotically Brownian functional) condition. The model satisfies LAQ (locally asymptotically quadraticity) for all  $\theta$ . Similar situations occur in its discrete time counterpart : the Gaussian autoregressive process of first order and other processes like the Galton-Watson branching processes, pure birth processes etc. (see [15]). Greenwood and Shirayayev [13] proved the uniform local asymptotic minimaxity of the SMLE of the parameter in the first order Gaussian autoregressive process by studying the uniform weak convergence of statistical experiments using the convergence of the associated Hellinger processes. Under the LAQ condition, Hajek’s minimax theorem is available, but the AC estimators do not attain the lower bound, i.e., they will not be locally asymptotically minimax. Greenwood and Wefelmeyer [14] showed that local asymptotic minimax bound is attained by asymptotically centering estimators even at critical points, which requires sequential sampling. In the nonlinear diffusion type model with sequential sampling, the more general functionally LAQ condition is satisfied which allows us to obtain locally asymptotic minimax bound for the normalized error of the sequential MLE. We now recall the definition of LAQ and functionally LAQ conditions.

**Definition 4.1** ([22, 33]). Let  $\mathcal{E}_n = (\Omega_n, \mathcal{F}_n, (P_\theta^n, \theta \in \Theta)), n \geq 1$  be a sequence of statistical experiments, where  $\Theta$  is an open subset of  $\mathbb{R}$ . We denote by

$$\Lambda_{\eta, \theta}^n = \log \left( \frac{dP_\eta^n}{dP_\theta^n} \right)$$

the log-likelihood between  $\eta$  and  $\theta$  at stage  $n$ .

We say that the sequence  $\mathcal{E}_n$  satisfies the *local asymptotically quadratic* (LAQ) condition at a point  $\theta \in \Theta$  if there are random variables  $\Delta_n$  and  $\Gamma_n$  defined on  $(\Omega_n, \mathcal{F}_n), \Gamma_n > 0$  a.s.  $[P_\theta^n]$  and a positive numerical sequence  $\phi_n \downarrow 0$  such that for each bounded sequence of numbers  $u_n$ ,

$$\Lambda_{\theta + \phi_n u_n, \theta}^n - \left( u_n \Delta_n - \frac{1}{2} u_n^2 \Gamma_n \right) \xrightarrow{P_\theta^n} 0$$

and

$$(\Delta_n, \Gamma_n) \rightarrow (\Delta, \Gamma) \text{ in } P_\theta^n\text{-distribution}$$

where  $\Delta$  and  $\Gamma$  are random variables on a measurable space  $(\Omega, \mathcal{F}, P)$  with  $\Gamma > 0$  a.s.  $(P)$  and

$$E_P \exp \left( u \Delta - \frac{1}{2} u^2 \Gamma \right) = 1.$$

The sequence of experiments is called *locally asymptotically Brownian functional* (LABF) if  $\Delta = \int_0^1 F_s dW_s$  and  $\Gamma = \int_0^1 F_s^2 ds$  with  $W$  a standard Brownian motion and  $F$  a predictable process with respect to some filtration in  $\mathcal{F}$ . It is called *locally asymptotically mixed normal* (LAMN) if  $\Delta = \Gamma^{1/2}W_1$  with  $W_1$  standard normal variable independent of  $\Gamma$  and *locally asymptotically normal* (LAN) if, in addition,  $\Gamma$  is nonrandom.

**Definition 4.2** ([15]). Let the sequence  $(\mathcal{E}_n)$  satisfy LAQ condition at a point  $\theta \in \Theta$ . A sequence of estimators  $\hat{\theta}_n$  is called *asymptotically centering* (AC) sequence at  $\theta$  if

$$\phi_n^{-1}(\hat{\theta}_n - \theta) - \Gamma_n^{-1} \Delta_n \xrightarrow{P_\theta^n} 0.$$

Asymptotically centering estimators are also called *asymptotic maximum likelihood estimators*.

Let  $(\Omega^n, \mathcal{F}^n, \{\mathcal{F}_t^n\}_{t \geq 0}, \{P_\theta^n, \theta \in \Theta\})$  where  $\Theta$  is an open subset of  $\mathbb{R}$ , be a sequence of filtered statistical experiments. Let  $P_{\theta,t}^n$  be the restriction of  $P_\theta^n$  to  $\mathcal{F}_t^n$ .

The log-likelihood process  $\Lambda_{\eta,\theta}^n$  at stage  $n$  between  $\eta$  and  $\theta$  at time  $t$  is defined by

$$\Lambda_{\eta,\theta,t}^n = \log \left( \frac{dP_{\eta,t}^n}{dP_{\theta,t}^n} \right), \quad t \geq 0.$$

**Definition 4.3** ([14]). We call the sequence of filtered experiments *functionally LAQ* at  $\theta$  if there exist processes  $\Delta_n$  and  $\Gamma_n > 0$  a.s. and a positive numerical sequence  $\phi_n \downarrow 0$  such that for each bounded sequence of numbers  $u_n$  and all  $t > 0$ ,

$$\sup_{s \leq t} \left| \Lambda_{\theta + \phi_n u_n, \theta, s}^n - \left( u_n \Delta_s^n - \frac{1}{2} u_n^2 \Gamma_s^n \right) \right| \xrightarrow{P_\theta^n} 0$$

and

$$(\Delta_t^n, \Gamma_t^n) \rightarrow (\Delta_t, \Gamma_t) \text{ in } P_\theta^n\text{-distribution}$$

where  $\Delta_t$  and  $\Gamma_t$  are processes on a filtered probability space  $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t \geq 0}, P)$  with  $\Gamma_t > 0$  a.s. and

$$E_P \exp \left( u \Delta_t - \frac{1}{2} u^2 \Gamma_t \right) = 1 \text{ for all } t \geq 0.$$

We call the sequence of filtered models *functionally LABF* if  $\Delta_t = \int_0^t F_s dW_s$  and  $\Gamma_t = \int_0^t F_s^2 ds$  where  $W$  is a standard Brownian motion and  $F$  is a predictable process.

**Theorem 4.1** ([14]). *Suppose the sequence of filtered models is functionally LAQ at  $\theta$ , with  $\Delta$  a continuous local martingale,  $\Gamma$  equal to the quadratic variation  $\langle \Delta \rangle$  of  $\Delta$ , and  $\Gamma$  strictly increasing to infinity a.s. Let  $\omega$  be a bounded, symmetric, bowl shaped loss function on the real line, and let  $\hat{\theta}^n$  be a sequence of estimator processes. For each  $n \in \mathbb{N}$  and  $t \geq 0$ , let*

$$\mathcal{T}_t^n = \inf \{s : \Gamma_s^n > t\}.$$

Then

$$\lim_{b \rightarrow \infty} \liminf_{n \rightarrow \infty} \sup_{|u| \leq b} E_{\theta + \phi_n u} \omega \left( \phi_n^{-1}(\hat{\theta}_{\mathcal{T}_t^n} - (\theta + \phi_n u)) \right) \geq E\omega(W_{1/t}).$$

If a filtered model satisfies the functionally LAN condition, then the filtered model time changed by  $T^n$  satisfies the functionally LAQ condition, which is evident from the following result in [14].

**Lemma 4.1** *Under the assumptions of Theorem 4.1, for each bounded sequence of numbers  $u_n$  and all  $t > 0$ ,*

$$\sup_{s \leq t} \left| \Lambda_{\theta + \phi_n u_n, \theta, \mathcal{T}_s^n} - \left( u_n \Delta_{\mathcal{T}_s^n} - \frac{1}{2} u_n^2 s \right) \right| \xrightarrow{P_\theta^n} 0$$

and

$$\Delta_{\mathcal{T}_t^n} \rightarrow W_1 \text{ in } P_\theta^n\text{-distribution.}$$

If the assertions of Lemma 4.1 hold then the sequence of models is said to satisfy the *functionally LAN* condition.

**Definition 4.4** ([14]). If the sequence of filtered models is functionally LAQ at  $\theta$ , we call a sequence of estimator process  $\hat{\theta}^n$  *functionally AC* at  $\theta$ , if for all  $t > 0$ ,

$$\sup_{s \leq t} \left| \phi_n^{-1}(\hat{\theta}_s^n - \theta) - \Delta_s^n (\Gamma_s^n)^{-1} \right| \xrightarrow{P_\theta^n} 0.$$

The filtered model observed up to  $\mathcal{T}_t^n$  is LAN, hence by the classical theory, the local asymptotic minimax theorem applies and  $\hat{\theta}_{\mathcal{T}_t^n}^n$  are locally asymptotically minimax if and only if they are AC.

Let us return to our problem. Let us introduce the time changed estimator processes. For each  $n \in \mathbb{N}$ , we define the retimed processes  $X_t^n = n^{-1/2} X_{nt}$  and  $W_t^n = n^{-1/2} W_{nt}$ ,  $t \geq 0$  and the filtration  $\{\mathcal{F}_t^n\}_{t \geq 0}$  be generated by  $X^n$ ,  $\mathcal{F}_t^n = \{X_s^n, s \leq t\} = \sigma\{X_s, s \leq nt\}$ . The log-likelihood process at stage  $n$  and time  $t$  between  $\theta_1$  and  $\theta$  is given by

$$\Gamma_{\theta_1, \theta, t}^n = \int_0^t [f(\theta_1, s, X_s^n) - f(\theta, s, X_s^n)] dW_s^n - \frac{1}{2} \int_0^t [f(\theta_1, s, X_s^n) - f(\theta, s, X_s^n)] ds.$$

We assume the following conditions in this section. There exist  $r_n \uparrow \infty$  as  $n \uparrow \infty$  and  $\nu > 0$  such that:

(C1)  $\frac{1}{r_n^2} \int_0^\nu f''^2(\theta, s, X_s^n) ds \xrightarrow{P_\theta^n} \zeta_\nu(\theta)$  as  $n \rightarrow \infty$ , where  $P_\theta^n[\zeta_\nu(\theta) > 0] > 0$ .

(C2)  $\frac{1}{r_n^2} \int_0^\nu f'(\theta, s, X_s^n) ds \xrightarrow{P_\theta^n} \xi_\nu(\theta)$  as  $n \rightarrow \infty$ , where  $P_\theta^n[\xi_\nu(\theta) > 0] > 0$ .

(C3)  $\frac{1}{r_n^2} \int_0^\nu f''(\theta, s, X_s^n) dW_s^n \xrightarrow{P_\theta^n} 0$  as  $n \rightarrow \infty$ .

**Theorem 4.2.** *Under the assumptions (C1) – (C3), the sequence of filtered models  $(\Omega^n, \mathcal{F}^n, \{\mathcal{F}_t^n\}_{t \geq 0}, \{P_\theta^n, \theta \in \Theta\})$  generated by  $X_t^n$  satisfy the functionally LAQ condition at  $\theta$  with*

$$\Delta_t = \int_0^t f'(\theta, s, X_s) dW_s \text{ and } \Gamma_t = \int_0^t f'^2(\theta, s, X_s) ds.$$

**Proof.** For  $\nu \leq t$ , we have

$$\begin{aligned} \Lambda_{\theta+r_n^{-1}u_n, \theta, \nu}^n &= \int_0^\nu [f(\theta + r_n^{-1}u_n, s, X_s^n) - f(\theta, s, X_s^n)] dW_s^n \\ &\quad - \frac{1}{2} \int_0^\nu [f(\theta + r_n^{-1}u_n, s, X_s^n) - f(\theta, s, X_s^n)]^2 ds. \end{aligned}$$

By Taylor's formula

$$f(\theta + r_n^{-1}u_n, s, X_s^n) - f(\theta, s, X_s^n) = r_n^{-1}u_n f'(\theta, s, X_s^n) + \frac{1}{2} r_n^{-2} u_n^2 f''(\bar{\theta}, s, X_s^n)$$

where

$$\bar{\theta} = \theta + q(s, X_s^n) r_n^{-1} u_n, \quad |q(\cdot, \cdot)| < 1.$$

Hence

$$\begin{aligned} \Lambda_{\theta+r_n^{-1}u_n, \theta, \nu}^n &= r_n^{-1} u_n \int_0^\nu f'(\theta, s, X_s^n) dW_s^n + \frac{1}{2} r_n^{-2} u_n^2 \int_0^\nu f''(\bar{\theta}, s, X_s^n) dW_s^n \\ &\quad - \frac{1}{2} r_n^{-2} u_n^2 \int_0^\nu f'^2(\theta, s, X_s^n) ds - \frac{1}{8} r_n^{-4} u_n^4 \int_0^\nu f''^2(\bar{\theta}, s, X_s^n) ds \\ &\quad - \frac{1}{8} r_n^{-3} u_n^3 \int_0^\nu f'(\theta, s, X_s^n) f''(\bar{\theta}, s, X_s^n) ds \\ &= r_n^{-1} u_n \int_0^\nu f'(\theta, s, X_s^n) dW_s^n - \frac{1}{2} r_n^{-2} u_n^2 \int_0^\nu f'^2(\theta, s, X_s^n) ds + o_{P_\theta^n}(1) \\ &\quad \text{(by assumption (C1) – (C3))} \\ &= u_n \Delta_\nu^n - \frac{1}{2} u_n^2 \Gamma_\nu^n + o_{P_\theta^n}(1), \end{aligned}$$

where

$$\Delta_\nu^n = r_n^{-2} \int_0^\nu f'(\theta, s, X_s^n) dW_s^n \text{ and } \Gamma_\nu^n = r_n^{-2} \int_0^\nu f'^2(\theta, s, X_s^n) ds.$$

Let

$$\Delta_\nu = \int_0^\nu f'(\theta, s, X_s) dW_s \text{ and } \Gamma_\nu = \int_0^\nu f'^2(\theta, s, X_s) ds.$$

By the functional CLT for martingales and stability of weak convergence (see [20]), we obtain

$$(\Delta_\nu^n, \Gamma_\nu^n) \xrightarrow{\mathcal{D}[P_\theta^n]} (\Delta_\nu, \Gamma_\nu) \text{ as } n \rightarrow \infty.$$

Here  $\Delta_\nu$  and  $\Gamma_\nu$  are processes on a filtered probability space  $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t \geq 0}, P)$  with  $\Gamma_\nu > 0$  a.s. and

$$E_P \exp \left( u \Delta_\nu - \frac{1}{2} u^2 \Gamma_\nu \right) = 1 \text{ for all } \nu \geq 0.$$

Thus the sequence of filtered models are functionally LAQ at  $\theta$ . □

We now obtain the local asymptotic minimax theorem for SMLE processes.

**Theorem 4.3.** *Let  $\omega$  be a bounded, symmetric, bowl shaped loss function on the real line. Let  $\theta_t^n$  be a sequence of MLE processes w.r.t. the filtered model  $(\Omega^n, \mathcal{F}^n, \{\mathcal{F}_t^n\}_{t \geq 0}, \{P_\theta, \theta \in \Theta\})$ .*

*For each  $n \in \mathbb{N}$  and  $t \geq 0$ , let*

$$\tau_H^n = \inf \{ t \geq 0 : r_n^{-2} \int_0^t f'^2(\theta_s^n, s, X_s^n) ds \geq H \}$$

*Let conditions (C1) – (C3) be satisfied. Then*

$$\lim_{b \rightarrow \infty} \liminf_{n \rightarrow \infty} \sup_{|u| \leq b} E_{\theta_{\tau_H^n}^{-1} u} \omega \left( \theta_{\tau_H^n}^n - (\theta + r_n^{-1} u) \right) \geq E \omega(W_{1/H}).$$

**Proof.** Since by Theorem 4.2 the sequence of filtered models generated by  $X_n^t$  is functionally LAQ at  $\theta$  with  $\Delta_t$  a continuous local martingale,  $\Gamma_t$  equal to the quadratic variation  $\langle \Delta \rangle_t$  of  $\Delta_t$ , and  $\Gamma_t \uparrow \infty$  a.s. hence the theorem follows from Theorem 4.1.

Note that the filtered model time-changed by  $\tau_H^n$  is functionally LAN i.e., for each bounded sequence of numbers  $u_n$  and all  $H > 0$

$$\sup_{G \leq H} \left| \Lambda_{\theta_{\tau_H^n}^{-1} u_n, \theta, \tau_G^n}^n - \left( u_n \Delta_{\tau_G^n}^n - \frac{1}{2} u^2 G \right) \right| = o_{P_{\theta_0^n}}(1)$$

and

$$\Delta_{\tau_H^n}^n \xrightarrow{\mathcal{D}[P_{\theta_0^n}]} W_1$$

by Lemma 4.1. Hence by Theorem 4.1 we obtain the local asymptotic minimax theorem. □

**Theorem 4.4.** *Under the conditions (B1) - (B3) and (C1) – (C3) the sequence of estimators  $\theta_{\tau_H^n}^n$  are locally asymptotically minimax (LAM), i.e., they attain the lower bound in Theorem 4.3.*

**Proof.** Here we have only to show that  $\theta_{\tau_H^n}^n$  are asymptotically centering (AC), that is

$$r_n(\theta_{\tau_H^n}^n - \theta) - H^{-1} \Delta_{\tau_H^n}^n = o_{P_{\theta_0^n}}(1) \text{ as } n \rightarrow \infty. \tag{4.1}$$

Note that

$$\begin{aligned} r_n(\theta_{\tau_H^n}^n - \theta) &= \frac{-r_n^{-1}l'_{\tau_H^n}(\theta)}{\gamma_n^{-2}l''_{\tau_H^n}(\theta + \beta_{\tau_H^n}(\theta_{\tau_H^n}^n - \theta))} \\ &\sim \frac{-r_n^{-1} \int_0^{\tau_H^n} f'(\theta, s, X_s^n) dW_s^n}{r_n^{-2} \int_0^{\tau_H^n} f''(\theta, s, X_s^n) dW_s^n - r_n^{-2} \int_0^{\tau_H^n} f'^2(\theta, s, X_s^n) ds} \end{aligned} \quad (4.2)$$

by the arguments similar to the proof of Theorem 3.1 (c). On the other hand,

$$H^{-1}\Delta_{\tau_H^n}^n = \frac{\gamma_n^{-1} \int_0^{\tau_H^n} f'(\theta, s, X_s^n) dW_s^n}{\gamma_n^{-2} \int_0^{\tau_H^n} f'^2(\theta, s, X_s^n) ds}. \quad (4.3)$$

From (4.2) and (4.3) using (C3) and Lemma 3.1, we see that (4.1) holds.  $\square$

## 5. ORNSTEIN-UHLENBECK PROCESS WITH MEMORY

We illustrate the results of the previous sections through the exponential memory Ornstein-Uhlenbeck process. Consider the Ornstein-Uhlenbeck type process which is a solution of the stochastic integro-differential equation (SIDE)

$$dX_t = \theta \left( \alpha \int_0^t e^{-\alpha(t-s)} X_s ds \right) dt + dW_t, \quad X_0 = 0$$

where  $\alpha > 0$  is known memory parameter and  $\theta \in \mathbb{R}_+$  is the parameter of interest. For each  $\theta$  the solution  $X$  is a diffusion type process where the nonanticipative drift coefficient depends on the whole past of the process. This is a nonhomogeneous Volterra integro-differential equation with a white noise input. Despite losing the Markov property, it describes a linear stochastic system. Here the range of the memory is governed by the parameter  $\alpha$ . When  $\alpha \rightarrow \infty$ , the process losses memory and converges almost surely to the classical Ornstein-Uhlenbeck process. Dietz [7] showed that for  $\theta < 0$ , the model is LAN and for  $\theta > 0$  the model is LAMN. Here the stopping time is given by

$$\tau_H = \inf\{v > 0 : \int_0^v \left( \int_0^t e^{-\alpha(t-s)} X_s ds \right)^2 dt \geq H\}$$

and the SMLE is given by

$$\theta_{\tau_H} = \frac{\int_0^{\tau_H} \left( \int_0^t e^{-\alpha(t-s)} X_s ds \right) dX_t}{\int_0^{\tau_H} \left( \int_0^t e^{-\alpha(t-s)} X_s ds \right)^2 dt}.$$

Here the model satisfies the functional LAN condition and the SMLE is unbiased, strongly consistent and uniformly normally distributed and locally asymptotically minimax.

## 6. CONCLUDING REMARKS

(1) It is worth investigating to generalize the results in this paper to a nonlinear semimartingale model which includes both the continuous and the discrete time models, e.g., diffusion processes, autoregressive processes and branching processes. For the linear semimartingale model, properties of sequential maximum likelihood estimator were studied in [39] extending the work in [42] for diffusion processes.

(2) It would be interesting to study the properties of sequential Bayes estimators for nonlinear diffusion models. Sequential Bayes estimation for exponential type processes was studied [10].

(3) Obtaining the limiting distribution of the stopping time would be an interesting problem to investigate.

(4) Likelihood ratio processes for interacting particle systems was studied in [36, 37]. It is worth investigating results of this paper for such models.

(5) Replacing the standard Brownian motion  $W$  by fractional Brownian motion, produces non-Markovian non-semimartingale solution process [3]. In our case, with still noise driven by standard Brownian motion, using memory in the drift coefficient, we have non-Markovian solution, but still in a semimartingale framework.

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