# THRESHOLD SELECTION IN THE GLR TEST FOR CHANGE DETECTION IN PARTIALLY OBSERVED DIFFUSION PROCESSES

F. Campillo, F. Le Gland INRIA Sophia Antipolis, BP 93 06902 SOPHIA ANTIPOLIS Cédex France

e-mail: campillo@sophia.inria.fr legland@sophia.inria.fr

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#### 1 Introduction

This paper is concerned with change detection in a partially observed diffusion model, i.e. detection of a change, occurring at some unknown change time, in the drift coefficient or the observation function. The problem is to decide, based on observations  $\{Y_t, 0 \le t \le T\}$  in a finite time interval, between:

• The null hypothesis  $(H_0)$ 

$$dX_t = b(X_t) dt + \varepsilon dW_t^{\varepsilon},$$

$$dY_t = h(X_t) dt + \varepsilon dV_t^{\varepsilon},$$

where  $\{W_t^{\varepsilon}, t \geq 0\}$  and  $\{V_t^{\varepsilon}, t \geq 0\}$  are independent Wiener processes under  $P_{\varepsilon}$ , and  $X_0 = \bar{x}$ .

• The alternate (multiple) hypothesis (H<sub>1</sub>) : For some  $0 \le \tau \le T'$ , with T' < T

$$dX_t = [b(X_t) + a(X_t) 1_{(t > \tau)}] dt + \varepsilon dW_t^{\varepsilon, \tau},$$

$$dY_t = [h(X_t) + g(X_t) 1_{(t \ge \tau)}] dt + \varepsilon dV_t^{\varepsilon, \tau} ,$$

where  $\{W_t^{\varepsilon,\tau}, t \geq 0\}$  and  $\{V_t^{\varepsilon,\tau}, t \geq 0\}$  are independent Wiener processes under  $P_{\varepsilon,\tau}$ , and  $X_0 = \bar{x}$ .

The proposed approach is to use a generalized likelihood ratio (GLR) test, i.e. to consider the following region for rejecting the null hypothesis  $(H_0)$ 

$$D_{\varepsilon} = \left\{ \sup_{0 \le \tau \le T'} \rho_{\varepsilon}(\tau) > c \right\} ,$$

where c is a given threshold, and  $\rho_{\varepsilon}(\tau) = \ell_{\varepsilon}(\tau) - \ell_{\varepsilon}(T)$  denotes a suitably normalized log-likelihood function for the estimation of the change time  $\tau$ , based on observations  $\{Y_t, 0 \le t \le T\}$ .

The purpose of this paper is to prove that the threshold c can be chosen in a such way that both the probability of false alarm and the probability of no detection go to zero as  $\epsilon \downarrow 0$ . These probabilities are defined respectively as

$$F_\varepsilon = P_\varepsilon(D_\varepsilon) \quad \text{and} \quad M_\varepsilon = \sup_{0 \le \tau_0 \le T'} P_{\varepsilon,\tau_0}(D_\varepsilon^c) \ .$$

This result is an extension to the partially observed case, of the results obtained in Campillo, Kutoyants, LeGland [2].

# 2 Log-likelihood Function

It was proved in Campillo, LeGland [1], that the log-likelihood function for the estimation of the change time  $\tau$ , based on observations  $\{Y_t, 0 \le t \le T\}$ , can be expressed as

$$\ell_{\varepsilon}(\tau) = \varepsilon^2 \log \int_{\Omega} \exp \left\{ \frac{1}{\varepsilon^2} F(\tau, \omega) \right\} dP_{\varepsilon, \tau}(\omega)$$

where  $\Omega = C([0,T]; \mathbf{R}^m)$ , and

$$F(\tau,\omega) = \int_0^T h^{\tau}(t,\omega_t) dY_t - \frac{1}{2} \int_0^T |h^{\tau}(t,\omega_t)|^2 dt$$
.

Throughout the paper, the following time–dependent coefficients, parametrized by the unknown parameter  $\tau$ , are used

$$b^{\tau}(t,x) = b(x) + a(x) 1_{(t > \tau)}$$

$$h^{\tau}(t,x) = h(x) + g(x) 1_{(t > \tau)}$$

An efficient way of computing the GLR test statistics has been proposed in [1], using a pair of forward-backward SPDE's, one involving the coefficients before the change, the other involving the coefficients after the change. With this formulation, integration over the path space  $\Omega$  is replaced by integration over the state space  $\mathbb{R}^m$ .

Indeed, consider the forward SPDE

$$d\mu_t^{\varepsilon} = \left\{ \frac{1}{2} \varepsilon^2 \Delta \mu_t^{\varepsilon} - \nabla (b \mu_t^{\varepsilon}) \right\} dt + \varepsilon^{-2} h \mu_t^{\varepsilon} dY_t ,$$

with Dirac initial condition  $\mu_0^{\varepsilon} = \delta_{\bar{x}}$ , and the backward SPDE

$$dv_t^{\varepsilon} + \left\{ \frac{1}{2} \varepsilon^2 \Delta v_t^{\varepsilon} + [b+a] \nabla v_t^{\varepsilon} \right\} dt$$

$$+\varepsilon^{-\,2}\,\left[h+g\right]\,v_{\,t}^{\varepsilon}\;dY_{t}\;=\;0\;,$$

with initial condition (at final time)  $v_T^{\varepsilon} \equiv 1$ .

**Proposition 2.1** The log-likelihood function  $\rho_{\varepsilon}(\tau)$  can be computed as

$$\rho_{\varepsilon}(\tau) = \varepsilon^2 \log \frac{\int_{\mathbf{R}^m} v_{\tau}^{\varepsilon}(x) \, \mu_{\tau}^{\varepsilon}(dx)}{\int_{\mathbf{R}^m} \mu_T^{\varepsilon}(dx)} ,$$

and the GLR test statistics as

$$\sup_{0 \le \tau \le T'} \rho_{\varepsilon}(\tau) = \varepsilon^2 \log \sup_{0 \le \tau \le T'} \frac{\int_{\mathbf{R}^m} v_{\tau}^{\varepsilon}(x) \, \mu_{\tau}^{\varepsilon}(dx)}{\int_{\mathbf{R}^m} \mu_T^{\varepsilon}(dx)} .$$

## 3 Large Deviations

The key idea to study the asymptotic behaviour of the error probabilities  $F_{\varepsilon}$  and  $M_{\varepsilon}$  when  $\varepsilon \downarrow 0$ , is to study the limiting expression of the GLR test statistics  $\rho_{\varepsilon}(\tau)$  as  $\varepsilon \downarrow 0$ , using large deviations arguments similar to those in James, LeGland [3]. The situation can be summarized as follows.

- Under the null hypothesis (H<sub>0</sub>)
- (i) when  $\varepsilon \downarrow 0$

$$P_{\varepsilon}(\sup_{0 \le t \le T} |Y_t - y_t| > \delta) \longrightarrow 0 ,$$

where  $\{y_t, 0 \le t \le T\}$  is the output of the following limiting deterministic system

$$\dot{x}_t = b(x_t) , \quad x_0 = \bar{x}$$

$$y_t = h(x_t) . \tag{1}$$

(ii)  $\{P_{\varepsilon}, \, \varepsilon > 0\}$  satisfies a large deviations principle, with rate function

$$I(\phi) = \frac{1}{2} \int_0^T |\dot{\phi}_t - b(\phi_t)|^2 dt$$
,

if  $\phi \in \Omega$  is absolutely continuous,  $I(\phi) = +\infty$  otherwise.

- Under the alternate hypothesis  $(H_1)$ : For all  $0 < \tau < T'$ , with T' < T
- (i) when  $\varepsilon \downarrow 0$

$$P_{\varepsilon,\tau}(\sup_{0 \le t \le T} |Y_t - y_t^{\tau}| > \delta) \longrightarrow 0$$
,

where  $\{y_t^{\tau}\,,\,0\leq t\leq T\}$  is the output of the following limiting deterministic system

$$\dot{x}_t^{\tau} = b(x_t^{\tau}) + a(x_t^{\tau}) \, \mathbf{1}_{\left(t \ge \tau\right)} \,, \quad x_0^{\tau} = \bar{x} 
(2)$$

$$y_t^{\tau} = h(x_t^{\tau}) + g(x_t^{\tau}) \, \mathbf{1}_{\left(t > \tau\right)} \,.$$

(ii)  $\{P_{\varepsilon,\tau}, \varepsilon>0\}$  satisfies a large deviations principle, with rate function

$$I( au,\phi) = rac{1}{2} \int_0^T |\dot{\phi}_t - b^{ au}(t,\phi_t)|^2 dt \; ,$$

if  $\phi \in \Omega$  is absolutely continuous,  $I(\tau, \phi) = +\infty$  otherwise.

These large deviations results are used in the next two sections, to obtain the limiting behaviour, under either the null hypothesis  $(H_0)$  or the alternate hypothesis  $(H_1)$ , of the log-likelihood function  $\rho_{\varepsilon}(\tau)$  as  $\varepsilon \downarrow 0$ . In both cases, the convergence result is stated in the form of a Varadhan theorem in probability, uniform w.r.t. the parameter  $\tau$  (see Proposition 4.1 and Proposition 5.1 below).

# 4 Probability of False Alarm

If no change has occurred, the following limiting expression holds for the statistics  $\rho_{\varepsilon}(\tau)$  under  $P_{\varepsilon}$  as  $\varepsilon \downarrow 0$ 

$$\rho_0(\tau) = -\inf_{\phi: \phi_0 = \bar{x}} \left[ \frac{1}{2} \int_0^T |\dot{\phi}_t - b^{\tau}(t, \phi_t)|^2 dt + \frac{1}{2} \int_0^T |y_t - h^{\tau}(t, \phi_t)|^2 dt \right] + \inf_{\phi: \phi_0 = \bar{x}} \left[ \frac{1}{2} \int_0^T |\dot{\phi}_t - b(\phi_t)|^2 dt \right]$$

$$\begin{split} & + \frac{1}{2} \int_0^T |y_t - h(\phi_t)|^2 \, dt \; \big] \\ \\ = & - \inf_{\phi \; : \; \phi_0 = \bar{x}} \left[ \; \frac{1}{2} \int_0^T |\dot{\phi}_t - b^\tau(t, \phi_t)|^2 \, dt \; \right. \\ \\ & + \frac{1}{2} \int_0^T |y_t - h^\tau(t, \phi_t)|^2 \, dt \; \big] \leq 0 \; , \end{split}$$

where  $\{y_t, t \geq 0\}$  is the output of the limiting deterministic system (1). Notice that the following expression is also available for  $\rho_0(\tau)$ 

$$\rho_0(\tau) = -\inf_{\phi: \phi_0 = \bar{x}} \left[ \frac{1}{2} \int_0^{\tau} |\dot{\phi}_t - b(\phi_t)|^2 dt + \frac{1}{2} \int_0^{\tau} |y_t - h(\phi_t)|^2 dt + \frac{1}{2} \int_{\tau}^{T} |\dot{\phi}_t - [b + a](\phi_t)|^2 dt + \frac{1}{2} \int_{\tau}^{T} |y_t - [h + g](\phi_t)|^2 dt \right].$$

**Proposition 4.1** The following large deviations result holds

$$P_{\varepsilon}(\sup_{0 \le \tau \le T'} |\rho_{\varepsilon}(\tau) - \rho_{0}(\tau)| > \delta) \longrightarrow 0$$
,

when  $\varepsilon \downarrow 0$ .

Define

$$\varrho^* = \sup_{0 < \tau < T'} \rho_0(\tau) \le 0.$$

**Proposition 4.2** The probability of false alarm  $F_{\varepsilon}$  goes to zero as  $\varepsilon \downarrow 0$ , provided the threshold c satisfies

$$c > c_{\min} = \rho_0^* . \tag{3}$$

The lower bound  $c_{\min}$  can be computed exactly, using a pair of forward-backward dynamic programming equations, one involving the coefficients before the change, the other involving the coefficients after the change. With this formulation, optimization over the path space  $\Omega$  is repaced by optimization over the state space  $\mathbf{R}^m$ .

Indeed, consider the forward dynamic programming equation

$$\frac{\partial S_t}{\partial t} = -\frac{1}{2} |\nabla S_t|^2 - b |\nabla S_t|^2 + \frac{1}{2} |y_t - h|^2,$$

with initial condition  $S_0(\bar{x}) = 0$ , and  $S_0(x) = \bar{S}$  (with  $\bar{S}$  large enough) for  $x \neq \bar{x}$ , and the backward dynamic programming equation

$$\frac{\partial V_t}{\partial t} - \frac{1}{2} |\nabla V_t|^2 + [b+a] |\nabla V_t| + \frac{1}{2} |y_t - [h+g]|^2 = 0 ,$$

with initial condition (at final time)  $V_T \equiv 0$ .

**Proposition 4.3** The limiting statistics  $\rho_0(\tau)$  can be computed as

$$\rho_0(\tau) = -\inf_{x \in \mathbf{R}^m} \left\{ S_{\tau}(x) + V_{\tau}(x) \right\} ,$$

and the threshold lower bound cmin as

$$c_{\min} = -\inf_{0 \le \tau \le T'} \inf_{x \in \mathbf{R}^m} \left\{ S_{\tau}(x) + V_{\tau}(x) \right\} .$$

As an alternative to the exact computation of the threshold lower bound  $c_{\min}$ , it is interesting to see whether it would be possible to obtain estimates that would be easier to compute, and therefore could be used in practice.

#### $\square$ Lower bound for $c_{\min}$

From the particular choice  $\phi \equiv x^{\tau}$ , it follows that

$$\rho_0(\tau) \ge -\frac{1}{2} \int_{\tau}^{T} |y_t - y_t^{\tau}|^2 dt$$

From the particular choice  $\phi \equiv x$ , it follows that

$$\rho_0(\tau) \ge -\left[\frac{1}{2} \int_{\tau}^{T} |a(x_t)|^2 dt + \frac{1}{2} \int_{\tau}^{T} |g(x_t)|^2 dt\right],$$

and therefore

$$c_{\min} \geq c''_{\min}$$

$$= - \left[ \frac{1}{2} \int_{T'}^{T} |a(x_t)|^2 dt + \frac{1}{2} \int_{T'}^{T} |g(x_t)|^2 dt \right] ,$$

where  $c''_{\min}$  would be exactly the threshold lower bound in the case of complete observation, see [2].

#### $\Box$ Upper bound for $c_{\min}$

From the definition of  $\rho_0(\tau)$ , it follows that

$$\rho_0(\tau) \le -\inf_{\phi} \left[ \frac{1}{2} \int_{\tau}^{T} |\dot{\phi}_t - [b+a](\phi_t)|^2 dt + \frac{1}{2} \int_{\tau}^{T} |y_t - [h+g](\phi_t)|^2 dt \right] ,$$

and therefore

$$c_{\min} \leq c'_{\min}$$

$$= -\inf_{\phi} \left[ \frac{1}{2} \int_{T'}^{T} |\dot{\phi}_{t} - [b+a](\phi_{t})|^{2} dt + \frac{1}{2} \int_{T'}^{T} |y_{t} - [h+g](\phi_{t})|^{2} dt \right] \le 0.$$

## 5 Probability of No Detection

If a change has occurred at time  $\tau_0$ , the following limiting expression holds for the statistics  $\rho_{\varepsilon}(\tau)$  under  $P_{\varepsilon,\tau_0}$  as  $\varepsilon \downarrow 0$ 

$$\rho(\tau_0, \tau) = -\inf_{\phi: \phi_0 = \bar{x}} \left[ \frac{1}{2} \int_0^T |\dot{\phi}_t - b^{\tau}(t, \phi_t)|^2 dt + \frac{1}{2} \int_0^T |y_t^{\tau_0} - h^{\tau}(t, \phi_t)|^2 dt \right] 
+ \inf_{\phi: \phi_0 = \bar{x}} \left[ \frac{1}{2} \int_0^T |\dot{\phi}_t - b(\phi_t)|^2 dt + \frac{1}{2} \int_0^T |y_t^{\tau_0} - h(\phi_t)|^2 dt \right] ,$$

where  $\{y_t^{\tau_0}, t \geq 0\}$  is the output of the limiting deterministic system (2).

**Proposition 5.1** The following large deviations result holds

$$P_{\varepsilon,\tau_0}(\sup_{0 \le \tau \le T'} |\rho_{\varepsilon}(\tau) - \rho(\tau_0,\tau)| > \delta) \longrightarrow 0$$
,

when  $\varepsilon \downarrow 0$ .

It is clear that the mapping  $\tau \mapsto \rho(\tau_0, \tau)$  achieves its maximum for  $\tau = \tau_0$ , which implies that the MLE for the estimation of the change time is consistent. Define

$$\rho^*(\tau_0) = \max_{0 \le \tau_0 \le T'} \rho(\tau_0, \tau) = \rho(\tau_0, \tau_0) ,$$

i e

$$\begin{split} \rho^*(\tau_0) \; &= \; \inf_{\phi \; : \; \phi_0 = \overline{x}} \left[ \; \frac{1}{2} \int_0^T \; |\dot{\phi}_t - b(\phi_t)|^2 \, dt \right. \\ & + \frac{1}{2} \int_0^T \; |y_t^{\tau_0} - h(\phi_t)|^2 \, dt \; \right] \geq 0 \; , \end{split}$$

where  $\{y_t^{\tau_0}, t \geq 0\}$  is the output of the limiting deterministic system (2).

**Proposition 5.2** The probability of no detection  $M_{\varepsilon}$  goes to zero as  $\varepsilon \downarrow 0$ , provided the threshold c satisfies

$$c < c_{\text{max}} = \inf_{0 < \tau_0 < T'} \rho^*(\tau_0)$$
 (4)

The upper bound  $c_{\max}$  can be computed exactly, using a family, parametrized by the true change time  $\tau_0$ , of dynamic programming equations, all of them involving the coefficients before the change, but using different outputs  $\{y_t^{\tau_0}, 0 \leq t \leq T\}$ . With this formulation, optimization over the path space  $\Omega$  is repaced by optimization over the state space  $\mathbb{R}^m$ .

Indeed, consider the forward dynamic programming equation

$$\frac{\partial S_t^{\tau_0}}{\partial t} = -\frac{1}{2} |\nabla S_t^{\tau_0}|^2 - b |\nabla S_t^{\tau_0}| + \frac{1}{2} |y_t^{\tau_0} - h|^2 ,$$

with initial condition  $S_0^{\tau_0}(\bar{x}) = 0$ , and  $S_0^{\tau_0}(x) = \bar{S}$  (with  $\bar{S}$  large enough) for  $x \neq \bar{x}$ .

**Proposition 5.3** The limiting statistics  $\rho^*(\tau_0)$  can be computed as

$$\rho^*(\tau_0) = \inf_{x \in \mathbf{R}^m} S_T^{\tau_0}(x) ,$$

and the threshold upper bound cmax as

$$c_{\max} = \inf_{0 \le \tau_0 \le T'} \inf_{x \in \mathbf{R}^m} S_T^{\tau_0}(x) .$$

Here again, as an alternative to the exact computation of the threshold upper bound  $c_{\rm max}$ , it is interesting to see whether it would be possible to obtain estimates that would be easier to compute, and therefore could be used in practice.

#### $\square$ Upper bound for $c_{\max}$

From the particular choice  $\phi \equiv x$ , it follows that

$$\rho^*(\tau_0) \le \frac{1}{2} \int_{\tau_0}^T |y_t - y_t^{\tau_0}|^2 dt$$

From the particular choice  $\phi \equiv x^{\tau_0}$ , it follows that

$$\rho^*(\tau_0) \le \frac{1}{2} \int_{\tau_0}^T |a(x_t^{\tau_0})|^2 dt + \frac{1}{2} \int_{\tau_0}^T |g(x_t^{\tau_0})|^2 dt ,$$

and therefore

$$c_{\text{max}} \leq c''_{\text{max}}$$

$$= \inf_{0 \le \tau_0 \le T'} \left[ \frac{1}{2} \int_{\tau_0}^T |a(x_t^{\tau_0})|^2 dt + \frac{1}{2} \int_{\tau_0}^T |g(x_t^{\tau_0})|^2 dt \right] ,$$

where  $c''_{\text{max}}$  would be exactly the threshold upper bound in the case of complete observation, see [2].

#### $\square$ Lower bound for $c_{\max}$

From the definition of  $\rho^*(\tau_0)$ , it follows that

$$\begin{split} \rho^*(\tau_0) \, &\geq \, \inf_{\phi} \, \left[ \, \frac{1}{2} \int_{\tau_0}^T |\dot{\phi}_t - b(\phi_t)|^2 \, dt \right. \\ &+ \frac{1}{2} \int_{\tau_0}^T |y_t^{\tau_0} - h(\phi_t)|^2 \, dt \, \left. \right] \; , \end{split}$$

and therefore

 $c_{\max} \geq c'_{\max}$ 

$$= \inf_{0 \le \tau_0 \le T'} \inf_{\phi} \left[ \frac{1}{2} \int_{\tau_0}^T |\dot{\phi}_t - b(\phi_t)|^2 dt + \frac{1}{2} \int_{\tau_0}^T |y_t^{\tau_0} - h(\phi_t)|^2 dt \right] \ge 0.$$

#### 6 Conclusion

From the previous discussion, it is possible to select the threshold c in such a way that both the probability of false alarm and the probability of no detection go to zero as  $\varepsilon \downarrow 0$ . Actually, the threshold c should satisfy simultaneously

$$c_{\min} < c < c_{\max}$$

where the threshold bounds  $c_{\min} \leq 0$  and  $c_{\max} \geq 0$  have been defined in (3) and (4) respectively. This is possible provided the following *detectability* assumption holds

$$c_{\min} < c_{\max} , \qquad (5)$$

i.e. whenever one of the two above quantities is non-zero. Remark that for this assumption to hold, it is necessary that T' < T.

Estimates

$$c''_{\min} \le c_{\min} \le c'_{\min} \le 0$$
,

and

$$0 \le c'_{\text{max}} \le c_{\text{max}} \le c''_{\text{max}}$$

have also been obtained, where  $c''_{\min}$  and  $c''_{\max}$  would be the threshold bounds in the case of complete observation. Therefore, a *sufficient* condition for (5) to hold, is

$$c'_{\min} < c'_{\max}$$
,

whereas a necessary condition would be

$$c''_{\min} < c''_{\max}$$
.

Robustness w.r.t. mis-specification of the change coefficients  $a(\cdot)$  and  $g(\cdot)$  can also be investigated, as in [2].

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