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# Nonparametric estimation in a mixed-effect Ornstein-Uhlenbeck model

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## Abstract

Two adaptive nonparametric procedures are proposed to estimate the density of the random effects in a mixed-effect Ornstein-Uhlenbeck model. First a kernel estimator is introduced with a new bandwidth selection method due to Goldenshluger and Lepski (2011). Then, we adapt an estimator from Comte *et al.* (2013) in the framework of small time interval of observation. Precisely we propose an estimator using deconvolution tools, which depends on two tuning parameters to be chosen in a data-driven way. The selection of these two parameters is achieved through a two-dimensional penalized criterion. For both adaptive estimators, risk bounds are provided in terms of integrated  $\mathbb{L}^2$ -error. The estimators are evaluated on simulations and show good results. Finally, these non-parametric estimators are applied to a neuronal database of interspike intervals, and are compared with previous parametric estimation.

**Keywords.** stochastic differential equations, Ornstein-Uhlenbeck process, mixed-effect model, nonparametric estimation, deconvolution method, kernel estimator, neuronal interspike interval.

## 1 Introduction

Stochastic differential models have been intensively surveyed in the theoretical literature with continuous observations (e.g. Kutoyants, 2004) or discrete observations, in the parametric field (e.g. Genon-Catalot and Jacod, 1993) or in the nonparametric field (e.g. Comte *et al.*, 2007; Hoffmann, 1999). More recently, stochastic differential equations with random effects have been introduced with various applications such as neuronal modelling or pharmacokinetic (e.g. Picchini *et al.*, 2008; Delattre and Lavielle, 2013; Donnet and Samson, 2013). Mixed-effects models are used to analyse repeated measurements with similar functional form but with some variability between experiments (see Pinheiro and Bates, 2000; Diggle *et al.*, 2002; Davidian and Giltinan, 1995). The advantage is that a single estimation procedure is used to fit the overall data simultaneously.

Estimation methods in stochastic differential models with random effects have been proposed, especially in the parametric framework (e.g. Donnet and Samson, 2008; Donnet *et al.*, 2010; Picchini *et al.*, 2010; Picchini and Ditlevsen, 2011; Delattre and Lavielle, 2013; Donnet and Samson, 2014; Delattre *et al.*, 2014; Genon-Catalot and Larédo, 2013). All these parametric estimation methods are developed assuming the normality of the random effect. However, one can wonder if

this assumption is reasonable depending on the application context. We focus here on the non-parametric estimation of the density of the random effect. To the best of our knowledge, the only reference in this context is Comte *et al.* (2013).

To simplify the presentation, we focus on the stochastic Ornstein-Uhlenbeck differential model with one additive random effect. More precisely, we consider  $N$  real valued stochastic processes  $(X_j(t), t \in [0, T])$ ,  $j = 1, \dots, N$ , with dynamics ruled by the following SDEs:

$$\begin{cases} dX_j(t) &= \left( \phi_j - \frac{X_j(t)}{\alpha} \right) dt + \sigma dW_j(t) \\ X_j(0) &= x_j \end{cases} \quad (1)$$

where  $(W_j)_{1 \leq j \leq N}$  are  $N$  independent Wiener processes, and  $(\phi_j)_{1 \leq j \leq N}$  are  $N$  unobserved independent and identically distributed (*i.i.d.*) random variables taking values in  $\mathbb{R}$ , with a common density  $f$ . The sequences  $(\phi_j)_{1 \leq j \leq N}$  and  $(W_j)_{1 \leq j \leq N}$  are independent. Here  $(x_1, \dots, x_N)$  are known values. The positive constants  $\sigma$  and  $\alpha$  are supposed to be known; in practice they are estimated from experimental data. The estimation of  $\sigma$  can be done using the quadratic variation of the process. The constant  $\alpha$  is a physical quantity. Picchini *et al.* (2008) give estimation of  $\alpha$  in the special case of the Ornstein-Uhlenbeck model where the likelihood function is explicit and one can compute maximum likelihood estimators. Each process  $(X_j(t), 0 \leq t \leq T)$  represents an individual and the variable  $\phi_j$  is the random effect of individual  $j$ . Due to the independence of the  $\phi_j$  and the  $W_j$ , the  $X_j(t)$ ,  $j = 1, \dots, N$  are *i.i.d.* random variables when  $t$  is fixed, and the  $N$  trajectories  $(X_j(t), 0 \leq t \leq T)$ ,  $j = 1, \dots, N$  are *i.i.d.* Nevertheless, differences between observations are due to the realization of both the  $W_j$  and  $\phi_j$ .

The purpose of the present work is to build nonparametric estimators of the random effect density  $f$ , considering that the processes are observed on  $[0, T]$  with  $T > 0$  given (which can possibly be small). In practice we consider discrete observations of the  $X_j$ 's with a very small time step  $\delta$ . We are able to evaluate the error made by this discretization. The main difficulty is that we do not observe the  $\phi_j$ 's but only the  $X_j(k\delta)$ 's. Thus the first step is to find an estimator of the random effects  $\phi_j$  and then to estimate  $f$ , taking into account the approximation introduced by the estimation of the  $\phi_j$ .

In the context of stochastic differential equations with random effects, Comte *et al.* (2013) propose different nonparametric estimators with good theoretical properties for large  $T$ . We want to propose estimators when  $T$  is small and we focus on a kernel estimator and on an estimator built by deconvolution. First, we consider a kernel estimator of  $f$  built from estimators of the random effects  $\phi_j$ . This kernel estimator depends on a bandwidth to be chosen from the data. Several methods to select the bandwidth of kernel estimators are known. The originality here is the selection method of the bandwidth we set up: we use a method proposed by Goldenshluger and Lepski (2011) which provides an adaptive estimator. This kind of non-asymptotic result is new in this context.

Secondly we study an estimator built by a deconvolution method (see Comte *et al.*, 2013; Butucea and Tsybakov, 2007, for example). The novelty lies in the introduction of an additional tuning parameter which allows to deal with small  $T$  and to control the variance of the noise. We obtain a collection of estimators depending on two parameters. To select the final estimator among this collection, we extend the Goldenshluger and Lepski method for two dimensional model selection (Goldenshluger and Lepski, 2011). Finally we have a consistent estimator satisfying an oracle inequality, for any value of  $T$ . This estimator is likely to be applied to experimental data with small  $T$ .

We illustrate the properties of the proposed estimators with a simulation study. Especially, we compare them with standard bandwidth selection method of cross-validation type. Then, the estimators are applied to neuronal data (interspike interval (ISI) measures). Intracellular measurements of the neuronal membrane potential between two spikes can be modelled with an Ornstein-Uhlenbeck model with one random effect as in (1). The potential being reset at a fixed initial value after a spike, we consider that the measure between two spike is an independent experimental unit with a different realization of the random effect. This assumption has already been considered with parametric strategies in Picchini *et al.* (2008) and Picchini *et al.* (2010),

where it is assumed that the random effect is Gaussian and proved that the Ornstein-Uhlenbeck model with one random effect fits better the data than the model without them. Our goal is to estimate nonparametrically the density of the random effect. This estimated density could be used in further works to model this phenomenon instead of the Gaussian density systematically.

The paper is organized as follows. Section 2 is dedicated to definitions and presentation of the estimators investigated in this work. Then in Section 3 we set up a method of bandwidth selection for the kernel estimator. In Section 4 we define and study the final data-driven estimator built by deconvolution. In Section 5 we calibrate the selection methods and illustrate the good performances of both estimators on simulated data. In Section 6 we experiment the procedures on a real database. We conclude this article with a discussion in Section 7. All proofs are gathered in Section 8, and the computation of the error made by discretization is done in Appendix A.

## 2 Presentation of the strategies

### 2.1 Notation and assumptions

Let us introduce some notations. For two functions  $g_1$  and  $g_2$  in  $\mathbb{L}^1(\mathbb{R}) \cap \mathbb{L}^2(\mathbb{R})$ , the convolution product of  $g_1$  and  $g_2$  for all  $x \in \mathbb{R}$ , is  $g_1 \star g_2(x) = \int_{\mathbb{R}} g_1(x-y)g_2(y)dy$  and the scalar product is:  $\langle g_1, g_2 \rangle = \int_{\mathbb{R}} g_1(x)\overline{g_2(x)}dx$ . Then the Fourier transform of  $g_1$  is  $g_1^*(x) = \int_{\mathbb{R}} e^{iux}g_1(u)du$  for all  $x \in \mathbb{R}$  and the  $\mathbb{L}^2$ -norm is  $\|g_1\|^2 = \int_{\mathbb{R}} |g_1(x)|^2 dx$ . Finally we recall the Plancherel-Parseval's formula:  $2\pi\|g_1\|^2 = \|g_1^*\|^2$ .

We assume **(A)**  $f \in \mathbb{L}^2(\mathbb{R})$ ,  $f^* \in \mathbb{L}^1(\mathbb{R}) \cap \mathbb{L}^2(\mathbb{R})$ .

### 2.2 Initial idea

As previously mentioned, the first step is to estimate the  $\phi_j$  which are not observed, while we want to recover their density. For this purpose, we introduce the following random variables for  $j = 1, \dots, N$  and  $\tau \in ]0, T]$ ,

$$Z_{j,\tau} := \frac{X_j(\tau) - X_j(0) - \int_0^\tau (-\frac{X_j(s)}{\alpha}) ds}{\tau} = \phi_j + \frac{\sigma}{\tau} W_j(\tau). \quad (2)$$

The  $(Z_{j,\tau})_\tau$  can be considered as estimators of the  $\phi_j$  based on the trajectory  $(X_j(t))$  (they correspond to the maximum in  $\varphi$  of the conditional likelihood of (1) given  $\phi_j = \varphi$ ) and the random variables  $Z_{j,\tau} - \phi_j$  are centred. The  $(Z_{j,\tau})_{j=1,\dots,N}$  are *i.i.d.* when  $\tau$  is fixed, due to the independence of  $(\phi_j)_{j=1,\dots,N}$  and  $(W_j)_{j=1,\dots,N}$ . At this point, two strategies materialize which we explain in the following Section.

### 2.3 Estimation strategies

Let us present the two investigated methods.

#### Kernel strategy

The first idea is to reduce the noise which appears in formula (2). Indeed,  $\text{Var}(\sigma W_j(\tau)/\tau) = \sigma^2/\tau$  leads to focus on the largest  $\tau$ :  $\tau = T$ . Moreover, when  $T$  is large  $Z_{j,T}$  clearly approximates  $\phi_j$  without needing to remove the noise. Then we are able to build a kernel estimator of the density  $f$  of the  $\phi_j$ 's based on the  $Z_{j,T}$  using directly the  $Z_{j,T}$  as an approximation of the non-observed random effects  $\phi_j$ . These  $N$  random variables are *i.i.d.* and the resulting kernel estimator is given for all  $x \in \mathbb{R}$ , by

$$\hat{f}_h(x) = \frac{1}{N} \sum_{j=1}^N K_h(x - Z_{j,T}) \quad (3)$$

where  $h > 0$  is a bandwidth, and  $K : \mathbb{R} \rightarrow \mathbb{R}$  is a  $\mathcal{C}^2$  kernel such that

$$\int K(u)du = 1, \quad \|K\|^2 = \int K^2(u)du < +\infty, \quad \int (K''(u))^2 du < +\infty, \quad K_h(x) = \frac{1}{h} K\left(\frac{x}{h}\right). \quad (4)$$

This natural estimator is studied in detail in Section 3.

### Deconvolution strategy

The other idea is to build an estimator of  $f$  using all variables  $Z_{j,\tau}$  for different  $\tau \in [0, T]$ . Recovering  $f$  from the noisy observations  $X_1(t), \dots, X_N(t)$  is called the deconvolution problem because the common density of  $(Z_{j,\tau})_{j=1, \dots, N}$  is a convolution product between two densities. Indeed, the two members of the sum (2) are independent when  $\tau$  is fixed which implies for all  $j = 1, \dots, N$ ,

$$f_{Z_\tau}(u) = f \star f_{\frac{\sigma}{\tau} W_j(\tau)}(u).$$

Then the characteristic function of  $\phi_j$  is recoverable from that of  $Z_\tau$ . Taking the Fourier transform under assumption **(A)** gives the simple product

$$f_{Z_\tau}^*(u) = f^*(u) f_{\frac{\sigma}{\tau} W_j(\tau)}^*(u),$$

with  $f_{\frac{\sigma}{\tau} W_j(\tau)}^*(u) = e^{-\frac{u^2 \sigma^2}{2\tau}}$ . In this particular case the noise is Gaussian and this convolution problem has been investigated in literature, see Fan (1991); Butucea and Tsybakov (2007) for example. However it has been proved in Carroll and Hall (1988) that the best rates of convergence obtained in this case are logarithmic. This suggests to improve the deconvolution procedure and this is the reason why we choose not to use previous estimators but to propose a new method, based on repeated observations and new parameters chosen properly. We have  $f^*(u) = f_{Z_\tau}^*(u) e^{u^2 \sigma^2 / 2\tau}$ . Finally the Fourier inversion gives the closed formula, for all  $x \in \mathbb{R}$ ,

$$f(x) = \frac{1}{2\pi} \int_{\mathbb{R}} e^{-iux} f_{Z_\tau}^*(u) e^{\frac{u^2 \sigma^2}{2\tau}} du. \quad (5)$$

Then, we estimate  $f_{Z_\tau}^*(u)$  by its empirical estimator  $\widehat{f}_{Z_\tau}^*(u) = (1/N) \sum_{j=1}^N e^{iuZ_{j,\tau}}$ . However, plugging this in formula (5) involves integrability problems. Indeed the integrability of  $\widehat{f}_{Z_\tau}^*(u) e^{u^2 \sigma^2 / 2\tau}$  is not ensured. Therefore, we have to introduce a cut-off. The nonparametric estimation using a deconvolution method in the Gaussian case commonly yields to bad speeds of convergence. To improve the rates, an idea of Comte and Samson (2012) for linear mixed models, was to link this cut-off and the time of the process. Comte *et al.* (2013) link the time of the process  $\tau$  and the cut-off as follows:

$$\widehat{f}_\tau(x) = \frac{1}{2\pi} \int_{-\sqrt{\tau}}^{\sqrt{\tau}} e^{-iux} \frac{1}{N} \sum_{j=1}^N e^{iuZ_{j,\tau}} e^{\frac{u^2 \sigma^2}{2\tau}} du. \quad (6)$$

Then the time  $\tau$  is chosen by a Goldenshluger and Lepski's method and the final estimator is denote  $\widehat{f}_{\widehat{\tau}}$ . Nevertheless, when  $\tau$  is small (which is the case for the real database we investigate), the integration domain is not large enough, and the estimators of  $f$  are not satisfactory. We adapt Comte *et al.* (2013) estimator to this small  $T$  framework. Indeed, to improve the previous estimator, we introduce a new parameter  $s$  in the cut-off:

$$\widehat{f}_{s,\tau}(x) = \frac{1}{2\pi} \int_{-s\sqrt{\tau}}^{s\sqrt{\tau}} e^{-iux} \frac{1}{N} \sum_{j=1}^N e^{iuZ_{j,\tau}} e^{\frac{u^2 \sigma^2}{2\tau}} du.$$

Then to simplify the theoretical study, we replace  $s\sqrt{\tau}$  in the integral by a new parameter  $m$ . The resulting estimator  $\widetilde{f}_{m,s}$  is defined when  $m^2/s^2 \in ]0, T]$ , by

$$\widetilde{f}_{m,s}(x) = \frac{1}{2\pi} \int_{-m}^m e^{-iux} \frac{1}{N} \sum_{j=1}^N e^{iuZ_{j,m^2/s^2}} e^{\frac{u^2 \sigma^2 s^2}{2m^2}} du \quad (7)$$

with  $m$  and  $s$  in two finite sets  $\mathcal{M}$  and  $\mathcal{S}$  that we make precise later.

In the following we survey in detail the two strategies.

### 3 Study of the kernel estimator

The kernel estimator given by (3) has been investigated in Comte *et al.* (2013). First we recall the MISE bound that the kernel estimator  $\hat{f}_h$  satisfies. Then we develop the bandwidth selection procedure we are interested in this work.

#### 3.1 Risk bound

Let us define  $f_h := K_h \star f$ , for  $h > 0$ . We denote for all  $p \in \mathbb{R}$ ,  $\|f\|_p = (\int |f(x)|^p dx)^{1/p}$  and for  $p = 2$  we still use  $\|f\|_2 = \|f\|$ . Notice that  $\|K_h\| = \|K\|/\sqrt{h}$  and  $\|K_h\|_1 = \|K\|_1$ . We recall the result proved in Comte *et al.* (2013) for the MISE.

**Proposition 1.** *Consider estimator  $\hat{f}_h$  given by (3), we have*

$$\mathbb{E}[\|\hat{f}_h - f\|^2] \leq 2\|f - f_h\|^2 + \frac{\|K\|^2}{Nh} + \frac{2\sigma^4\|K''\|^2}{3T^2h^5}. \quad (8)$$

The right hand side of (8) involves three terms, the middle one is the integrated variance. The integrated bias is  $\|\mathbb{E}[\hat{f}_h] - f\|^2 \leq 2\|f - f_h\|^2 + 2\|\mathbb{E}[\hat{f}_h] - f_h\|^2$ , with

$$\|\mathbb{E}[\hat{f}_h] - f_h\|^2 \leq \frac{\sigma^4\|K''\|^2}{3T^2h^5}. \quad (9)$$

Therefore, the first term  $\|f - f_h\|^2$  is a bias term, which decreases when  $h$  decreases. The second term is the term of variance which increases when  $h$  decreases. Finally, the third term, also given in (9), is an unusual error term due to the approximation of the  $\phi_j$ 's by the  $Z_{j,T}$  also increasing when  $h$  decreases. It is clear on this term that its rate  $\frac{\sigma^2}{T}$  should be small.

#### 3.2 Adaptation of the bandwidth

Now that we have at hand a collection of estimators depending on a bandwidth  $h$ , we focus on the crucial matter: how to choose the bandwidth from the data. The best choice of  $h$  is the one which minimizes the sum of these three terms. The selection of the bandwidth can be done for example using cross validation, see *e.g.* the R-function *density* which is commonly used. However, the only theoretical results known for cross-validation procedure are asymptotic and to the best of our knowledge there is no adaptive result on the final estimator. In the present work, we propose to adapt a selection method due to Goldenshluger and Lepski (2011) mentioned before, which provides a data driven bandwidth for which we provide non-asymptotic theoretical results.

We denote  $\mathcal{H}_{N,T}$  the finite set of bandwidths  $h$ , to be defined later. The best theoretical choice of the bandwidth is the  $h$  which minimizes the bound on the MISE given by (8). Nevertheless, in practice, the bias term is unknown, and this bound has to be estimated.

To choose  $h$  adequately, we use a Goldenshluger and Lepski's criterion settled up in Goldenshluger and Lepski (2011). The idea is to estimate  $\|f - f_h\|^2$  by the  $\mathbb{L}^2$ -distance between two estimators defined in (3). But this induces an error which has to be corrected by the variance term. Then the estimator of the bias term is

$$A(h) = \sup_{h' \in \mathcal{H}_{N,T}} \left( \|\hat{f}_{h,h'} - \hat{f}_h\|^2 - V(h') \right)_+ \quad (10)$$

with

$$\hat{f}_{h,h'}(x) := K_{h'} \star \hat{f}_h(x) = \frac{1}{N} \sum_{j=1}^N K_{h'} \star K_h(x - Z_{j,T})$$

and  $V$  correspond to the two terms of variance

$$V(h) = \kappa_1 \frac{\|K\|_1^2 \|K\|^2}{Nh} + \kappa_2 \frac{\sigma^4 \|K\|_1^2 \|K''\|^2}{T^2 h^5} \quad (11)$$

with  $\kappa_1$  and  $\kappa_2$  two purely numerical positive constants. We will prove that  $A(h)$  has the order of the bias term (see equation (23)). Finally the bandwidth is selected as follows

$$\hat{h} = \operatorname{argmin}_{h \in \mathcal{H}_{N,T}} \{A(h) + V(h)\} \quad (12)$$

with  $\mathcal{H}_{N,T}$  a discrete set of bandwidths  $h$ : such that

$$\mathcal{H}_{N,T} = \left\{ h > 0, \frac{1}{Nh} \leq 1, \frac{\sigma^4}{h^5 T^2} \leq 1, \forall c > 0, \exists S(c) < \infty, \sum_{h \in \mathcal{H}_{N,T}} h^{-1/2} e^{-c/\sqrt{h}} \leq S(c) \right\}.$$

Then we can prove the following Theorem.

**Theorem 2.** Consider estimator  $\hat{f}_h$  given by (3) with  $h \in \mathcal{H}_{N,T}$ . Then, there exists two penalty constants  $\kappa_1, \kappa_2$  such that

$$\mathbb{E}[\|\hat{f}_h - f\|^2] \leq C_1 \inf_{h \in \mathcal{H}_{N,T}} \{\|f - f_h\|^2 + V(h)\} + \frac{C_2}{N}$$

where  $C_1, C_2$  are two positive constants such that  $C_1$  depends on  $\|K\|_1$  and  $C_2$  depends on  $\|f\|, \|K\|, \|K\|_1, \|K\|_{4/3}$ .

The theoretical study gives  $\kappa_1 \geq \max(40/\|K\|_1^2, 40)$  and  $\kappa_2 \geq \max(10/3, 10/(3\|K\|_1^2))$ . But in practice these two constants are calibrated from a simulation study (and always smaller than the theoretical ones). Theorem 2 is an oracle inequality: the bias variance compromise is automatically obtained and in a data-driven and non-asymptotic way.

It is important to notice that if we take for example  $\mathcal{H}_{N,T} = \{1/k^2, k = 1, \dots, \sqrt{N}\}$  then the sum  $\sum_{h \in \mathcal{H}_{N,T}} h^{-1/2} e^{-c/\sqrt{h}}$  converges, which is a necessary condition for the proof. The error implied by the discrete observations and the use of Riemann sums to compute the  $Z_{j,T}$  is detailed in Comte *et al.* (2013).

## 4 Study of the deconvolution estimator

### 4.1 Risk bound

Let us emphasize that the estimator  $\tilde{f}_{m,s}$  given by (7) depends on two parameters which have to be selected from the data. This is not usual in the deconvolution setting, where only one cut-off parameter is often introduced. The selection of these two parameters  $(m, s)$  among the finite sets  $\mathcal{M}, \mathcal{S}$  is thus more difficult. It is even more challenging here because the cut-off  $m$  appears both in the integral and in the integrand. But this will induce gains in the rates of the estimators. Before proposing a selection method of  $(m, s)$  we start by evaluating the quality of the estimator with the mean integrated squared error (MISE):

$$\mathbb{E} \left[ \|\tilde{f}_{m,s} - f\|^2 \right] = \|f - \mathbb{E}[\tilde{f}_{m,s}]\|^2 + \mathbb{E} \left[ \|\tilde{f}_{m,s} - \mathbb{E}[\tilde{f}_{m,s}]\|^2 \right].$$

In Proposition 3 we prove that  $\mathbb{E}[\tilde{f}_{m,s}] = f_m$  where  $f_m$  is defined by its Fourier transform

$$f_m^* := f^* \mathbf{1}_{[-m,m]}.$$

It means that the bias does not depend on  $s$ . We obtain the following bound on the MISE of  $\tilde{f}_{m,s}$ .

**Proposition 3.** Under (A), the estimator  $\tilde{f}_{m,s}$  given by (7) is an unbiased estimator of  $f_m$  and we have

$$\mathbb{E} \left[ \|\tilde{f}_{m,s} - f\|^2 \right] \leq \|f_m - f\|^2 + \frac{m}{\pi N} \int_0^1 e^{\sigma^2 s^2 v^2} dv. \quad (13)$$

The proofs are relegated to Section 8. Let us look at the risk bound. The first term of the bound (13) is the bias term. It represents the error resulting from estimating  $f$  by  $f_m$  and it decreases when  $m$  increases, indeed:

$$\|f_m - f\|^2 = \frac{1}{2\pi} \int_{|u| \geq m} |f^*(u)|^2 du.$$

The second term is the variance term, and increases with  $m$  and  $s$ . One can notice that it is bounded as soon as  $s$  is bounded and  $m \leq N$ .

We specify the two sets  $\mathcal{M}$  and  $\mathcal{S}$ . We notice that the quality of the estimate in the Fourier domain is good on an interval around zero with length related with  $\sigma$ . The chosen set for  $s$  is

$$\mathcal{S} := \{s_l = \frac{1}{2^l} \frac{2}{\sigma}, 1/2^{P-1} \leq \sigma s_l \leq 2, l = 0, \dots, P\}.$$

Moreover with this chosen collection  $\mathcal{S}$ , the order of the variance term is  $m/N$ . With the idea that  $m^2/s^2$  is homogeneous to a time, we choose  $m$  in the finite collection:

$$\mathcal{M} := \{m = \frac{\sqrt{k\Delta}}{\sigma}, k \in \mathbb{N}^*, 0 < m \leq N\}$$

with  $0 < \Delta < 1$  a small step to be fixed. The collection of couples of parameters is

$$\mathcal{C} := \{(m, s) \in \mathcal{M} \times \mathcal{S}, m^2/s^2 \leq T\}.$$

The final estimator is the estimator from the collection  $\mathcal{C}$  which achieves the bias-variance compromise. Choosing the final estimator is not an easy task except if we know the regularity of  $f$ . Indeed, let us assume that  $f$  is in the Sobolev ball with regularity parameter  $b$ , i.e.  $f$  belongs to the set defined by

$$\mathcal{A}_b(L) = \{f \in \mathbb{L}^1(\mathbb{R}) \cap \mathbb{L}^2(\mathbb{R}), \int_{\mathbb{R}} |f^*(x)|^2 (1+x^2)^b dx \leq L\}$$

with  $b > 0, L > 0$ . For example the standard normal distribution is in a space  $\mathcal{A}_b(L)$  for some  $L$  and for all  $b > 0$ , an exponential distribution is in some  $\mathcal{A}_b(L)$  for  $b < 1/2$  or more generally a Gamma distribution with scale parameter  $k$  is in some  $\mathcal{A}_b(L)$  for  $b < (k - 1/2)$ . Thus when  $f \in \mathcal{A}_b(L)$ , the bias term satisfies:

$$\|f_m - f\|^2 = \frac{1}{2\pi} \int_{|u| \geq m} |f^*(u)|^2 du \leq \frac{L}{2\pi} m^{-2b}.$$

Consequently, the  $\mathbb{L}^2$ -risk of  $\tilde{f}_{m,s}$  is bounded by,

$$\mathbb{E}[\|\tilde{f}_{m,s} - f\|^2] \leq \frac{L}{2\pi} m^{-2b} + \frac{m}{\pi N} e^{\sigma^2 s^2}.$$

Therefore, the best theoretical choice of  $s$  is  $s_P$  the smallest  $s$  in our collection, and

$$m = m^* = K_b N^{\frac{1}{2b+1}}$$

with  $K_b = (bL \exp(-1/(2^{2(P-1)})))^{1/(2b+1)}$ . Then we obtain the following asymptotic result.

**Corollary 4.** *If  $f \in \mathcal{A}_b(L)$ , and if we choose  $s = s_P$  and  $m = m^*$ , there exists a constant  $K$  depending on  $b, L, P$ , such that*

$$\mathbb{E}[\|\tilde{f}_{m^*, s_P} - f\|^2] \leq KN^{-\frac{2b}{2b+1}}.$$

The order of the risk in this case is  $N^{-2b/(2b+1)}$  for a large  $N$ , it is the nonparametric estimation rate of convergence obtained when the observation are  $N$  realizations of the variable of interest. Nevertheless, this choice is theoretical because it depends on the regularity  $b$  of  $f$  which is unknown. The next section provides a data-driven method to select  $(m, s)$ .



## 4.2 Selection of the final estimator

In this Section we deal with the choice of the best estimator among the available collection of  $\tilde{f}_{m,s}$ . In the previous work Comte *et al.* (2013),  $s$  was fixed to  $s = 1$  and  $m$  was selected. But we saw empirically that it did not work in the setting corresponding to the data. This is why we experimented different values for  $s$ . But then we did not find any reliable criterion to select  $m$  for any given  $s$ . On the contrary, if we look at the bound and try to select  $s$  first, we just get  $s = 0$  which is not of interest if we are looking to improve the estimator through  $s$  in particular. This implies to select the couple  $(m, s)$  minimizing the MISE and realizing the compromise between the two terms, in a data-driven way. This is a crucial issue. Indeed, the role of the two parameters is not the same. Thus we propose a new criterion adapted from the Goldenshluger and Lepski (2011) method.

The idea is to select the couple which minimizes the MISE:  $\mathbb{E} \left[ \|\tilde{f}_{m,s} - f\|^2 \right]$ . As it is unknown, we have to find a computable approximation of this quantity. We define the best couple  $(m, s)$  as the one minimizing a criterion defined as the sum of a squared bias term and a variance term called penalty. We define the penalty function, which has the same order as the bound on the variance term:

$$\text{pen}(m, s) = \kappa \frac{m}{N} e^{\sigma^2 s^2},$$

where  $\kappa$  is a numerical constant to be calibrated. Note that for  $m \in \mathcal{M}$  and  $s \in \mathcal{S}$ , the penalty function is bounded.

To estimate the bias term, we generalize Goldenshluger and Lepski's criterion for a two dimensional index. The method is inspired by the ideas developed for kernel estimators by Goldenshluger and Lepski (2011) and adapted to model selection in one dimension in Comte and Johannes (2012) and in two dimensions by Chagny (2013). The idea is to estimate  $\|f - f_m\|^2$  by the  $\mathbb{L}^2$ -distance between two estimators defined in (7). But this induces a bias which has to be corrected by the penalty function. We consider the following estimator of the bias, with  $(m', s') \wedge (m, s) := (m' \wedge m, s' \wedge s)$ ,

$$\Gamma_{m,s} = \max_{(m',s') \in \mathcal{C}} \left( \|\tilde{f}_{m',s'} - \tilde{f}_{(m',s') \wedge (m,s)}\|^2 - \text{pen}(m', s') \right)_+$$

for  $(m, s) \in \mathcal{C}$ . Finally the selected couple is:

$$(\tilde{m}, \tilde{s}) = \arg \min_{(m,s) \in \mathcal{C}} \{ \Gamma_{m,s} + \text{pen}(m, s) \}. \quad (14)$$

We are now able to obtain the following result.

**Theorem 5.** *Under (A), consider the estimator  $\tilde{f}_{\tilde{m}, \tilde{s}}$  given by (7) and (14). There exists  $\kappa_0$  a numerical constant such that, for all penalty constants  $\kappa \geq \kappa_0$ ,*

$$\mathbb{E}[\|\tilde{f}_{\tilde{m}, \tilde{s}} - f\|^2] \leq C \inf_{(m,s) \in \mathcal{C}} \{ \|f - f_m\|^2 + \text{pen}(m, s) \} + \frac{C'(P+1)}{N} \quad (15)$$

where  $C > 0$  is a numerical constant and  $C'$  is a constant depending on  $\|f\|$ ,  $\sigma$ ,  $\Delta$ , and  $P+1$  the cardinality of  $\mathcal{S}$ .

The key of the proof is to prove that

$$\mathbb{E}[\Gamma_{m,s}] \leq 18\|f - f_m\|^2 + \frac{C'(P+1)}{N}$$

(see the proof in Section 8.3.) Inequality (15) means that  $\tilde{f}_{\tilde{m}, \tilde{s}}$  automatically makes the bias-variance trade-off. Moreover, our result is of non asymptotic nature w.r.t.  $N$ .

One should notice that this new parameter  $s$  generalizes the results of Comte *et al.* (2013) even if  $T$  is large. We choose the two parameters in an adaptive way, thus this gives more flexibility in the choice of the estimator.

The numerical constant  $\kappa$  is calibrated by simulation experiments. From the theoretical part we get  $\kappa_0 = 24$  which is much too large in practice. Besides the cardinality  $P$  of the set  $\mathcal{S}$  is chosen

small in practice ( $P = 3$  or  $10$  for example).

In Appendix A.3 we investigate the error implied by the discrete observations and thus of the discretization of  $Z_{j,\tau}$  given by (2).

## 5 Simulation study

In the following we compare on simulations the two procedures we compute  $\hat{f}_{\hat{h}}$  and  $\tilde{f}_{\tilde{m},\tilde{s}}$ , the estimator of Comte *et al.* (2013)  $\tilde{f}_{\tilde{\tau}}$  and we compare our bandwidth selection method with the estimator from the R-function *density* with the cross-validation option "bw=ucv", on the  $Z_{j,T}, j = 1, \dots, N$ , we denote it  $\hat{f}_{cv}$ .

We simulate data by computing the exact solutions of (1) given by Itô's formula,

$$X_j(t) = X_j(0)e^{-t/\alpha} + \phi_j\alpha(1 - e^{-t/\alpha}) + \sigma e^{-t/\alpha} \int_0^t e^{s/\alpha} dW_j(s) \quad (16)$$

at discrete times  $t_k \in \mathcal{T} := \{k\delta, k \in \{0, \dots, J\}, J\delta = T\}$ . For the simulation study, we have to fix  $N, \delta, T, \sigma, \alpha$ , and the density  $f$ . We take  $\sigma = 0.0135, 0.05, 1$  and  $\sigma = 0.05, \alpha = 0.039, 1, 39$ . For the time  $T$ , we choose  $T = 0.3, 10, 50, 100, 300$  with different values of  $\delta$  the discrete time step at which observations are recorded. Thus the value of  $J$ , the number of observations for one trajectory ranges from 150 to 5000. All these parameter values are chosen in relation with the parameters of the real database. In this study we hope to highlight the influence of each one. For  $f$ , we investigate four different distributions:

- Gaussian distribution  $\mathcal{N}(0.278, (0.041)^2)$
- Gamma distribution  $\Gamma(1.88, 0.148)$
- mixed Gaussian distribution  $0.3\mathcal{N}(0, (0.02)^2) + 0.7\mathcal{N}(1, (0.02)^2)$
- mixed Gamma distribution  $0.4\Gamma(3, 0.08) + 0.6\Gamma(30, 0.035)$

where we write  $\Gamma(k, \theta)$  with  $k$  the scale parameter and  $\theta$  the shape.

First, we implement the two collections of estimators:  $\hat{f}_{\hat{h}}$  and  $\tilde{f}_{\tilde{m},\tilde{s}}$ . We begin by computing the random variables used by both estimators:  $Z_{j,\tau}$  given by (2), with Riemann sums approximations (see Appendix A.3 for details). For the deconvolution estimator given by (7) we also use Riemann sums to compute the integral. For the collection of  $m$ , we choose  $\Delta = 0.08$  and  $\delta$  changes. Furthermore, for the kernel estimator given by (3), we choose a Gaussian kernel:  $K(u) = (1/\sqrt{2\pi})e^{-u^2/2}$ . In this case  $\|K\|_1 = 1$ ,  $\|K\|_2^2 = 1/(2\sqrt{\pi})$ ,  $\|K''\|_2^2 = (1 + 1/\sqrt{2})/(\sqrt{2\pi})$ . Then, the selected bandwidth  $\hat{h}$  is given by Equation (12). Note that for all  $(h, h') \in \mathcal{H}^2$ ,

$$K_{h'} \star K_h(x) = \frac{1}{\sqrt{2\pi}\sqrt{h'^2 + h^2}} e^{-x^2/[2(h'^2+h^2)]}.$$

We use this relation to compute the  $\hat{f}_{\hat{h},h'}$ .

Secondly, we have to calibrate the penalty constants:  $\kappa_1, \kappa_2$  for the kernel estimator and  $\kappa$  for the deconvolution estimator. Classically, the constants are fixed thanks to preliminary simulation experiments. Different functions  $f$  have been investigated with different parameter values, and a large number of replications. Comparing the MISE obtained as functions of the constants  $\kappa_1, \kappa_2$  and  $\kappa$  yields to select values making a good compromise over all experiences. Finally we choose  $\kappa_1 = 1, \kappa_2 = 0.0001$  and  $\kappa = 0.3$ .

On Figure 1 25 estimators  $\hat{f}_{\hat{h}}$  are plotted and on Figure 2 25 estimators  $\tilde{f}_{\tilde{m},\tilde{s}}$ , for the 4 investigated densities  $f$ . The batch of estimators is close to the estimated density.

In order to evaluate the performances of each estimator on the different designs, we compare their empirical MISE computed from 100 simulated data sets.

Table 1 summarises the results for different parameters values. It shows the bad performances of the estimator of Comte *et al.* (2013)  $\tilde{f}_{\tilde{\tau}}$  when  $T$  is small compared to  $\tilde{f}_{\tilde{m},\tilde{s}}$ . It performs clearly better

when  $T$  is increasing. Besides we notice that both kernel estimators have good results. Nevertheless it appears that the  $\hat{f}_{cv}$  fits better the Gaussian or Gamma densities, while our estimator  $\hat{f}_h$  fits slightly better mixture densities. Note that the computation time is the same. We show the results for different values of  $\alpha$  which does not seem to influence the quality of estimators (while the selected  $h, m, s$  are very different). Figure 3 illustrates the performances of estimators.

In the following as the two kernel estimators seem very close we only show the results for  $\hat{f}_h$  which is of interest here. Besides we no longer investigate the previous estimator  $\tilde{f}_{\tilde{\tau}}$  in light of Table 1 for  $T < N$ .

We further compare  $\hat{f}_h$  and  $\tilde{f}_{\tilde{m}, \tilde{s}}$ . The two estimators seem close to the true density on graphs compare Figure 1 and 2. In Table 2 on the MISE it is clear that the kernel estimator is the best. Furthermore, we can point out some differences. The first row of the Table corresponds to simulation with the parameters of the real database. In the first column, the Gaussian case, the MISE are 10 times larger than the ones for other cases. This can be easily explained: the values of the estimated density are 10 times larger than others. Nevertheless, on lines 3 and 4 for the Gaussian case, the MISE are very large. This is due to the bad estimation of the  $\phi_j$  by the  $Z_{j,T}$  with  $\sigma = 0.05$  and  $T = 0.3$ <sup>1</sup>. The quality of the estimation is significantly better when we try a  $\mathcal{N}(0.278, 0.2)$  (0.2 is the variance of the mixed Gaussian density we implement for example). In general one can notice that when  $\sigma$  is larger than the standard deviation of the density of the random effects  $f$ , the estimation is less precise, which is coherent in term of signal to noise ratio. For the kernel estimator, the theoretical condition  $\sigma^4/h^5 < T^2$  is satisfied because of the small value of  $\sigma$ .

Table 2 shows that if  $T$  increases, it improves the results for  $\sigma = 0.05$ , compare cases 2 and 5 with 4 and 7 for example. If  $J$  is large enough, meaning if  $\delta$  is small enough, (which is the case even for  $J = 150$  when  $T = 0.3$ ) the deconvolution estimator fits well the density. In practice, when  $T$  increases, the selected value of  $s$  decreases, which could have been predicted. The results are still satisfying for large  $T$ .

Furthermore, an other point is that it is obvious on simulations that the larger  $N$  the better the estimator  $\hat{f}_h$ . However, the role of  $N$  is not as clear for the deconvolution estimator. We can refer to Comte *et al.* (2013) for a study with different values for  $N$ . It highlights the influence of  $N$  when the estimated density has two modes for example with  $N = 50$  the estimation is clearly less precise than for  $N = 200$ .

A main difference between our two estimators  $\hat{f}_h$  and  $\tilde{f}_{\tilde{m}, \tilde{s}}$  is the computation time: a few seconds for the first one and ten minutes for the second one. Thus kernel estimator with the method of bandwidth selection is very efficient especially in the case of multi-modal densities and performs often better than the deconvolution one.

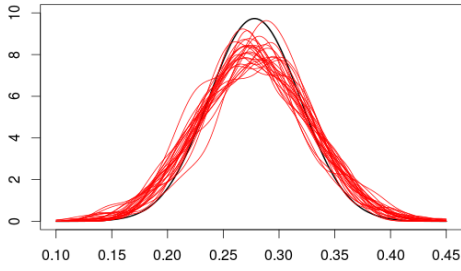
## 6 Application to neuronal data

### 6.1 Database

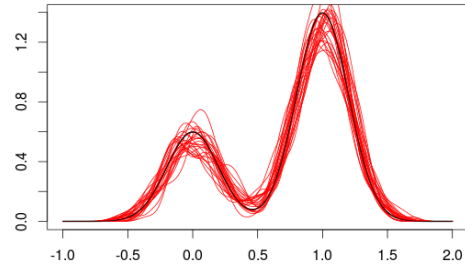
The data are measurements of the membrane potential in volts along time, for one single neuron of a pig between the spikes (see Yu *et al.*, 2004; Lansky *et al.*, 2006, for details on data acquisition). In this neuronal context, between the  $(j-1)$ <sup>th</sup> and the  $j$ <sup>th</sup> spike, the depolarization of the membrane potential receiving a random input, can be described by the Ornstein Uhlenbeck model with one random effect (1). The spikes are not intrinsic to the model but are generated when the voltage reaches for the first time a certain threshold  $S$ , then the process is reset to a fixed initial voltage. Thus each trajectory is observed on an interval  $[0, T_j]$  where  $T_j = \inf\{t > 0, X_j(t) \geq S\}$ . The initial voltage (the value following a spike) is assumed to be equal to the resting potential and set to zero:  $x_j = 0$ .

The positive constant parameter  $\alpha$  is called the time constant of the neuron (the coefficient of decay in the exponential, when there is no noise), which is fixed to  $\alpha = 0.039$  [s] (Lansky

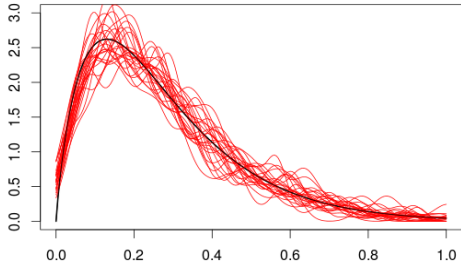
<sup>1</sup>We insist that this bad estimation is not due to the fact the noise is Gaussian. Indeed even if Fan (1991) proves the rates to be logarithmic in that case, the rates are improved and can be polynomial when the density under estimation is of the same type of the noise (see Lacour (2006), Comte *et al.* (2006)).



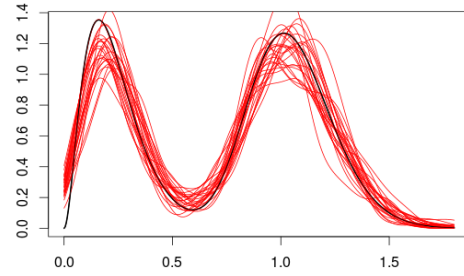
(a)  $f$  Gaussian



(b)  $f$  mixed Gaussian density



(c)  $f$  Gamma

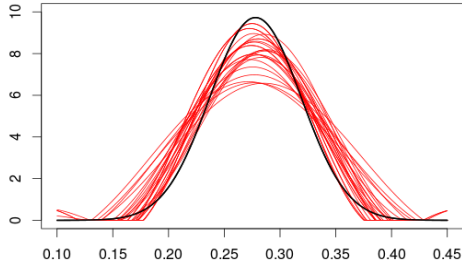


(d)  $f$  mixed Gamma density

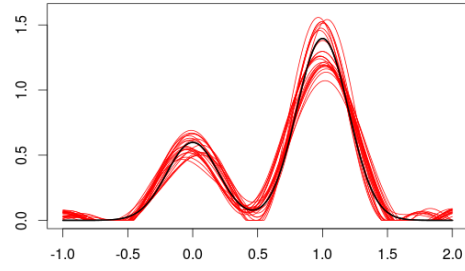
Figure 1: Simulated data. In red 25 estimators  $\hat{f}_h$  with parameters:  $N = 240$ ,  $T = 0.3$ ,  $\delta = 0.00015$ ,  $\sigma = 0.0135$ ,  $\alpha = 0.039$  and the bold black line the density true density  $f$

Table 1: Empirical MISE computed from 100 simulated data sets, with  $N = 200$ , with various  $T$ ,  $\delta$ ,  $\sigma$  and  $\alpha$  for two kernel estimators  $\hat{f}_{cv}$ ,  $\hat{f}_h$  and two deconvolution estimators  $\tilde{f}_{\tilde{\tau}}$  and  $\tilde{f}_{\tilde{m}, \tilde{s}}$

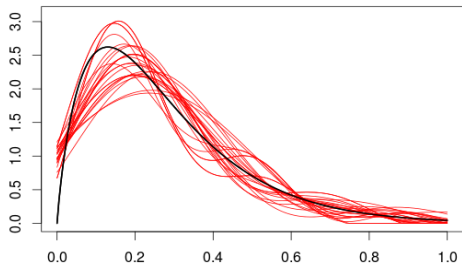
	$\hat{f}_{cv}$	$\hat{f}_h$	$\tilde{f}_{\tilde{\tau}}$	$\tilde{f}_{\tilde{m}, \tilde{s}}$
Cas $f$ Gamma				
$T = 0.3 \delta = 0.0005 \sigma = 0.0135 \alpha = 0.039$	0.043	0.043	1.547	0.071
$T = 50 \delta = 0.1 \sigma = 0.05 \alpha = 1$	0.040	0.042	0.218	0.050
$T = 300 \delta = 0.5 \sigma = 0.5 \alpha = 39$	0.041	0.040	0.049	0.055
Cas $f$ mixed Gamma				
$T = 0.3 \delta = 0.0005 \sigma = 0.0135 \alpha = 0.039$	0.032	0.032	0.712	0.035
$T = 50 \delta = 0.1 \sigma = 0.05 \alpha = 1$	0.021	0.023	0.145	0.043
$T = 300 \delta = 0.5 \sigma = 0.5 \alpha = 39$	0.031	0.032	0.035	0.043



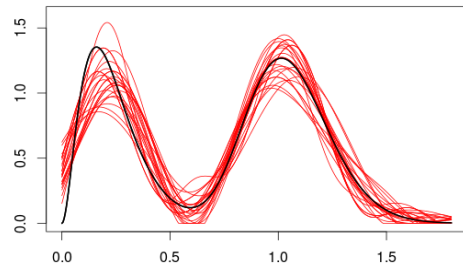
(a)  $f$  Gaussian



(b)  $f$  mixed Gaussian



(c)  $f$  Gamma



(d)  $f$  mixed Gamma

Figure 2: Simulated data. In red 25 estimators  $\tilde{f}_{\tilde{m},\tilde{s}}$  with parameters:  $N = 240$ ,  $T = 0.3$ ,  $\delta = 0.00015$ ,  $\sigma = 0.0135$ ,  $\alpha = 0.039$  and the bold black line the true density  $f$

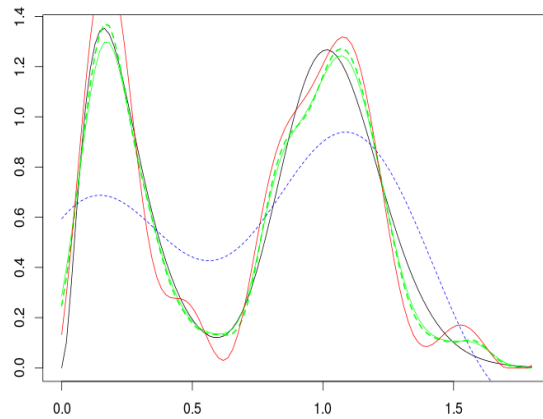


Figure 3: Simulated data. In black curve is the true density  $f$  Gamma, the estimator  $\hat{f}_{cv}$  is in dotted green, estimator  $\hat{f}_h$  is in green, estimator  $\hat{f}_\tau$  is blue and estimator  $\hat{f}_{\tilde{m},\tilde{s}}$  is in red, with  $N = 200$ ,  $T = 50$ ,  $\delta = 0.1$ ,  $\sigma = 0.05$ ,  $\alpha = 1$ .

Table 2: Empirical MISE computed from 100 simulated data sets, with  $N = 240$ ,  $\alpha = 0.039$  and various  $T$ ,  $\delta$ ,  $\sigma$  for the kernel estimator  $\hat{f}_h$  and the deconvolution estimator  $\tilde{f}_{\tilde{m}, \tilde{s}}$

Case	$T$	$\delta$	$\sigma$	Estimator	$f$			
					Gaussian	gamma	mixed Gaussian	mixed gamma
1	0.3	0.0002	0.0135	$\hat{f}_h$	0.234	0.034	0.015	0.026
				$\tilde{f}_{\tilde{m}, \tilde{s}}$	0.381	0.072	0.021	0.038
2	0.3	0.002	0.0135	$\hat{f}_h$	0.240	0.034	0.015	0.025
				$\tilde{f}_{\tilde{m}, \tilde{s}}$	1.584	0.071	0.019	0.038
3	0.3	0.0002	0.05	$\hat{f}_h$	2.535	0.095	0.025	0.054
				$\tilde{f}_{\tilde{m}, \tilde{s}}$	3.402	0.231	0.078	0.226
4	0.3	0.002	0.05	$\hat{f}_h$	2.524	0.093	0.026	0.053
				$\tilde{f}_{\tilde{m}, \tilde{s}}$	3.269	0.154	0.029	0.232
5	10	0.002	0.0135	$\hat{f}_h$	0.096	0.036	0.016	0.024
				$\tilde{f}_{\tilde{m}, \tilde{s}}$	0.080	0.037	0.035	0.052
6	10	0.02	0.0135	$\hat{f}_h$	0.105	0.032	0.015	0.023
				$\tilde{f}_{\tilde{m}, \tilde{s}}$	0.151	0.048	0.033	0.034
7	10	0.002	0.05	$\hat{f}_h$	0.111	0.037	0.014	0.026
				$\tilde{f}_{\tilde{m}, \tilde{s}}$	0.687	0.061	0.016	0.034
8	10	0.02	0.05	$\hat{f}_h$	0.121	0.037	0.016	0.026
				$\tilde{f}_{\tilde{m}, \tilde{s}}$	0.181	0.053	0.023	0.040
9	100	0.2	0.0135	$\hat{f}_h$	0.106	0.032	0.015	0.024
				$\tilde{f}_{\tilde{m}, \tilde{s}}$	0.123	0.062	0.091	0.046

*et al.*, 2006), and  $\sigma = 0.0135$  [V/ $\sqrt{s}$ ] (Picchini *et al.*, 2008). The  $\phi_j$  represents the local average input that the neuron receives during the  $j^{\text{th}}$  ISI. We assume that  $\phi_j$  changes from one ISI to another because of other neurons or environment influence, for example. So parameters  $\phi$  and  $\sigma$  characterize the input, while  $\alpha$ ,  $x_j$  (the resting potential), and  $S$  (the firing threshold) describe the neuron irrespectively of the incoming signal (Picchini *et al.*, 2008).

Data are composed of  $N = 312$  ISIs. For each interval  $[0, T_j]$  the time step is the same:  $\delta = 0.00015$  [s]. We decide to keep only realizations with more than 2000 observations ( $T_j/\delta \geq 2000$ ). Finally we have  $N = 240$  realizations with  $J = 2000$  observations and for  $j = 1, \dots, N$ ,  $T = T_j = 0.3$  [s]. Also the data are normalized in order to begin with zero at the initial time.

The study of the units of measurement can highlight the collections given in Section 4. One can notice that the unit of measurement of  $v$  in the integrand must be [s/V] (same unit as  $1/Z_{j,\tau}$ ) such that the exponential terms are without unit. The unit of  $s$  is [ $\sqrt{s}/V$ ], and the choice of  $\mathcal{M}$  with the same unit as  $v$  seems natural.

The normality of the  $Z_{j,T}$  is rejected by Shapiro and Wilk test (p-value  $10^{-7}$ ) and Kolmogorov-Smirnov test (p-value  $10^{-3}$ ). This suggests that the  $\phi_j$ 's are not Gaussian. Thus we want to estimate nonparametrically their density. In the following we compare our results to the estimation obtained in Picchini *et al.* (2010) under the parametric Gaussian assumption.

## 6.2 Comparison of estimators

The estimation of the density  $f$  obtained by Picchini *et al.* (2010) under the Gaussian assumption on this database are  $\mathcal{N}(\mu = 0.278, \eta^2 = (0.041)^2)$ . Using a maximum-likelihood estimator on the  $(Z_{j,T})$ 's we obtain for the mean 0.270 and for the standard deviation 0.046. We notice that these two estimations are close to the one of Picchini *et al.* (2010) even if the  $Z_{j,T}$  are noisy when  $T$  is small. We use our two nonparametric estimators to see how close to a Gaussian density they are.

On Figure 4 we represent both estimators  $\hat{f}_h$  and  $\tilde{f}_{\tilde{m}, \tilde{s}}$  applied to the real database and the density  $\mathcal{N}(\mu, \eta^2)$ . The two estimations are close, and close to the estimation of Picchini *et al.* (2010). However, it is also legitimate to think about a Gamma distribution to model the random parameters  $\phi_j$ 's because it is a non negative local average input. Thus, a Gamma distribution may seem more appropriate than a Gaussian distribution, even if the chosen Gaussian has small probability to be negative. We look for the Gamma distribution which has for mean  $\mu = 0.278$  and for standard deviation  $\eta = 0.041$ . This corresponds to a Gamma distribution with the scale parameter 46.3 and the shape parameter 0.006. We notice the similarity between the previous Gaussian curve and the new one. Thus this distribution seems also suitable to fit the distribution of the  $\phi_j$ 's as shows Figure 4.

The Gaussian assumption is strong and leads to parametric tractable models. The present work confirms that this approximation is acceptable. However, the nonparametric estimation gives a density for the  $\phi_j$ 's that can be used to simulate the random effect and could be closer to the true one.

Notice that, as mentioned in introduction, Comte *et al.* (2013)'s estimator cannot handle small values of  $T$  while our new proposals are successful in such case. One can wonder if the new estimators are robust when increasing  $T$ . Indeed, our method works for larger  $T$ . Precisely changing volts in millivolts and seconds in milliseconds implies  $T = 300$ ,  $\sigma = 0.426$ , and on simulated data we reconstruct well the shape of the density.

## 7 Discussion

In this work we study a stochastic differential Ornstein-Uhlenbeck mixed-effects model. We propose two estimators of the density of the random effect. Both estimators are not very sensitive to the effect of the time of observation  $T$ . Indeed the kernel strategy corresponds to a context with large  $T$  while we built a deconvolution estimator especially for small values of  $T$ . Both are data-driven and satisfy an oracle type inequality. According to the numerical study the kernel estimator seems to be the efficient one: the numerical results are convincing and close to the one obtained by cross-validation. Besides we provide non-asymptotic theoretical result.

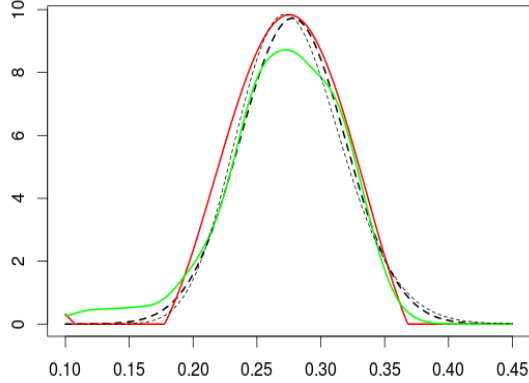


Figure 4: Real data. In green estimator  $\hat{f}_h$ , in red  $\tilde{f}_{\tilde{m}, \tilde{s}}$ , the black dotted and bold line the density  $\mathcal{N}(\mu, \eta^2)$  from Picchini *et al.* (2010) and the black dotted thin line the density  $\Gamma(46.3, 0.006)$

Furthermore we study neuronal data (ISI) with nonparametric estimation strategy. Instead of making any parametric assumptions for the random effect distribution, we build an estimator of its density. Future work based on this estimation could be more precise and closer to the real neuronal data. To complete the study, some goodness-of-fit tests could be produced, we refer to Bissantz *et al.* (2007) who construct confidence bands for estimator of  $f$  in the ordinary smooth deconvolution problem.

The model can be improved by adding another random effect: the time constant of the neuron. Picchini and Ditlevsen (2011) have investigated this model in a parametric way. This will be taken into consideration in further works.

Moreover, a model with a drift  $b(X_j(t)) + \phi_j$  where  $b$  is a known function, can be treated with the same method. However, dealing with a diffusion  $\sigma(X_j(t))$  where  $\sigma$  is a known function is more complex problem.

## Acknowledgements

The author would like to thank Fabienne Comte and Adeline Samson for very useful discussions and advice.

## 8 Proofs

### 8.1 Proof of Theorem 2

Given  $h \in \mathcal{H}_{N,T}$ , we denote:

$$V(h) = \kappa_1 \frac{\|K\|_1^2 \|K\|^2}{Nh} + \kappa_2 \frac{\sigma^4 \|K\|_1^2 \|K''\|^2}{T^2 h^5} =: V_1(h) + V_2(h).$$

Using the definition of  $A(h)$  and of  $\hat{h}$  we obtain

$$\begin{aligned} \|\hat{f}_{\hat{h}} - f\|^2 &\leq 3\|\hat{f}_{\hat{h}} - \hat{f}_{h, \hat{h}}\|^2 + 3\|\hat{f}_{h, \hat{h}} - \hat{f}_h\|^2 + 3\|\hat{f}_h - f\|^2 \\ &\leq 3\left(A(h) + V(\hat{h})\right) + 3\left(A(\hat{h}) + V(h)\right) + 3\|\hat{f}_h - f\|^2 \\ &\leq 6A(h) + 6V(h) + 3\|\hat{f}_h - f\|^2. \end{aligned}$$



Thus,

$$\mathbb{E}[\|\widehat{f}_h - f\|^2] \leq 6\mathbb{E}[A(h)] + 6V(h) + 3\mathbb{E}[\|\widehat{f}_h - f\|^2],$$

hence, we only have to study the term  $\mathbb{E}[A(h)]$ . We can decompose  $\|\widehat{f}_{h,h'} - \widehat{f}_{h'}\|^2$  as follows:

$$\|\widehat{f}_{h,h'} - \widehat{f}_{h'}\|^2 \leq 5\|\widehat{f}_{h,h'} - \mathbb{E}[\widehat{f}_{h,h'}]\|^2 + 5\|\mathbb{E}[\widehat{f}_{h,h'}] - f_{h,h'}\|^2 + 5\|f_{h,h'} - f_{h'}\|^2 + 5\|f_{h'} - \mathbb{E}[\widehat{f}_{h'}]\|^2 + 5\|\mathbb{E}[\widehat{f}_{h'}] - \widehat{f}_{h'}\|^2$$

thus

$$A(h) \leq 5(D_1 + D_2 + D_3 + D_4 + D_5)$$

with:

$$D_1 := \sup_{h' \in \mathcal{H}_{N,T}} \|f_{h,h'} - f_{h'}\|^2,$$

$$D_2 := \sup_{h' \in \mathcal{H}_{N,T}} \left( \|\widehat{f}_{h'} - \mathbb{E}[\widehat{f}_{h'}]\|^2 - \frac{V_1(h')}{10} \right)_+, \quad D_3 := \sup_{h' \in \mathcal{H}_{N,T}} \left( \|\widehat{f}_{h,h'} - \mathbb{E}[\widehat{f}_{h,h'}]\|^2 - \frac{V_1(h')}{10} \right)_+$$

$$D_4 := \sup_{h' \in \mathcal{H}_{N,T}} \left( \|\mathbb{E}[\widehat{f}_{h'}] - f_{h'}\|^2 - \frac{V_2(h')}{10} \right)_+, \quad D_5 := \sup_{h' \in \mathcal{H}_{N,T}} \left( \|\mathbb{E}[\widehat{f}_{h,h'}] - f_{h,h'}\|^2 - \frac{V_2(h')}{10} \right)_+.$$

According to Young's inequality (see Theorem 7), we obtain

$$\|f_{h,h'} - f_{h'}\|^2 = \|K_{h'} \star (f_h - f)\|^2 \leq \|K_{h'}\|_1^2 \|f_h - f\|^2 = \|K\|_1^2 \|f_h - f\|^2$$

thus

$$D_1 \leq \|K\|_1^2 \|f_h - f\|^2. \quad (17)$$

Let us study the term  $D_2$ . We denote  $\mathcal{B}(1) = \{g \in \mathbb{L}^2(\mathbb{R}), \|g\| = 1\}$ . We define

$$\nu_{N,h}(g) := \langle g, \widehat{f}_h - \mathbb{E}[\widehat{f}_h] \rangle$$

then  $|\nu_{N,h}(g)| \leq \|g\| \|\widehat{f}_h - \mathbb{E}[\widehat{f}_h]\|$  thus, the estimator  $\widehat{f}_h$  satisfies:

$$\|\widehat{f}_h - \mathbb{E}[\widehat{f}_h]\|^2 = \sup_{g \in \mathcal{B}(1)} (\nu_{N,h}(g))^2.$$

We can also compute the scalar product which defines  $\nu_{N,h}$  and we obtain

$$\nu_{N,h}(g) = \frac{1}{N} \sum_{j=1}^N (g \star K_h^-(Z_{j,T}) - \mathbb{E}[g \star K_h^-(Z_{j,T})]) \quad (18)$$

with  $K_h^-(x) := K_h(-x)$ . This finally conducts to:

$$\mathbb{E}[D_2] \leq \sum_{h' \in \mathcal{H}_{N,T}} \mathbb{E} \left[ \sup_{g \in \mathcal{B}(1)} (\nu_{N,h'}(g))^2 - \frac{V_1(h')}{10} \right]_+.$$

This bound and Equation (18) leads to apply Talagrand's Theorem (8). We have to compute 3 quantities:  $M$ ,  $H^2$  and  $v$ .

First:

$$\begin{aligned} \sup_{g \in \mathcal{B}(1)} \|g \star K_{h'}^-\|_\infty &= \sup_{g \in \mathcal{B}(1)} \sup_{x \in \mathbb{R}} \left| \int g(y) K_{h'}^-(x-y) dy \right| = \sup_{g \in \mathcal{B}(1)} \sup_{x \in \mathbb{R}} | \langle g, K_{h'}^-(\cdot - x) \rangle | \\ &\leq \sup_{g \in \mathcal{B}(1)} \|g\| \|K_{h'}^-\| = \frac{\|K\|}{\sqrt{h'}} := M. \end{aligned} \quad (19)$$

Secondly, the bound of Proposition 1 gives

$$\mathbb{E} \left[ \sup_{g \in \mathcal{B}(1)} (\nu_{N,h}(g))^2 \right] = \mathbb{E} [\|\widehat{f}_h - \mathbb{E}[\widehat{f}_h]\|^2] \leq \frac{\|K\|^2}{Nh} := H^2. \quad (20)$$

Thirdly:

$$\begin{aligned} \sup_{g \in \mathcal{B}(1)} (\text{Var}(g \star K_{h'}^-(Z_{1,T}))) &\leq \sup_{g \in \mathcal{B}(1)} \mathbb{E}[(g \star K_{h'}^-(Z_{1,T}))^2] \\ &\leq 2 \sup_{g \in \mathcal{B}(1)} \mathbb{E}[(g \star K_{h'}^-(\phi_1))^2] + 2 \sup_{g \in \mathcal{B}(1)} \mathbb{E}[(g \star (K_{h'}^-(Z_{1,T}) - K_{h'}^-(\phi_1)))^2]. \end{aligned}$$

Let us investigate the two terms separately. Young's inequality gives:

$$\mathbb{E}[(g \star K_{h'}^-(\phi_1))^2] = \int (g \star K_{h'}^-(x))^2 f(x) dx \leq \|f\| \|g \star K_{h'}^-\|_4^2 = \frac{\|f\| \|K\|_{4/3}^2}{\sqrt{h'}} := v_1. \quad (21)$$

Then, one can write:  $K_{h'}(x - Z_{1,T}) - K_{h'}(x - \phi_1) = (\phi_1 - Z_{1,T}) \int_0^1 (K_{h'})'(x - \phi_1 + u(\phi_1 - Z_{1,T})) du$ , thus

$$\begin{aligned} (g \star K_{h'}^-(Z_{1,T}) - g \star K_{h'}^-(\phi_1))^2 &= (\phi_1 - Z_{1,T})^2 \left( \int g(x) \int_0^1 (K_{h'})'(x - \phi_1 + u(\phi_1 - Z_{1,T})) du dx \right)^2 \\ &\leq (\phi_1 - Z_{1,T})^2 \int g^2(x) \left( \int_0^1 (K_{h'})'^2(x - \phi_1 + u(\phi_1 - Z_{1,T})) du \right) dx \\ &\leq (\phi_1 - Z_{1,T})^2 \|g\|^2 \int (K_{h'})'^2(y) dy = (\phi_1 - Z_{1,T})^2 \|(K_{h'})'\|^2. \end{aligned}$$

With  $\mathbb{E}[(\phi_1 - Z_{1,T})^2] = \frac{\sigma^2}{T^2} \mathbb{E}[W_1(T)^2] = \frac{\sigma^2}{T}$ , the assumption  $T^{-1} \leq h^{5/2}$  leads to

$$\mathbb{E}[(g \star K_{h'}^-(Z_{1,T}) - g \star K_{h'}^-(\phi_1))^2] \leq \frac{\|K'\|^2 \sigma^2}{h^3 T} \leq \frac{\|K'\|^2 \sigma^2}{\sqrt{h'}} := v_2. \quad (22)$$

Finally  $v = v_1 + v_2 = A_0/\sqrt{h'}$  with  $A_0 = \|f\| \|K\|_{4/3}^2 + \|K'\|^2 \sigma^2$ .

If  $\kappa_1 \|K\|_1^2 \geq 40$ , with the assumption  $1/(Nh) \leq 1$ , Talagrand's inequality (under the assumptions of the Theorem 2) gives

$$\begin{aligned} \mathbb{E} \left( \sup_{g \in \mathcal{B}(1)} (\nu_{N,h'}(g))^2 - \frac{V_1(h')}{10} \right)_+ &\leq \frac{C_1}{N\sqrt{h'}} e^{-C_2/\sqrt{h'}} + C_3 \frac{1}{h'N^2} e^{-C_4\sqrt{N}} \\ &\leq \frac{C_5}{N} \sum_{h' \in \mathcal{H}_{N,T}} \frac{1}{\sqrt{h'}} e^{-C_6/\sqrt{h'}} \leq \frac{C_5 S(C_6)}{N}. \end{aligned}$$

One can lead the study of  $D_3$  as we have done for  $D_2$ , using the same steps and tools. However  $K_h \star K_{h'}$  instead of  $K_{h'}$ , adds  $\|K\|_1$  in  $M$  and  $\|K\|_1^2$  in  $H^2$  and  $v$ .

Then, let us study the term  $D_4$ . If  $\kappa_2 \geq 10/(3\|K\|_1^2)$ , the bound (9) leads us to

$$\begin{aligned} D_4 &= \sup_{h' \in \mathcal{H}_{N,T}} \left( \|\mathbb{E}[\widehat{f}_{h'}]\| - f_{h'} \|^2 - \frac{V_2(h')}{10} \right)_+ \\ &\leq \sup_{h' \in \mathcal{H}_{N,T}} \left( \frac{\|K''\|^2 \sigma^4}{3h'^5 T^2} - \frac{\kappa_2 \|K\|_1^2 \|K''\|^2 \sigma^4}{10T^2 h'^5} \right)_+ = 0 \end{aligned}$$

thus  $D_4 = 0$ . Finally, similarly, if  $\kappa_2 \geq 10/3$ , we obtain

$$\begin{aligned} D_5 &= \sup_{h' \in \mathcal{H}_{N,T}} \left( \|\mathbb{E}[\widehat{f}_{h,h'}] - f_{h,h'}\|^2 - \frac{V_2(h')}{10} \right)_+ \\ &\leq \sup_{h' \in \mathcal{H}_{N,T}} \left( \frac{\|K''\|^2 \|K\|_1^2 \sigma^4}{3h^5 T^2} - \frac{\kappa_2 \|K\|_1^2 \|K''\|^2 \sigma^4}{10T^2 h'^5} \right)_+ = 0. \end{aligned}$$

Thus finally we obtained that:

$$\mathbb{E}[A(h)] \leq 5 \left( \|K\|_1^2 \|f_h - f\|^2 + \frac{c}{N} \right) \quad (23)$$

with  $c$  a constant depending on  $\|f\|, \|K\|_1, \|K\|, \|K\|_{4/3}$ . Finally we have shown that for all  $h \in \mathcal{H}_{N,T}$ :

$$\begin{aligned} \mathbb{E}[\|\widehat{f}_h - f\|^2] &\leq 6\kappa_1 \frac{\|K\|_1^2 \|K\|^2}{Nh} + 6\kappa_2 \frac{\|K\|_1^2 \|K''\|^2 \sigma^4}{T^2 h^5} + 3 \left( 2\|f - f_h\|^2 + \frac{\|K\|^2}{Nh} + \frac{2\|K''\|^2 \sigma^4}{3T^2 h^5} \right) \\ &\quad + 30 \left( \|K\|_1^2 \|f - f_h\|^2 + \frac{c}{N} \right) \\ &\leq \left( 6 + \frac{3}{\|K\|_1^2 \kappa_1} \right) V_1(h) + \left( 6 + \frac{9}{2\|K\|_1^2 \kappa_2} \right) V_2(h) + (30\|K\|_1^2 + 6)\|f_h - f\|^2 + \frac{C}{N} \\ &\leq C_1 \inf_{h \in \mathcal{H}_{N,T}} \{\|f - f_h\|^2 + V(h)\} + \frac{C_2}{N}. \end{aligned}$$

where  $C_1$  depends on  $\|K\|_1, \kappa_1, \kappa_2$  and  $C_2$  depends on  $\|f\|, \|K\|_1, \|K\|, \|K\|_{4/3}$ .  $\square$

## 8.2 Proof of Proposition 3

The bias term is  $\|f - \mathbb{E}[\widetilde{f}_{m,s}]\|^2$ . Let us compute  $\mathbb{E}[\widetilde{f}_{m,s}]$ . As the  $Z_{j,\tau}$  are *i.i.d.* when  $\tau$  is fixed and due to the independence of  $\phi_1$  and  $W_1$ , we obtain:

$$\begin{aligned} \mathbb{E}[\widetilde{f}_{m,s}(x)] &= \frac{1}{2\pi} \int_{-m}^m e^{-iux} \mathbb{E} \left[ e^{iuZ_{1,m^2/s^2} + u^2 \sigma^2 s^2 / (2m^2)} \right] du \\ &= \frac{1}{2\pi} \int_{-m}^m e^{-iux} \mathbb{E} \left[ e^{iu\phi_1 + iu\sigma W_1(m^2/s^2)s^2/m^2 + u^2 \sigma^2 s^2 / (2m^2)} \right] du \\ &= \frac{1}{2\pi} \int_{-m}^m e^{-iux + u^2 \sigma^2 s^2 / (2m^2)} f^*(u) \mathbb{E} \left[ e^{iu\sigma W_1(m^2/s^2)s^2/m^2} \right] du \\ &= \frac{1}{2\pi} \int_{-m}^m e^{-iux + u^2 \sigma^2 s^2 / (2m^2)} f^*(u) e^{-u^2 \sigma^2 s^2 / (2m^2)} du \\ &= \frac{1}{2\pi} \int_{-m}^m e^{-iux} f^*(u) du =: f_m(x). \end{aligned}$$

Therefore this gives  $\mathbb{E}[\widetilde{f}_{m,s}(x)] = f_m(x)$ , and  $\|f - \mathbb{E}[\widetilde{f}_{m,s}]\|^2 = \|f - f_m\|^2 = \frac{1}{2\pi} \int_{|u| \geq m} |f^*(u)|^2 du$ . The variance term is:

$$\begin{aligned} \mathbb{E}[\|\widetilde{f}_{m,s} - f_m\|^2] &= \frac{1}{2\pi} \mathbb{E} \left[ \int_{-m}^m \left| \frac{1}{N} \sum_{j=1}^N e^{iuZ_{j,m^2/s^2}} e^{\frac{u^2 \sigma^2 s^2}{2m^2}} - f^*(u) \right|^2 du \right] \\ &= \frac{1}{2\pi N} \int_{-m}^m e^{\frac{u^2 \sigma^2 s^2}{m^2}} \text{Var} \left( e^{iuZ_{1,m^2/s^2}} \right) du \\ &\leq \frac{1}{2\pi N} \int_{-m}^m e^{\frac{u^2 \sigma^2 s^2}{m^2}} du = \frac{m}{\pi N} \int_0^1 e^{s^2 \sigma^2 v^2} dv. \quad \square \end{aligned}$$

### 8.3 Proof of Theorem 5

Let us study the term  $\|\tilde{f}_{\tilde{m}, \tilde{s}} - f\|^2$ . We decompose it into a sum of three terms and the definition of  $(\tilde{m}, \tilde{s})$  (14) implies for all  $(m, s) \in \mathcal{C}$

$$\begin{aligned} \|\tilde{f}_{\tilde{m}, \tilde{s}} - f\|^2 &\leq 3 \left( \|\tilde{f}_{\tilde{m}, \tilde{s}} - \tilde{f}_{(\tilde{m}, \tilde{s}) \wedge (m, s)}\|^2 + \|\tilde{f}_{(\tilde{m}, \tilde{s}) \wedge (m, s)} - \tilde{f}_{m, s}\|^2 + \|\tilde{f}_{m, s} - f\|^2 \right) \\ &\leq 3(\Gamma_{m, s} + \text{pen}(\tilde{m}, \tilde{s})) + 3(\Gamma_{\tilde{m}, \tilde{s}} + \text{pen}(m, s)) + 3\|\tilde{f}_{m, s} - f\|^2 \\ &\leq 6\Gamma_{m, s} + 6\text{pen}(m, s) + 3\|\tilde{f}_{m, s} - f\|^2 \end{aligned} \quad (24)$$

Now we study  $\Gamma_{m, s}$ . First:

$$\|\tilde{f}_{(m, s) \wedge (m', s')} - \tilde{f}_{m', s'}\|^2 \leq 3 \left( \|\tilde{f}_{m', s'} - f_{m'}\|^2 + \|f_{m'} - f_{m \wedge m'}\|^2 + \|f_{m \wedge m'} - \tilde{f}_{(m', s') \wedge (m, s)}\|^2 \right).$$

Thus:

$$\begin{aligned} \Gamma_{m, s} &\leq \max_{(m', s') \in \mathcal{C}} \left( 3\|\tilde{f}_{m', s'} - f_{m'}\|^2 + 3\|f_{m'} - f_{m \wedge m'}\|^2 + 3\|f_{m \wedge m'} - \tilde{f}_{(m', s') \wedge (m, s)}\|^2 - \text{pen}(m', s') \right)_+ \\ &\leq 3 \max_{(m', s') \in \mathcal{C}} \left( \|\tilde{f}_{m', s'} - f_{m'}\|^2 - \frac{1}{6}\text{pen}(m', s') \right)_+ \\ &+ 3 \max_{(m', s') \in \mathcal{C}} \left( \|\tilde{f}_{(m', s') \wedge (m, s)} - f_{m \wedge m'}\|^2 - \frac{1}{6}\text{pen}(m', s') \right)_+ \\ &+ 3 \max_{m' \in \mathcal{M}} \|f_{m'} - f_{m \wedge m'}\|^2. \end{aligned}$$

The last maximum can be explicit. If  $m' \leq m$ , then  $\|f_{m'} - f_{m \wedge m'}\|^2 = \|f_{m'} - f_{m'}\|^2 = 0$ . Otherwise,

$$\|f_{m'} - f_{m \wedge m'}\|^2 = \|f_{m'} - f_m\|^2 = \int_{m \leq |u| \leq m'} |f^*(u)|^2 du \leq \|f - f_m\|^2.$$

Finally:

$$\max_{m' \in \mathcal{M}} \|f_{m'} - f_{m \wedge m'}\|^2 \leq \|f - f_m\|^2.$$

We get the following bound for  $\Gamma_{m, s}$ :

$$\begin{aligned} \Gamma_{m, s} &\leq 3 \max_{(m', s') \in \mathcal{C}} \left( \|\tilde{f}_{m', s'} - f_{m'}\|^2 - \frac{1}{6}\text{pen}(m', s') \right)_+ \\ &+ 3 \max_{(m', s') \in \mathcal{C}} \left( \|\tilde{f}_{(m', s') \wedge (m, s)} - f_{m \wedge m'}\|^2 - \frac{1}{6}\text{pen}(m', s') \right)_+ \\ &+ 3\|f - f_m\|^2. \end{aligned} \quad (25)$$

Then we gather Equations (24) and (25):

$$\begin{aligned} \|\tilde{f}_{\tilde{m}, \tilde{s}} - f\|^2 &\leq 6\text{pen}(m, s) + 3\|\tilde{f}_{m, s} - f\|^2 + 18\|f - f_m\|^2 + \max_{(m', s') \in \mathcal{C}} 18 \left( \|\tilde{f}_{m', s'} - f_{m'}\|^2 - \frac{1}{6}\text{pen}(m', s') \right)_+ \\ &+ \max_{(m', s') \in \mathcal{C}} 18 \left( \|\tilde{f}_{(m', s') \wedge (m, s)} - f_{m \wedge m'}\|^2 - \frac{1}{6}\text{pen}(m', s') \right)_+. \end{aligned}$$

We first notice that our penalty function is increasing in  $s$  and  $m$ , thus we get the following bound for the last term:

$$\begin{aligned}
& \mathbb{E} \left[ \max_{(m', s') \in \mathcal{C}} \left( \|\tilde{f}_{(m', s') \wedge (m, s)} - f_{m \wedge m'}\|^2 - \frac{1}{6} \text{pen}((m', s') \wedge (m, s)) \right)_+ \right] \\
& \leq \mathbb{E} \left[ \max_{m' \leq m, s' \leq s} \left( \|\tilde{f}_{m', s'} - f_{m'}\|^2 - \frac{1}{6} \text{pen}(m', s') \right)_+ \right] + \mathbb{E} \left[ \max_{m \leq m', s \leq s'} \left( \|\tilde{f}_{m, s} - f_m\|^2 - \frac{1}{6} \text{pen}(m, s) \right)_+ \right] \\
& \quad + \mathbb{E} \left[ \max_{m \leq m', s' \leq s} \left( \|\tilde{f}_{m, s'} - f_m\|^2 - \frac{1}{6} \text{pen}(m, s') \right)_+ \right] + \mathbb{E} \left[ \max_{m' \leq m, s \leq s'} \left( \|\tilde{f}_{m', s} - f_{m'}\|^2 - \frac{1}{6} \text{pen}(m', s) \right)_+ \right] \\
& \leq 4 \sum_{m' \in \mathcal{M}} \sum_{s' \in \mathcal{S}} \mathbb{E} \left[ \|\tilde{f}_{m', s'} - f_{m'}\|^2 - \frac{1}{6} \text{pen}(m', s') \right]_+.
\end{aligned}$$

Moreover, according to Proposition 3 and using the inequality  $\int_0^1 e^{\sigma^2 s^2 v^2} dv \leq e^{\sigma^2 s^2}$ , we obtain, for all  $(m, s) \in \mathcal{C}$ ,

$$\begin{aligned}
\mathbb{E}[\|\tilde{f}_{\tilde{m}, \tilde{s}} - f\|^2] & \leq 5 \times 18 \sum_{m' \in \mathcal{M}} \sum_{s' \in \mathcal{S}} \mathbb{E} \left[ \|\tilde{f}_{m', s'} - f_{m'}\|^2 - \frac{1}{6} \text{pen}(m', s') \right]_+ + 6 \text{pen}(m, s) \\
& \quad + 3 \frac{m}{\pi N} e^{\sigma^2 s^2} + 21 \|f - f_m\|^2.
\end{aligned}$$

Then we obtain the announced result with the following Lemma.

**Lemma 6.** *There exists a constant  $C' > 0$  such that for  $\text{pen}(m, s)$  defined by  $\text{pen}(m, s) = \kappa \frac{m}{N} e^{\sigma^2 s^2}$ ,*

$$\sum_{m' \in \mathcal{M}} \sum_{s' \in \mathcal{S}} \mathbb{E} \left[ \|\tilde{f}_{m', s'} - f_{m'}\|^2 - \frac{1}{6} \text{pen}(m', s') \right]_+ \leq \frac{C'(P+1)}{N}.$$

According to Lemma 6, to be proved next, we choose  $\text{pen}(m, s) = \kappa \frac{m}{N} e^{\sigma^2 s^2}$ , thus, there exist two constants  $C, C' > 0$  such that,

$$\begin{aligned}
\mathbb{E}[\|\tilde{f}_{\tilde{m}, \tilde{s}} - f\|^2] & \leq 5 \times 18 \sum_{m' \in \mathcal{M}} \sum_{s' \in \mathcal{S}} \mathbb{E} \left[ \|\tilde{f}_{m', s'} - f_{m'}\|^2 - \frac{1}{6} \text{pen}(m', s') \right]_+ + (6\kappa + \frac{3}{\pi}) \frac{m}{N} e^{\sigma^2 s^2} + 21 \|f - f_m\|^2 \\
& \leq C \inf_{(m, s) \in \mathcal{C}} \{ \|f - f_m\|^2 + \frac{m}{N} e^{\sigma^2 s^2} \} + \frac{C'}{N}. \quad \square
\end{aligned}$$

*Proof of Lemma 6*

For a couple  $(m, s) \in \mathcal{C}$  fixed, let us consider the subset  $S_m := \{t \in \mathbb{L}^1(\mathbb{R}) \cap \mathbb{L}^2(\mathbb{R}), \text{supp}(t^*) = [-m, m]\}$ . For  $t \in S_m$ ,

$$\nu_N(t) = \frac{1}{N} \sum_{j=1}^N (\varphi_t(Z_{j, m^2/s^2}) - \mathbb{E}[\varphi_t(Z_{j, m^2/s^2})])$$

with  $\varphi_t(x) := \frac{1}{2\pi} \int \overline{t^*(u)} e^{iux + \sigma^2 u^2 s^2 / (2m^2)} du$ , then  $\nu_N(t) = \frac{1}{2\pi} \langle t^*, (\tilde{f}_{m, s} - f_m)^* \rangle$ . This leads to

$$\|\tilde{f}_{m, s} - f_m\|^2 = \sup_{t \in S_m, \|t\|=1} |\nu_N(t)|^2. \quad (26)$$

We also have by Cauchy-Schwarz inequality

$$\begin{aligned}
\|\varphi_t\|_\infty & \leq \frac{1}{2\pi} \int |t^*(u)| e^{\sigma^2 u^2 s^2 / (2m^2)} du \leq \frac{1}{2\pi} \left( \int_{-m}^m |t^*(u)|^2 du \right)^{1/2} \left( \int_{-m}^m e^{\sigma^2 u^2 s^2 / m^2} du \right)^{1/2} \\
& \leq \frac{\sqrt{2m}}{\sqrt{2\pi}} e^{\sigma^2 s^2 / 2}
\end{aligned}$$

thus

$$\sup_{t \in S_m, \|t\|=1} \|\varphi_t\|_\infty \leq \frac{\sqrt{m}}{\sqrt{\pi}} e^{\sigma^2 s^2 / 2} := M.$$

Then, by Proposition 3,

$$\mathbb{E} \left[ \sup_{t \in S_m, \|t\|=1} |\nu_N(t)|^2 \right] = \mathbb{E} \left[ \|\tilde{f}_{m,s} - f_m\|^2 \right] \leq \frac{m}{\pi N} \int_0^1 e^{\sigma^2 s^2 v^2} dv \leq \frac{m}{\pi N} e^{\sigma^2 s^2} := H^2.$$

Using Fubini and Cauchy-Schwarz inequalities we obtain for all  $(m, s) \in \mathcal{C}$ :

$$\begin{aligned} 4\pi \sup_{t \in S_m, \|t\|=1} \text{Var}(\varphi_t(Z_{j,m^2/s^2})) &\leq \sup_{t \in S_m, \|t\|=1} \iint t^*(u)t^*(-v) \mathbb{E} \left[ e^{i(u-v)Z_{j,m^2/s^2}} \right] e^{(u^2+v^2)\sigma^2 s^2 / (2m^2)} dudv \\ &\leq 2\pi \left( \iint_{[-m,m]^2} |f^*(u-v)|^2 e^{(u^2+v^2)\sigma^2 s^2 / m^2} dudv \right)^{1/2} \\ &\leq 2\pi \left( e^{2\sigma^2 s^2} \iint_{[-m,m]^2} |f^*(u-v)|^2 dudv \right)^{1/2} \\ &\leq 2\pi e^{\sigma^2 s^2} \sqrt{2m} \left( \int_{-2m}^{2m} |f^*(z)|^2 dz \right)^{1/2} \leq 2\sqrt{2m} \sqrt{2\pi} \sqrt{\pi} e^{\sigma^2 s^2} \|f\| =: 4\pi^2 v, \\ v &:= \frac{\sqrt{m} e^{\sigma^2 s^2} \|f\|}{\sqrt{\pi}}. \end{aligned}$$

Finally using that  $m \leq N$ ,  $s \leq 2/\sigma$  and  $\sum_{s \in \mathcal{S}} s = (4/\sigma)(1 - (1/2)^{P+1}) < 4/\sigma$ , the Talagrand's inequality with  $\alpha = 1/2$  if  $4H^2 \leq \text{pen}(m, s)/6$  implies,

$$\begin{aligned} \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} \mathbb{E} \left[ \|\tilde{f}_{m,s} - f_m\|^2 - \frac{1}{6} \text{pen}(s, m) \right]_+ &\leq \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} \left( \frac{C_1 \|f\|}{N} e^{\sigma^2 s^2} \sqrt{m} e^{-C_2 \frac{\sqrt{m}}{\|f\|}} + C_3 \frac{m}{N^2} e^{\sigma^2 s^2} e^{-C_4 \sqrt{N}} \right) \\ &\leq \sum_{s \in \mathcal{S}} \frac{C_1 \|f\|}{N} e^{\sigma^2 s^2} \left( \sum_{m \in \mathcal{M}} \sqrt{m} e^{-C_2 \frac{\sqrt{m}}{\|f\|}} \right) + \sum_{s \in \mathcal{S}} \sum_{m \in \mathcal{M}} C_3 e^4 \frac{1}{N} e^{-C_4 \sqrt{m}} \\ &\leq \frac{C_1 \|f\| (P+1) e^4}{N} \left( \sum_{m \in \mathcal{M}} \sqrt{m} e^{-C_2 \frac{\sqrt{m}}{\|f\|}} \right) + C_3 e^4 \frac{P+1}{N} \sum_{m \in \mathcal{M}} e^{-C_4 \sqrt{m}} \\ &\leq \frac{C'(P+1)}{N} \end{aligned}$$

because with the definition of  $\mathcal{M}$ ,  $\sum_{m \in \mathcal{M}} \sqrt{m} e^{-C_2 \frac{\sqrt{m}}{\|f\|}} \leq a_1 \sum_{k \in \mathbb{N}} k^{1/4} e^{-a_2 k^{1/4}} < +\infty$ , and  $\sum_{m \in \mathcal{M}} e^{-C_4 m^{1/2}} \leq \sum_{k \in \mathbb{N}} e^{-a_3 k^{1/4}} < +\infty$ , with  $a_1, a_2, a_3$  three positive constants. Notice that  $C' > 0$  depends on  $\sigma, \|f\|, \Delta$ .

We choose  $\text{pen}(m, s) = \kappa m e^{\sigma^2 s^2} / N$  with  $\kappa \geq 24$ .  $\square$

## A Appendix

### A.1 Young inequality

This inequality can be found in Briane and Pagès (2006) for example.

**Theorem 7.** *Let  $f$  be a function belonging to  $\mathbb{L}^p(\mathbb{R})$  and  $g$  belonging to  $\mathbb{L}^q(\mathbb{R})$ , let  $p, q, r$  be real numbers in  $[1, +\infty]$  and such that*

$$\frac{1}{p} + \frac{1}{q} = \frac{1}{r} + 1.$$

Then,

$$\|f \star g\|_r \leq \|f\|_p \|g\|_q.$$

## A.2 Talagrand's inequality

The following result follows from the Talagrand concentration inequality given in Klein and Rio (2005) and arguments in Birgé and Massart (1998).

**Theorem 8.** Consider  $n \in \mathbb{N}^*$ ,  $\mathcal{F}$  a class at most countable of measurable functions, and  $(X_i)_{i \in \{1, \dots, N\}}$  a family of real independent random variables. One defines, for all  $f \in \mathcal{F}$ ,

$$\nu_N(f) = \frac{1}{N} \sum_{i=1}^N (f(X_i) - \mathbb{E}[f(X_i)]).$$

Supposing there are three positive constants  $M$ ,  $H$  and  $v$  such that  $\sup_{f \in \mathcal{F}} \|f\|_\infty \leq M$ ,

$\mathbb{E}[\sup_{f \in \mathcal{F}} |\nu_N(f)|] \leq H$ , and  $\sup_{f \in \mathcal{F}} (1/N) \sum_{i=1}^N \text{Var}(f(X_i)) \leq v$ , then for all  $\alpha > 0$ ,

$$\begin{aligned} \mathbb{E} \left[ \left( \sup_{f \in \mathcal{F}} |\nu_N(f)|^2 - 2(1 + 2\alpha)H^2 \right)_+ \right] &\leq \frac{4}{a} \left( \frac{v}{N} \exp \left( -a\alpha \frac{NH^2}{v} \right) \right. \\ &\quad \left. + \frac{49M^2}{aC^2(\alpha)N^2} \exp \left( -\frac{\sqrt{2}aC(\alpha)\sqrt{\alpha} NH}{7M} \right) \right) \end{aligned}$$

with  $C(\alpha) = (\sqrt{1 + \alpha} - 1) \wedge 1$ , and  $a = \frac{1}{6}$ .

## A.3 Discretization

Indeed, if we assume that the times of observations are the  $t_k = k\delta$ ,  $k = 1, \dots, N$  and  $0 < \delta < 1$ , we must study the error applied by discretization of the  $Z_{j,\tau}$ . Then, for any  $0 < m^2/s^2 \leq T$  we use:

$$\widehat{Z}_{j,m^2/s^2} = \frac{s^2}{m^2} \left[ X_j(\delta[m^2/(s^2\delta)]) - X_j(0) + \frac{\delta}{\alpha} \sum_{k=1}^{[m^2/(s^2\delta)]} X_j((k-1)\delta) \right] \quad (27)$$

to approximate  $Z_{j,m^2/s^2}$  given by (2). The corresponding estimator of  $f$  is

$$\widehat{f}_{m,s}(x) = \frac{1}{2\pi} \int_{-m}^m e^{-iux} \frac{1}{N} \sum_{j=1}^N e^{iu\widehat{Z}_{j,m^2/s^2}} e^{\frac{u^2\sigma^2 s^2}{2m^2}} du. \quad (28)$$

We investigate the error:

$$\mathbb{E}[\|\widehat{f}_{m,s} - f\|^2] \leq 2\mathbb{E}[\|\widehat{f}_{m,s} - \widetilde{f}_{m,s}\|^2] + 2\mathbb{E}[\|\widetilde{f}_{m,s} - f\|^2]$$

where the second term of the right hand side is bounded by Proposition 3. Then, Plancherel-Parseval's Theorem implies:

$$\begin{aligned} \mathbb{E}[\|\widehat{f}_{m,s} - \widetilde{f}_{m,s}\|^2] &\leq \frac{1}{2\pi} \mathbb{E} \left[ \int_{-m}^m \frac{1}{N} \sum_{j=1}^N e^{u^2\sigma^2 s^2/m^2} \left| e^{iu\widehat{Z}_{j,m^2/s^2}} - e^{iuZ_{j,m^2/s^2}} \right|^2 du \right] \\ &\leq \frac{1}{2\pi} \int_{-m}^m e^{u^2\sigma^2 s^2/m^2} \mathbb{E} \left[ \left| e^{iu\widehat{Z}_{1,m^2/s^2}} - e^{iuZ_{1,m^2/s^2}} \right|^2 \right] du \end{aligned}$$

and

$$\mathbb{E} \left[ \left| e^{iu\widehat{Z}_{1,m^2/s^2}} - e^{iuZ_{1,m^2/s^2}} \right|^2 \right] \leq |u|^2 \mathbb{E} \left[ \left| \widehat{Z}_{1,m^2/s^2} - Z_{1,m^2/s^2} \right|^2 \right]$$

thus we study the last term. For all  $(m, s) \in \mathcal{C}$ ,  $m^2/s^2 \leq T$ ,

$$\begin{aligned} Z_{1,m^2/s^2} - \widehat{Z}_{1,m^2/s^2} &= \frac{s^2}{m^2} (X_j(m^2/s^2) - X_j(\delta[m^2/(s^2\delta)])) \\ &\quad + \frac{s^2}{\alpha m^2} \sum_{k=1}^{\lfloor m^2/(s^2\delta) \rfloor} \int_{(k-1)\delta}^{k\delta} (X_j(s) - X_j((k-1)\delta)) ds \end{aligned}$$

then by Cauchy-Schwarz's inequality we obtain

$$\begin{aligned} (Z_{1,m^2/s^2} - \widehat{Z}_{1,m^2/s^2})^2 &\leq \frac{2s^4}{m^4} (X_j(m^2/s^2) - X_j(\delta[m^2/(s^2\delta)]))^2 \\ &\quad + \frac{2s^4}{\alpha^2 m^4} \left[ \sum_{k=1}^{\lfloor m^2/(s^2\delta) \rfloor} \int_{(k-1)\delta}^{k\delta} (X_j(s) - X_j((k-1)\delta)) ds \right]^2. \end{aligned}$$

Hölder's inequality yields

$$\begin{aligned} \left[ \sum_{k=1}^{\lfloor \frac{m^2}{s^2\delta} \rfloor} \int_{(k-1)\delta}^{k\delta} (X_j(s) - X_j((k-1)\delta)) ds \right]^2 &\leq \sum_{k=1}^{\lfloor \frac{m^2}{s^2\delta} \rfloor} \left[ \int_{(k-1)\delta}^{k\delta} (X_j(s) - X_j((k-1)\delta)) ds \right]^2 \left[ \frac{m^2}{s^2\delta} \right] \\ &\leq \left[ \frac{m^2}{s^2\delta} \right] \delta \sum_{k=1}^{\lfloor \frac{m^2}{s^2\delta} \rfloor} \int_{(k-1)\delta}^{k\delta} (X_j(s) - X_j((k-1)\delta))^2 ds. \end{aligned}$$

Let us study  $\mathbb{E}[(X_j(s) - X_j((k-1)\delta))^2]$ , for  $(k-1)\delta \leq s \leq k\delta$ :

$$X_j(s) - X_j((k-1)\delta) = \int_{(k-1)\delta}^s \left( \phi_j - \frac{X_j(u)}{\alpha} \right) du + \int_{(k-1)\delta}^s \sigma dW_j(u)$$

and Cauchy-Schwarz's inequality gives

$$\begin{aligned} \mathbb{E}[(X_j(s) - X_j((k-1)\delta))^2] &\leq 2\mathbb{E} \left[ \left( \int_{(k-1)\delta}^s \left( \phi_j - \frac{X_j(u)}{\alpha} \right) du \right)^2 \right] + 2\mathbb{E} \left[ \left( \int_{(k-1)\delta}^s \sigma dW_j(u) \right)^2 \right] \\ &\leq 2\mathbb{E} \left[ \int_{(k-1)\delta}^s \left( \phi_j - \frac{X_j(u)}{\alpha} \right)^2 du \right] + 2\delta\sigma^2 \\ &\leq 4\delta^2 \left( \mathbb{E}(\phi_j^2) + \frac{1}{\alpha^2} \sup_{s \geq 0} \mathbb{E}[X_j(s)^2] \right) + 2\delta\sigma^2. \end{aligned} \quad (29)$$

Finally, after simplification and using for all  $x \in \mathbb{R}^+$ ,  $[x] \leq x$ ,

$$\begin{aligned} \mathbb{E} \left[ (Z_{1,m^2/s^2} - \widehat{Z}_{1,m^2/s^2})^2 \right] &\leq \frac{2s^4}{m^4} \mathbb{E}[(X_j(m^2/s^2) - X_j(\delta[m^2/(s^2\delta)]))^2] \\ &\quad + \frac{2}{\alpha^2} \left( 4\delta^2 \left( \mathbb{E}(\phi_j^2) + \frac{1}{\alpha^2} \sup_{s \geq 0} \mathbb{E}[X_j(s)^2] \right) + 2\delta\sigma^2 \right) \end{aligned}$$

and we can deal with the term  $\mathbb{E}[(X_j(m^2/s^2) - X_j(\delta[m^2/(s^2\delta)]))^2]$  using formula (29) and  $m^2/s^2 - \delta[m^2/(s^2\delta)] \leq \delta$ . Thus:

$$\mathbb{E} \left[ (Z_{1,m^2/s^2} - \widehat{Z}_{1,m^2/s^2})^2 \right] \leq \left( \frac{2s^4}{m^4} + \frac{2}{\alpha^2} \right) \left( 4\delta^2 \left( \mathbb{E}(\phi_j^2) + \frac{1}{\alpha^2} \sup_{s \geq 0} \mathbb{E}[X_j(s)^2] \right) + 2\delta\sigma^2 \right).$$



Besides, for model (1), Equation (16) implies  $\mathbb{E}[X_j(s)^2] \leq 3x_j^2 + 3\alpha^2\mathbb{E}[\phi_j^2] + 3\sigma^2$ , and  $0 < \delta < 1$  implies

$$\mathbb{E} \left[ (Z_{1,m^2/s^2} - \widehat{Z}_{1,m^2/s^2})^2 \right] \leq C\delta \left( \frac{2s^4}{m^4} + \frac{2}{\alpha^2} \right)$$

with  $C$  a positive constant which does not depend on  $\delta$  or  $m^2/s^2$ . Finally,

$$\begin{aligned} \mathbb{E}[\|\widehat{f}_{m,s} - \widetilde{f}_{m,s}\|^2] &\leq C\delta \left( \frac{2s^4}{m^4} + \frac{2}{\alpha^2} \right) \frac{1}{2\pi} \int_{-m}^m u^2 e^{u^2\sigma^2s^2/m^2} du \\ &\leq C'\delta \left( \int_0^1 v^2 e^{v^2\sigma^2s^2} dv \right) \left( \frac{s^4}{m} + \frac{m^3}{\alpha^2} \right). \end{aligned}$$

But  $s \leq 2/\sigma$  and  $m = \sqrt{k\Delta}/\sigma$ , with  $k \in \mathbb{N}^*$  and  $0 < \Delta < 1$ , thus we obtain

$$\mathbb{E}[\|\widehat{f}_{m,s} - \widetilde{f}_{m,s}\|^2] \leq \frac{C'}{\sigma^3} \left( \int_0^1 v^2 e^{v^2\sigma^2s^2} dv \right) \left( 2^4\sqrt{k} \left( \frac{\delta}{\sqrt{\Delta}} \right) + \frac{k^{3/2}}{\alpha^2} (\delta\Delta^{3/2}) \right).$$

**Proposition 9.** *Under (A), assuming  $\mathbb{E}[\phi_j^2] < +\infty$ , the estimator  $\widehat{f}_{m,s}$  given by (28) satisfies*

$$\mathbb{E} \left[ \|\widehat{f}_{m,s} - f\|^2 \right] \leq \|f_m - f\|^2 + \frac{\sqrt{k\Delta}}{\sigma\pi N} e^{\sigma^2s^2} + \frac{C'}{\sigma^3} \frac{e^{\sigma^2s^2}}{2\sigma^2s^2} \left( 2^4\sqrt{k} \left( \frac{\delta}{\sqrt{\Delta}} \right) + \frac{k^{3/2}}{\alpha^2} (\delta\Delta^{3/2}) \right).$$

Finally if  $\Delta$  is fixed and  $\delta$  is small, the error is acceptable. For example is  $\delta = \Delta$  the error is of order  $\sqrt{\delta}$ .

For study on the kernel estimator we refer to Comte *et al.* (2013).

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