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Abstract

This paper presents a new and efficient method for the construction of optimal designs for regression models with dependent error processes. In contrast to most of the work in this field, which starts with a model for a finite number of observations and considers the asymptotic properties of estimators and designs as the sample size converges to infinity, our approach is based on a continuous time model. We use results from stochastic analysis to identify the best linear unbiased estimator (BLUE) in this model. Based on the BLUE, we construct an efficient linear estimator and corresponding optimal designs in the model for finite sample size by minimizing the mean squared error between the optimal solution in the continuous time model and its discrete approximation with respect to the weights (of the linear estimator) and the optimal design points, in particular in the multi-parameter case.

In contrast to previous work on the subject the resulting estimators and corresponding optimal designs are very efficient and easy to implement. This means that they are practically not distinguishable from the weighted least squares estimator and the corresponding optimal designs, which have to be found numerically by non-convex discrete optimization. The advantages of the new approach are illustrated in several numerical examples.

Keywords and Phrases: linear regression, correlated observations, optimal design, Gaussian white mouse model, Doob representation, quadrature formulas
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1 Introduction

The construction of optimal designs for dependent observations is a very challenging problem in statistics, because - in contrast to the independent case - the dependency yields non-convex optimization problems. As a consequence, classical tools of convex optimization theory as described, for example, in Pukelsheim (2006) are not applicable. Most of the discussion is restricted to very simple models and we refer to Dette et al. (2008); Kiselak and Stehlík (2008); Harman and Štulajter (2010) for some exact optimal designs for linear regression models. Several authors have proposed to determine optimal designs using asymptotic arguments [see, for example, Sacks and Ylvisaker (1966, 1968), Bickel and Herzberg (1979), Näther (1985a), Zhigljavsky et al. (2010)], but the resulting approximate optimal design problems are still non-convex and extremely difficult to solve. As a consequence, approximate optimal designs have mainly been determined analytically for the location model (in this case the corresponding optimization problems are in fact convex) and for a few one-parameter linear models [see Boltze and Näther (1982), Näther (1985a), Ch. 4, Näther (1985b), Pázman and Müller (2001) and Müller and Pázman (2003) among others].

Recently, substantial progress has been made in the construction of optimal designs for regression models with a dependent error process. Dette et al. (2013) determined (asymptotic) optimal designs for least squares estimation, under the additional assumption that the regression functions are eigenfunctions of an integral operator associated with the covariance kernel of the error process. Although this approach is able to deal with the multi-parameter case, the class of models for which approximate optimal designs can be determined explicitly is still rather small, because it refers to specific kernels with corresponding eigenfunctions. For this reason Dette et al. (2015) proposed a different strategy to obtain optimal designs and efficient estimators. Instead of constructing an optimal design for a particular estimator (such as least squares or weighted least squares), these authors proposed to consider the problem of optimizing the estimator and the design of experiment simultaneously. They constructed a class of estimators and corresponding optimal designs with a variance converging (as the sample size increases) to the optimal variance in the continuous time model. In other words, asymptotically these estimators achieve the same precision as the best linear unbiased estimator computed from the whole trajectory of the process. While this approach yields a satisfactory solution for one-dimensional parametric models using signed least squares estimators, it is not transparent and in many cases not efficient in the multi-parameter model. In particular, it is based on matrix-weighted linear estimators and corresponding designs which are difficult to implement in practice and do not yield the same high efficiencies as in the one-dimensional case.

In this paper we present an alternative approach for the construction of estimators and corresponding optimal designs for regression models with dependent error processes, which has important advantages compared to the currently used methodology. First - in contrast to all other methods - the estimators with corresponding optimal designs proposed here are very easy to implement. Secondly, it is demonstrated that the new estimator and design yield a method which is practically not distinguishable from the best linear estimator (BLUE) with corresponding optimal design. Third, in many cases the new estimator and a uniform design are already very efficient.

Compared to most of the work in this field, which begins with a model for a finite number of observations and considers the asymptotic properties of estimators as the sample size converges to infinity, an essential difference of our approach is that it is directly based on the continuous time model. In Section 2 we derive the best linear unbiased estimate in this model using results about the absolute continuity of measures on the space $C([a,b])$. This yields a representation of the best linear estimator as a stochastic integral and provides an efficient tool for constructing estimators with corresponding optimal designs for finite samples which are practically not distinguishable from the optimal (weighted least squares) estimator and corresponding optimal design. We emphasize again that the latter design has to be determined by discrete non-convex optimization. To be more precise, in Section 3 we propose a weighted mean, say $\sum_{i=1}^n \mu_i Y_{t_i}$ (here Y_{t_i} denotes the response at the point t_i and n is the sample size), where the weights $\mu_1, \ldots, \mu_n$ (which are vectors in case of models with more than one parameter) and design points $t_1, \ldots, t_n$ are determined by minimizing the mean squared error between the optimal solution in the continuous time model (represented by a stochastic integral with respect to the underlying process) and its discrete approximation with respect to the weights (of the linear estimator) and the optimal design points. In Section 4 we discuss several examples and demonstrate the superiority of the new approach to the method which was recently proposed in Dette et al. (2015), in particular for multi-parameter models. Some more details on best linear unbiased estimation in the continuous time model are given in Section 5, where we discuss degenerate cases, which appear - for example - by a constant term in the regression function. For a more transparent presentation of the ideas some technical details are additionally deferred to the Appendix.

We finally note that this paper is a first approach which uses results from stochastic analysis in the context of optimal design theory. The combination of these two fields yields a practically implementable and satisfactory solution of optimal design problems for a broad class of regression models with dependent observations.

2 Optimal estimation in continuous time models

Consider a linear regression model of the form

$$Y_{t_i} = Y(t_i) = \theta^T f(t_i) + \varepsilon_{t_i}, \qquad i = 1, \ldots, n\,, \tag{2.1}$$

where $\{\varepsilon_t \mid t \in [a,b]\}$ is a Gaussian process, $\mathbb{E}[\varepsilon_{t_i}] = 0$, $K(t_i, t_j) = \mathbb{E}[\varepsilon_{t_i}\varepsilon_{t_j}]$ denotes the covariance between observations at the points t_i and t_j $(i, j = 1, \dots, n)$, $\theta = (\theta_1, \dots, \theta_m)^T$ is a vector of unknown parameters, $f(t) = (f_1(t), \dots, f_m(t))^T$ is a vector of continuously differentiable linearly independent functions, and the explanatory variables $t_1, \dots, t_n$ vary in a compact interval, say $[a, b]$. If $\mathbf{Y} = (Y_{t_1}, \dots, Y_{t_n})^T$ denotes the vector of observations the weighted least squares estimator of θ is defined by

$$\widehat{\theta}_{WLSE} = (\mathbf{X}^T\mathbf{\Sigma}^{-1}\mathbf{X})^{-1}\mathbf{X}^T\mathbf{\Sigma}^{-1}\mathbf{Y},$$

where $\mathbf{X} = (f_p(t_j))_{j=1,\dots,n}^{p=1,\dots,m}$ is the $n \times m$ design matrix and $\mathbf{\Sigma} = (K(t_i, t_j))_{i,j=1,\dots,n}$ is the $n \times n$ matrix of variances/covariances. It is well known that $\hat{\theta}_{WLSE}$ is the BLUE in model (2.1). The corresponding minimal variance is given by

$$\mathrm{Var}(\widehat{\theta}_{WLSE}) \ = \ (\mathbf{X}^T\mathbf{\Sigma}^{-1}\,\mathbf{X})^{-1}, \tag{2.2}$$

and an optimal design for the estimation of the parameter θ in model (2.1) minimizes an appropriate real-valued functional of this matrix. As pointed out before, the direct minimization of this type of criterion is an extremely challenging non-convex discrete optimization problem and explicit solutions are not available in nearly all cases of practical interest. For this reason many authors propose to consider asymptotic optimal designs as the sample size n converges to infinity [see Sacks and Ylvisaker (1966, 1968), Bickel and Herzberg (1979), Näther (1985a), Zhigljavsky et al. (2010)].

In the following discussion we consider - parallel to model (2.1) - its *continuous time* version, that is

$$Y_t = \theta^T f(t) + \varepsilon_t \ , \quad t \in [a,b], \tag{2.3}$$

where the full trajectory of the process $\{Y_t|\ t \in [a,b]\}$ can be observed and $\{\varepsilon_t|\ t \in [a,b]\}$ is a centered Gaussian process with continuous covariance kernel K, i.e. $K(t,t') = \mathbb{E}[\varepsilon_t\varepsilon_{t'}]$. We will focus on *triangular kernels*, which are of the form

$$K(t,t') = u(t)v(t') \quad \text{for} \ \ t \le t', \tag{2.4}$$

$(K(t,t') = K(t',t)$ for $t > t')$, where $u(\cdot)$ and $v(\cdot)$ are some functions defined on the interval $[a,b]$. An alternative representation of K is given by

$$K(t,t') = v(t)v(t')\min\{q(t), q(t')\}; \quad (t, t' \in [a,b]),$$

where $q(t) = u(t)/v(t)$. We assume that the process $\{\varepsilon_t|\ [a,b]\}$ is non-degenerate on the open interval (a,b), which implies that the function q is positive on the interval (a,b) and strictly increasing and continuous on $[a,b]$, see Mehr and McFadden (1965) for more details. Consequently, the functions u and v must have the same sign and can be assumed to be positive on the interval (a, b) without loss of generality. Note that the majority of covariance kernels considered in the literature belong to this class, see, for example, Näther (1985a); Zhigljavsky et al. (2010) or Harman and Štulajter (2011). The simple triangular kernel

$$K(t, t') = t \wedge t',$$

is obtained for the choice $u(t) = t$ and $v(t) = 1$ and corresponds to the Brownian motion. As pointed out in Dette et al. (2015), the solutions of the optimal design problems with respect to different triangular kernels are closely related. In particular, if a best linear unbiased estimator (BLUE) for a particular triangular kernel has to be found for the continuous time model, it can be obtained by simple nonlinear transformation from the BLUE in a different continuous time model (on a possibly different interval) with a Brownian motion as error process (see Remark 2.1(b) below for more details). For this reason we will concentrate on the covariance kernel of the Brownian motion throughout this section. Our first result provides the optimal estimator in the continuous time model (2.3), where the error process is given by a Brownian motion on the interval $[a, b]$, where $a > 0$ (the case $a = 0$ will be discussed in Section 5). We begin with a lemma which is crucial for the definition of the estimator. The proof can be found in the Appendix.

Lemma 2.1 *Consider the continuous time linear regression model* (2.3) *on the interval* $[a, b]$, $a > 0$, *with a continuously differentiable vector of regression functions* f *and a Brownian motion as error process. Then the* $m \times m$ *matrix*

$$C = \int_a^b \dot{f}(t)\dot{f}^T(t)\, dt + \frac{f(a)f^T(a)}{a} \tag{2.5}$$

is non-singular.

Theorem 2.1 *Consider the continuous time linear regression model* (2.3) *on the interval* $[a, b]$, $a > 0$, *with a continuously differentiable vector of regression functions* f *and a Brownian motion as error process. The best linear unbiased estimate is given by*

$$\hat{\theta}_{\text{BLUE}} = C^{-1}\Big(\int_a^b \dot{f}(t)\, dY_t + \frac{f(a)}{a} Y_a\Big). \tag{2.6}$$

Moreover, the minimum variance is given by

$$C^{-1} = \Big(\int_a^b \dot{f}(t)\dot{f}^T(t)\, dt + \frac{f(a)f^T(a)}{a}\Big)^{-1}. \tag{2.7}$$

Proof of Theorem 2.1. Note that the continuous time model (2.3) can be written as a Gaussian white noise model

$$Y_t = \int_0^t s_1(u)\, du + \int_0^t d\varepsilon_u, \quad t \in [0, b],$$

where the function s_1 is defined as

$$s_1(u) = I_{[a,b]}(u)\theta^T \dot{f}(u) + I_{[0,a]}(u)\frac{\theta^T f(a)}{a}.$$

Let $\mathbb{P}_\theta$ and $\mathbb{P}_0$ denote the measure on $C([0,b])$ associated with the process $Y = \{Y_t |\ t \in [0,b]\}$ and $\{\varepsilon_t |\ t \in [0,b]\}$, respectively. From Theorem 1 in Appendix II of Ibragimov and Has'minskii (1981) it follows that $\mathbb{P}_1$ is absolute continuous with respect to $\mathbb{P}_2$ with Radon-Nikodym derivative given by

$$\begin{aligned}\frac{d\mathbb{P}_\theta}{d\mathbb{P}_0}(Y) &= \exp\left\{\int_0^b s_1(t)\,dY_t - \frac{1}{2}\int_0^b s_1^2(t)\,dt\right\}\\ &= \exp\left\{\left(\int_a^b \theta^T \dot{f}(t)\,dY_t + \frac{\theta^T f(a)}{a}Y_a\right) - \frac{1}{2}\left(\int_a^b (\theta^T \dot{f}(t))^2\,dt + \frac{(\theta^T f(a))^2}{a}\right)\right\}.\end{aligned}$$

The maximum likelihood estimator can be determined by solving the equation

$$\frac{\partial}{\partial\theta}\log\frac{d\mathbb{P}_\theta}{d\mathbb{P}_0}(Y) = \int_a^b \dot{f}(t)\,dY_t + \frac{f(a)}{a}Y_a - \Big(\int_a^b \dot{f}(t)\dot{f}^T(t)\,dt + \frac{f(a)f^T(a)}{a}\Big)\theta = 0.$$

The solution coincides with the linear estimate (2.6), and a straightforward calculation, using Ito's formula and the fact that the random variables $\int_a^b \dot{f}(t)d\varepsilon_t$ and ε_a are independent, gives

$$\begin{aligned}\mathrm{Var}_\theta(\hat{\theta}_{\mathrm{BLUE}}) &= C^{-1}\mathbb{E}_\theta\Big[\Big(\int_a^b \dot{f}(t)d\varepsilon_t + \frac{f(a)}{a}\varepsilon_a\Big)\Big(\int_a^b \dot{f}(t)d\varepsilon_t + \frac{f(a)}{a}\varepsilon_a\Big)^T\Big]C^{-1}\\ &= C^{-1}\Big(\int_a^b \dot{f}(t)\dot{f}^T(t)dt + \frac{f(a)f^T(a)}{a}\Big)C^{-1} = C^{-1},\end{aligned}$$

where the matrix C is defined in (2.5). It has been shown in Dette et al. (2015) that this matrix is the variance/covariance matrix of the BLUE in the continuous time model, which proves Theorem 2.1. □

Remark 2.1

(a) Dette et al. (2015) determined the best linear estimator for the continuous time linear regression model (2.3) with a twice continuously differentiable vector of regression functions and Brownian motion as

$$C^{-1}\Big\{\dot{f}(b)Y_b + \Big(\frac{f(a)}{a} - \dot{f}(a)\Big)Y_a - \int_a^b \ddot{f}(t)Y_t dt\Big\}. \tag{2.8}$$

Using integration by parts gives

$$\int_a^b \dot{f}(t)\,dY_t = \dot{f}(b)Y_b - \dot{f}(a)Y_a - \int_a^b \ddot{f}(t)Y_t\,dt,$$

and it is easily seen that the expression (2.8) coincides with (2.6). This means that a BLUE in the continuous time model (2.3) is even available under the weaker assumption of a once continuously differentiable function f.

(b) The best linear estimator in the continuous time model (2.3) with a general triangular kernel of the form (2.4) can easily be obtained from Appendix B in Dette et al. (2015). To be precise, consider a triangular kernel of the form (2.4), define

$$q(t) = \frac{u(t)}{v(t)},\ \alpha(t) = v(t),$$

and consider the stochastic process

$$\varepsilon_t = \alpha(t)\tilde{\varepsilon}_{q(t)},$$

where $\{\tilde{\varepsilon}_{\tilde{t}}|\ \tilde{t} \in [\tilde{a}, \tilde{b}]\}$ is a Brownian motion on the interval $[\tilde{a}, \tilde{b}]$ and $\tilde{a} = q(a)$, $\tilde{b} = q(b)$. It follows from Doob (1949) that $\{\varepsilon_t|\ t \in [a, b]\}$ is a centered Gaussian process on the interval $[a, b]$ with covariance kernel (2.4). Moreover, if we consider the continuous time model

$$\tilde{Y}_{\tilde{t}} = \theta^T \tilde{f}(\tilde{t}) + \tilde{\varepsilon}_{\tilde{t}}, \quad \tilde{t} \in [\tilde{a}, \tilde{b}], \tag{2.9}$$

and use the transformations

$$\tilde{f}(\tilde{t}) = \frac{f(q^{-1}(\tilde{t}))}{v(q^{-1}(\tilde{t}))}\ ,\ \tilde{\varepsilon}_{\tilde{t}} = \frac{\varepsilon_{q^{-1}(\tilde{t})}}{v(q^{-1}(\tilde{t}))}\ ,\ \tilde{Y}_{\tilde{t}} = \frac{Y_t}{v(t)}, \tag{2.10}$$

then it follows from Dette et al. (2015) that the BLUE for the continuous time model (2.3) (with a general triangular covariance kernel) can be obtained from the BLUE in model (2.9) by the transformation $\tilde{t} = q(t)$. Therefore an application of Theorem 2.1 gives for the best linear estimator in the continuous time model (2.3) with triangular covariance kernel of the form (2.4) the representation

$$\hat{\theta}_{\mathrm{BLUE}} = C^{-1}\Big[\int_a^b \frac{\dot{f}(t)v(t) - \dot{v}(t)f(t)}{\dot{u}(t)v(t) - u(t)\dot{v}(t)}\, d\left(\frac{Y_t}{v(t)}\right) + \frac{f(a)}{u(a)v(a)}Y_a\Big]\ ,$$

where the matrix C is given by

$$C = \int_a^b \frac{[\dot{f}(t)v(t) - \dot{v}(t)\dot{f}(t)][\dot{f}(t)v(t) - \dot{v}(t)\dot{f}(t)]^T}{v^2(t)[\dot{u}(t)v(t) - u(t)\dot{v}(t)]}\, dt + \frac{f(a)f^T(a)}{u(a)v(a)}.$$

(c) Using integration by parts it follows (provided that the functions f, u, and v are twice continuously differentiable) that the BLUE in the continuous time model (2.3) can be represented as

$$\hat{\theta}_{\mathrm{BLUE}} = \int_a^b Y_t\, \mu^*(dt),$$

where μ^* is a vector of signed measures defined by $\mu^*(dt) = P_a\delta_a + p(t)dt + P_b\delta_b$, δ_t denotes the Dirac measure at the point $t \in [0, 1]$ and the "masses" P_a, P_b and the density p are given by

$$
\begin{aligned}
P_a &= C^{-1}\frac{1}{u(a)}\frac{f(a)\dot u(a)-\dot f(a)u(a)}{\dot u(a)v(a)-u(a)\dot v(a)}\ , \quad P_b = C^{-1}\frac{1}{v(b)}\frac{\dot f(b)v(b)-\dot v(b)f(b)}{\dot u(b)v(b)-u(b)\dot v(b)} \\
p(t) &= -C^{-1}\frac{d}{dt}\Big(\frac{1}{v(t)}\frac{\dot f(t)v(t)-\dot v(t)f(t)}{\dot u(t)v(t)-u(t)\dot v(t)}\Big)\frac{1}{v(t)}
\end{aligned}
$$

respectively. Now, if $\hat\theta_n = \sum_{i=1}^n \omega_i Y_{t_i}$ denotes an unbiased linear estimate in model (2.1) with vectors $\omega_i \in \mathbb{R}^m$, we can represent this estimator as

$$
\hat\theta_n = \int_a^b Y_t\,\hat\mu_n(dt),
$$

in the continuous time model (2.3), where $\hat\mu_n$ is a discrete signed vector valued measure with "masses" ω_i at the points t_i. Consequently, we obtain from Theorem 2.1 that

$$
C^{-1} = \mathrm{Var}(\hat\theta_{\mathrm{BLUE}}) \le \mathrm{Var}(\hat\theta_n),
$$

(in the Loewner ordering). In other words, C^{-1} is a lower bound for any linear estimator in the linear regression model (2.1).

3 Optimal estimators and designs for finite sample size

We have determined the BLUE and corresponding minimal variance/covariance matrix in the continuous time model (2.3). In the present section we now explain how the particular representation of the BLUE as a stochastic integral can be used to derive efficient estimators and corresponding optimal designs in the original model (2.1), which are practically not distinguishable from the BLUE in model (2.1) based on an optimal design. Our approach is based on a comparison of the mean squared error of the difference between the best linear unbiased estimator derived in Theorem 2.1 and a discrete approximation of the stochastic integral in (2.6). For the sake of a clear representation, we discuss the one-dimensional case first.

3.1 One-parameter models

Consider the estimator $\hat\theta_{\mathrm{BLUE}}$ defined by (2.6) for the continuous time model (2.3) with $m = 1$ and define an estimator $\hat\theta_n$ in the original regression model by an approximation of the stochastic integral, that is

$$
\hat\theta_n = C^{-1}\Big\{\sum_{i=2}^n \omega_i \dot f(t_{i-1})(Y_{t_i} - Y_{t_{i-1}}) + \frac{f(a)}{a}Y_a\Big\}. \tag{3.1}
$$

Here $a = t_1 < t_2 < \ldots < t_{n-1} < t_n = b$ are n design points in the interval $[a, b]$ and $\omega_2, \ldots, \omega_n$ are corresponding (not necessarily positive) weights. Obviously, the estimator depends on the weights ω_i only through the quantities $\mu_i = \omega_i \dot{f}(t_{i-1})$ and therefore we use the notation

$$\hat{\theta}_n = C^{-1}\Big\{ \sum_{i=2}^{n} \mu_i (Y_{t_i} - Y_{t_{i-1}}) + \frac{f(a)}{a} Y_a \Big\}, \tag{3.2}$$

in the following discussion. We will determine optimal weights $\mu_2^*, \dots, \mu_n^*$ and design points $t_2^*, \dots, t_{n-1}^*$ minimizing the mean squared error $\mathbb{E}[(\hat{\theta}_{\mathrm{BLUE}} - \hat{\theta}_n)^2]$ between the estimators $\hat{\theta}_{\mathrm{BLUE}}$ and $\hat{\theta}_n$. Our first result provides an explicit expression for this quantity. The proof is omitted because we prove a more general result later in the multi-parameter case (see Section A.3).

Lemma 3.1 *Consider the continuous time model* (2.3) *in the one-dimensional case. If the assumptions of Theorem 2.1 are satisfied, then*

$$\begin{aligned} \mathbb{E}_\theta[(\hat{\theta}_{\mathrm{BLUE}} - \hat{\theta}_n)^2] =& C^{-1}\Big\{ \sum_{i=2}^{n} \int_{t_{i-1}}^{t_i} \big[\dot{f}(s) - \mu_i)\big]^2 \, ds \\ &+ \theta^2 \Big(\sum_{i=2}^{n} \int_{t_{i-1}}^{t_i} \big[\dot{f}(s) - \mu_i\big] \dot{f}(s)\, ds \Big)^2 \Big\} C^{-1}. \end{aligned} \tag{3.3}$$

In order to find "good" weights for the linear estimator $\hat{\theta}_n$ in (3.1) we propose to consider only estimators with weights $\mu_2, \dots, \mu_n$ such that the second term in (3.3) vanishes, that is

$$\sum_{i=2}^{n} \int_{t_{i-1}}^{t_i} \big[\dot{f}(s) - \mu_i\big] \dot{f}(s) \, ds = 0. \tag{3.4}$$

It is easy to see that this condition is equivalent to the property that the estimator $\hat{\theta}_n$ in (3.1) is also unbiased, that is $\mathbb{E}[\hat{\theta}_n] = \theta$, or equivalently

$$\sum_{i=2}^{n} \mu_i (f(t_i) - f(t_{i-1})) = \int_a^b [\dot{f}(s)]^2 ds. \tag{3.5}$$

The following result describes the weights minimizing $\mathbb{E}[(\hat{\theta}_{\mathrm{BLUE}} - \hat{\theta}_n)^2]$ under the constraint (3.4).

Lemma 3.2 *Consider the continuous time model* (2.3) *in the one-dimensional case. If the assumptions of Theorem 2.1 are satisfied, then the optimal weights minimizing* $\mathbb{E}[(\hat{\theta}_{\mathrm{BLUE}} - \hat{\theta}_n)^2]$ *in the class of all unbiased linear estimators of the form* (3.1) *are given by*

$$\mu_i^* = \kappa(t_1, \dots, t_n) \frac{f(t_i) - f(t_{i-1})}{t_i - t_{i-1}}\,, \tag{3.6}$$

where

$$\kappa(t_1, \dots, t_n) = \frac{\int_a^b [\dot{f}(s)]^2 \, ds}{\sum_{j=2}^{n} [f(t_j) - f(t_{j-1})]^2 / (t_j - t_{j-1})}\,.$$

Proof of Lemma 3.2. Under the condition (3.4) the mean squared error simplifies to

$$\begin{aligned}\mathbb{E}_\theta[(\hat\theta_{\mathrm{BLUE}} - \hat\theta_n)^2] &= C^{-1}\Big\{\sum_{i=2}^n \int_{t_{i-1}}^{t_i} \big[\dot f(s) - \mu_i\big]^2\, ds\Big\}C^{-1} \\ &= C^{-1}\Big\{-\int_a^b [\dot f(s)]^2\, ds + \sum_{i=2}^n \mu_i^2 (t_i - t_{i-1})\Big\}C^{-1}.\end{aligned}$$

Using Lagrangian multiplies to minimize this expression subject to the constraint (3.5) yields

$$\mu_i = \frac{\lambda[f(t_i) - f(t_{i-1})]}{2(t_i - t_{i-1})}\ , \quad i = 2, \dots, n,$$

where λ denotes the Lagrangian multiplier. Substituting this into (3.4) gives

$$\lambda/2 = \frac{\int_a^b [\dot f(s)]^2\, ds}{\sum_{i=2}^n [f(t_i) - f(t_{i-1})]^2/(t_i - t_{i-1})} = \kappa(t_1, \dots, t_n).$$

Therefore, the optimal weights are given by (3.6). □.

Inserting these weights in the mean squared error gives the function

$$\mathbb{E}_\theta[(\hat\theta_{\mathrm{BLUE}} - \hat\theta_n)^2] \ = \ C^{-1}\Big\{\Big(\int_a^b [\dot f(s)]^2 ds\Big)^2 \Big\{\sum_{i=2}^n \frac{(f(t_i) - f(t_{i-1}))^2}{t_i - t_{i-1}}\Big\}^{-1} - \int_a^b [\dot f(s)]^2 ds\Big\}C^{-1},$$

which finally has to be minimized by the choice of the design points $t_2, \dots, t_{n-1}$. Because we discuss the one-parameter case in this section and the matrix C does not depend on $t_2, \dots, t_n$, this optimization corresponds to the minimization of

$$\Phi(t_1, \dots, t_n) = \Big(\int_a^b [\dot f(s)]^2 ds\Big)\Big\{\sum_{i=2}^n \frac{(f(t_i) - f(t_{i-1}))^2}{t_i - t_{i-1}}\Big\}^{-1} - 1. \tag{3.7}$$

Remark 3.1 Let

$$\begin{aligned}\mathrm{eff}(t_2, \dots, t_{n-1}) \ &= \ \frac{\mathrm{Var}_\theta(\hat\theta_{\mathrm{BLUE}})}{\mathrm{Var}_\theta(\hat\theta_n)]} = \frac{C^{-1}}{C^{-1}\int_a^b [\dot f(s)]^2 ds\, \Phi(t_1, \dots, t_n) C^{-1} + C^{-1}} \\ &= \left(1 + \frac{\Phi(t_1, \dots, t_n)}{1 + \frac{f^2(a)}{a} / \int_a^b [\dot f(s)]^2 ds}\right)^{-1},\end{aligned}$$

denote the efficiency of an estimator $\hat\theta_n$ defined by (3.1) with optimal weights. Note that from the proof of Lemma 3.2 it follows that the function Φ is non-negative for all $t_1, \dots, t_n$. Consequently, minimizing Φ with respect to the design points means that $t_1 = a < t_2 < \dots < t_{n-1} < t_n = b$ have to be determined such that

$$\sum_{i=2}^n \frac{(f(t_i) - f(t_{i-1}))^2}{t_i - t_{i-1}},$$

approximates the integral $\int_a^b [\dot{f}(s)]^2 ds$ most precisely (this produces an efficiency close to 1). Now, if f is sufficiently smooth, we have for any $\xi_i \in [t_{i-1}, t_i]$

$$\Big| \frac{(f(t_i) - f(t_{i-1}))^2}{t_i - t_{i-1}} - [\dot{f}(\xi_i)]^2 (t_i - t_{i-1}) \Big| \ \leq \ G,$$

for all $i = 2, \ldots, n$, where

$$G := 2 \max_{\xi \in [a,b]} |f'(\xi)| \max_{\xi \in [a,b]} |f''(\xi)| \cdot \max_{i=2,\ldots,n} |t_i - t_{i-1}|^2.$$

This gives

$$0 \leq A(t_1, \ldots, t_n) := \int_a^b \dot{f}^2(t) dt - \sum_{i=2}^n \frac{(f(t_i) - f(t_{i-1}))^2}{t_i - t_{i-1}} \leq (n-1)G.$$

As the function Φ has the representation

$$\Phi(t_1, \ldots, t_n) = \frac{A(t_1, \ldots, t_n)}{\int_a^b \dot{f}^2(s) ds - A(t_1, \ldots, t_n)}$$

it follows that (note that the expression on the right-hand side is increasing with $A(t_1, \ldots, t_n)$)

$$\Phi(t_1, \ldots, t_n) \leq \frac{(n-1) \cdot \max_{i=2,\ldots,n} |t_i - t_{i-1}|^2}{H(f) + (n-1) \cdot \max\limits_{i=2,\ldots,n} |t_i - t_{i-1}|^2}, \tag{3.8}$$

where

$$H(f) = \frac{\int_a^b \dot{f}^2(s) ds}{2 \max\limits_{\xi \in [a,b]} |\dot{f}(\xi)| \max\limits_{\xi \in [a,b]} |\ddot{f}(s)|}.$$

This shows that for most models a substantial improvement of the approximation by the choice of $t_2, \ldots, t_n$ can only be achieved if the sample size is small. For moderate or large sample sizes one could use the points $u_i = a + \frac{i-1}{n-1}(b-a)$, which gives already the estimate

$$\Phi(u_1, \ldots, u_n) \leq \frac{1}{1 + (n-1)H(f)} = O\big(\frac{1}{n}\big)$$

(note that we consider worst case scenarios to obtain these estimates). Consequently, in many cases the design points can be chosen in an equidistant way, because the choice of the points $t_2, \ldots, t_{n-1}$ is irrelevant from a practical point of view, provided that the weights of the estimator $\hat{\theta}_n$ are already chosen in an optimal way.

Example 3.1 Consider the quadratic regression model $Y_t = \theta t^2 + \varepsilon_t$, where $t \in [a,b]$. Then $f(t) = t^2$, $\dot{f}(t) = 2t$, and the function Φ in (3.7) reduces to

$$\Phi(t_1, \ldots, t_n) = \frac{4(b^3 - a^3)}{3} \Big\{ \sum_{i=2}^n (t_i + t_{i-1})^2 (t_i - t_{i-1}) \Big\}^{-1} - 1.$$

It follows by a straightforward computation that the optimal points are given by

$$t_i^* = a + \frac{i-1}{n-1}(b-a)\,; \qquad i = 1, \dots, n, \tag{3.9}$$

while the corresponding minimal value is

$$\Phi(t_1^*, \dots, t_n^*) = \frac{(a-b)^3}{4(n-1)^2(a^3-b^3)-(a-b)^3} \qquad (n \geq 2).$$

Note that this term is of order $O(\frac{1}{n^2})$. Remark 3.1 gives the bound

$$\Phi(t_1^*, \dots, t_n^*) \leq \frac{1}{1+\frac{b^3-a^3}{2b}(n-1)} = O(\frac{1}{n}) \ ,$$

which shows that (3.8) is not necessarily sharp. For the efficiency we obtain

$$\mathrm{eff}(t_1^*, \dots, t_n^*) = 1 - \frac{4(a-b)^3(a^3-b^3)}{3a^3(a-b)^3+4(n-1)^2(a^3-b^3)(a-b)^3},$$

which is of order $1 - O(\frac{1}{n^2})$. On the other hand, if $f(t) = t^3$ the function Φ is given by

$$\begin{aligned}\Phi(t_1, \dots, t_n) &= \frac{9}{5}(b^5-a^5)\Big\{\sum_{i=2}^{n}(t_i - t_{i-1})(t_i^2 + t_i t_{i-1} + t_{i-1}^2)^2\Big\}^{-1} - 1 \\ &= \frac{(a-b)^2[5(n-1)^2(a^3-b^3)-(a-b)^3]}{9(n-1)^4(a^5-b^5)-(a-b)^2[5(n-1)^2(a^3-b^3)-(a-b)^3]}\end{aligned}$$

and optimal points have to be found numerically. However, we can evaluate the efficiency of the uniform design in (3.9), which is given by

$$\mathrm{eff}(t_1^*, \dots, t_n^*) = 1 - \frac{9(b^5-a^5)(a-b)^2[5(n-1)^2(a^3-b^3)-(a-b)^3]}{9(9b^5-4a^5)(a^5-b^5)(n-1)^4+5a^5(a-b)^2[5(n-1)^2(a^3-b^3)-(a-b)^3]}$$

$(n \geq 2)$ and also of order $1 - O(\frac{1}{n^2})$. Thus, although the uniform design is not optimal, its efficiency (with respect to the continuous case) is extremely high.

3.2 Multi-parameter models

In this section we derive corresponding results for the multi-parameter case. If $m \geq 1$ we propose a linear estimator with matrix weights as an analogue of (3.1), that is

$$\begin{aligned}\hat{\theta}_n &= C^{-1}\Big\{\sum_{i=2}^{n}\Omega_i \dot{f}(t_{i-1})(Y_{t_i} - Y_{t_{i-1}}) + \frac{f(a)}{a}Y_a\Big\} \qquad (3.10)\\ &= C^{-1}\Big\{\sum_{i=2}^{n}\mu_i(Y_{t_i} - Y_{t_{i-1}}) + \frac{f(a)}{a}Y_a\Big\},\end{aligned}$$

where C^{-1} is given in (2.7), $\Omega_2, \dots, \Omega_n$ are $m \times m$ matrices and $\mu_2 = \Omega_2 \dot{f}(t_i), \dots, \mu_n = \Omega_n \dot{f}(t_{n-1})$ are m-dimensional vectors, which have to be chosen in a reasonable way. For this purpose we derive a representation of the mean squared error between the best linear estimate in the continuous time model and its discrete approximation in the multi-parameter case first. The proof can be found in Appendix A.3.

Lemma 3.3 *Consider the continuous time model* (2.3). *If the assumptions of Theorem 2.1 are satisfied, then*

$$\mathbb{E}_\theta[(\hat{\theta}_{\mathrm{BLUE}} - \hat{\theta}_n)(\hat{\theta}_{\mathrm{BLUE}} - \hat{\theta}_n)^T] = C^{-1} \Big\{ \sum_{i=2}^n \int_{t_{i-1}}^{t_i} \big[\dot{f}(s) - \mu_i\big] \big[\dot{f}(s) - \mu_i\big]^T ds$$
$$+ \sum_{i=2}^n \int_{t_{i-1}}^{t_i} \big[\dot{f}(s) - \mu_i\big] \dot{f}^T(s)\, ds\, \theta\, \theta^T \sum_{j=2}^n \int_{t_{j-1}}^{t_j} \dot{f}(s) \big[\dot{f}(s) - \mu_j\big]^T ds \Big\} C^{-1}. \qquad (3.11)$$

In the following we choose optimal vectors (or equivalently matrices Ω_i) $\mu_i = \Omega_i \dot{f}(t_{i-1})$ and design points t_i, such that the linear estimate (3.10) is unbiased and the mean squared error matrix in (3.11) "becomes small". An alternative criterion is to replace the mean squared error $\mathbb{E}_\theta[(\hat{\theta}_{\mathrm{BLUE}} - \hat{\theta}_n)(\hat{\theta}_{\mathrm{BLUE}} - \hat{\theta}_n)^T]$ by the mean squared error

$$\mathbb{E}_\theta[(\hat{\theta}_n - \theta)(\hat{\theta}_n - \theta)^T]$$

between the estimate $\hat{\theta}_n$ defined in (3.10) and the "true" vector of parameters. The following result shows that both optimization problems will yield the same solution in the class of all unbiased estimators. The proof can be found in Appendix A.4.

Theorem 3.1 *The estimator $\hat{\theta}_n$ defined in* (3.1) *is unbiased if and only if the identity*

$$\int_a^b \dot{f}(s) \dot{f}^T(s)\, ds = \sum_{i=2}^n \mu_i \int_{t_{i-1}}^{t_i} \dot{f}^T(s)\, ds = \sum_{i=2}^n \mu_i (f(t_i) - f(t_{i-1}))^T, \qquad (3.12)$$

is satisfied. Moreover, for any linear unbiased estimator of the form $\tilde{\theta}_n = \int_a^b g(s) dY_s$ we have

$$\mathbb{E}_\theta[(\tilde{\theta}_n - \theta)(\tilde{\theta}_n - \theta)^T] = \mathbb{E}_\theta[(\tilde{\theta}_n - \hat{\theta}_{\mathrm{BLUE}})(\tilde{\theta}_n - \hat{\theta}_{\mathrm{BLUE}})^T] + C^{-1}.$$

In order to describe a solution in terms of optimal "weights" μ_i^* and design points t_i^* we recall that the condition of unbiasedness of the estimate $\hat{\theta}_n$ in (3.10) is given by (3.12) and introduce the notation

$$\beta^{(i)} = [f(t_i) - f(t_{i-1})]/\sqrt{t_i - t_{i-1}}, \qquad (3.13)$$
$$\gamma^{(i)} = \mu_i \sqrt{t_i - t_{i-1}}.$$

It follows from Lemma 3.3 that for an unbiased estimate $\hat{\theta}_n$ the mean squared error has the representation

$$\mathbb{E}_\theta\big[(\hat{\theta}_{\text{BLUE}} - \hat{\theta}_n)^T(\hat{\theta}_{\text{BLUE}} - \hat{\theta}_n)\big] = -C^{-1}MC^{-1} + \sum_{i=2}^n C^{-1}\gamma^{(i)}\gamma^{(i)^T}C^{-1}, \tag{3.14}$$

which has to be "minimized" subject to the constraint

$$M = (m_{\ell,k})_{\ell,k}^m = \int_a^b \dot{f}(s)\dot{f}^T(s)ds = \sum_{i=2}^n \gamma^{(i)}\beta^{(i)^T}. \tag{3.15}$$

The following result shows that a minimization with respect to the weights μ_i (or equivalently γ_i) can actually be carried out with respect to the Loewner ordering.

Theorem 3.2 *Assume that the assumptions of Theorem 2.1 are satisfied and that the matrix*

$$B = \sum_{i=2}^n \frac{[f(t_i) - f(t_{i-1})][f(t_i) - f(t_{i-1})]^T}{t_i - t_{i-1}},$$

is non-singular. Let $\mu_2^*, \dots, \mu_n^*$ denote $m \times 1$ vectors satisfying the equations

$$\mu_i^* = MB^{-1}\frac{f(t_i) - f(t_{i-1})}{t_i - t_{i-1}} \qquad i = 2, \dots, n, \tag{3.16}$$

then $\mu_2^*, \dots, \mu_n^*$ are optimal (vector) weights minimizing $\mathbb{E}_\theta[(\hat{\theta}_{\text{BLUE}} - \hat{\theta}_n)(\hat{\theta}_{\text{BLUE}} - \hat{\theta}_n)^T]$ with respect to the Loewner ordering among all unbiased estimators of the form (3.10)*.*

Proof of Theorem 3.2. Let A denote a positive definite $m \times m$ matrix and consider the problem of minimizing the linear criterion

$$\text{tr}\Big\{A \ \mathbb{E}_\theta[(\hat{\theta}_{\text{BLUE}} - \hat{\theta}_n)(\hat{\theta}_{\text{BLUE}} - \hat{\theta}_n)^T]\Big\}$$

subject to the constraint (3.15). Observing (3.14) this yields the Lagrange function

$$-\text{tr}\{AC^{-1}MC^{-1}\} + \sum_{i=2}^n (C^{-1}\gamma^{(i)})^T A(C^{-1}\gamma^{(i)}) - \sum_{k,\ell=1}^m \lambda_{k,\ell}\Big(m_{k,\ell} - \sum_{i=2}^n \gamma_k^{(i)}\beta_\ell^{(i)}\Big),$$

where $C = (c_{k,\ell})_{k,\ell=1}^m$, $\gamma^{(i)} = (\gamma_1^{(i)}, \dots, \gamma_m^{(i)})^T$, $\beta^{(i)} = (\beta_1^{(i)}, \dots, \beta_m^{(i)})^T$ and $\Lambda = (\lambda_{k,\ell})_{k,\ell=1}^m$ is a matrix of Lagrange multipliers. This function is obviously convex with respect to $\gamma^{(2)}, \dots, \gamma^{(n)}$. Therefore, taking derivatives with respect to $\gamma_j^{(i)}$ yields as necessary and sufficient for the extremum

$$\sum_{p=1}^m c^{p,j}\sum_{\ell=1}^m a_{p,\ell}\sum_{k=1}^m c^{\ell,k}\gamma_k^{(i)} + \sum_{p=1}^m\sum_{k=1}^m c^{p,k}\gamma_k^{(i)}\sum_{\ell=1}^m a_{p,\ell}c^{\ell,j} + \sum_{\ell=1}^m \lambda_{j,\ell}\beta_\ell^{(i)} = 0 \qquad j = 1, \dots, k,$$

where $A = (a_{\ell,k})_{\ell,k=1}^m$ and $C^{-1} = (c^{\ell,k})_{\ell,k=1}^m$ is the inverse of the matrix C defined in (2.6). Rewriting this system of linear equations in matrix form gives

$$C^{-1}AC^{-1}\gamma^{(i)} + C^{-1}A^TC^{-1}\gamma^{(i)} + \Lambda\beta^{(i)} = 0 \qquad i = 2, \dots, n,$$

or equivalently

$$C^{-1}(A + A^T)C^{-1}\gamma^{(i)} = -\Lambda\beta^{(i)} \qquad i = 2, \dots, n.$$

Substituting this expression in (3.15) and using the non-singularity of the matrices C and B yields for the matrix of Lagrangian multipliers

$$\Lambda = -C^{-1}(A + A^T)C^{-1}MB^{-1},$$

which finally gives

$$\gamma^{(i)} = MB^{-1}\beta^{(i)} \qquad i = 2, \dots, n.$$

Observing the notations in (3.13) shows that the optimal vector weights are given by (3.16). Thus the optimal weights in (3.16) do not depend on the matrix A and provide the solution for all linear optimality criteria. Consequently, using the matrices $A = vv^T + \varepsilon I_m$ with $v \in \mathbb{R}^m$, and considering the limit as $\varepsilon \to 0$, shows that the weights defined in (3.16) minimize $\mathbb{E}_\theta[(\hat{\theta}_{\text{BLUE}} - \hat{\theta}_n)(\hat{\theta}_{\text{BLUE}} - \hat{\theta}_n)^T]$ with respect to the Loewner ordering.

□

Remark 3.2 If the matrix B in Theorem 3.2 is singular, the optimal vectors are not uniquely determined and we propose to replace the inverse B by its Moore-Penrose inverse.

Note that for fixed design points $t_1, \dots, t_n$ Theorem 3.2 yields universally optimal weights $\mu_2^*, \dots, \mu_n^*$ (with respect to the Loewner ordering) for estimators of the form (3.10) satisfying (3.12). On the other hand, a further optimization with respect to the Loewner ordering with respect to the choice of the points $t_1, \dots, t_n$ is not possible, and we have to apply a real valued optimality criterion for this purpose. More precisely, let $\hat{\theta}_n^*$ denote the estimator of the form (3.10) with optimal weights $\gamma^{*(i)} = \mu_i^*\sqrt{t_i - t_{i-1}}$ given by (3.16), then we choose $t_1, \dots, t_n$, such that

$$\begin{aligned}\operatorname{tr}\Big(\mathbb{E}_\theta\big[(\hat{\theta}_{\text{BLUE}} - \hat{\theta}_n^*)^T(\hat{\theta}_{\text{BLUE}} - \hat{\theta}_n^*)\big]\Big) &= \operatorname{tr}\Big\{ - C^{-1}MC^{-1} + \sum_{i=2}^n C^{-1}\gamma^{*(i)}\gamma^{*(i)^T}C^{-1}\Big\} \\ &= \operatorname{tr}\Big\{-C^{-1}MC^{-1} + C^{-1}M\Big(\sum_{i=2}^n \frac{(f(t_i) - f(t_{i-1})(f(t_i) - f(t_{i-1}))^T}{t_i - t_{i-1}}\Big)^{-1}MC^{-1}\Big\}\end{aligned}$$

is minimal. The performance of this method will be illustrated in the following section.

4 Some numerical examples

In this section we illustrate our new methodology using several model and covariance kernel examples. Note that (under smoothness assumptions) our approach allows us to calculate a lower bound for the trace (or any other monotone functional) of the variance of any (unbiased) linear estimator for the parameter vector θ in model (2.1) [see Remark 2.1(c)]. Therefore we evaluate the quality of an estimator (with corresponding design), say $\hat{\theta}$, by the efficiency

$$\mathrm{eff}(\hat{\theta}) \;=\; \frac{\mathrm{tr}\{\mathrm{Var}_\theta(\hat{\theta}_{BLUE})\}}{\mathrm{tr}\{\mathrm{Var}_\theta(\hat{\theta})\}} \;=\; \frac{\mathrm{tr}(C^{-1})}{\mathrm{tr}\{\mathrm{Var}_\theta(\hat{\theta})\}},$$

Throughout this section the estimator defined by (3.2) and Lemma 3.2 in the case of $m = 1$ and by (3.10) and Theorem 3.2 for $m > 1$, will be denoted by $\hat{\theta}^*_n$. As before the univariate and multivariate cases are studied separately.

4.1 One-parameter models

Consider model (2.1) with $m = 1$ and $n = 5$ observations in the interval $[a, b] = [1, 2]$, where the regression function is given by $f(t) = t^2$, $t^2 - 0.5$ and t^4 with kernel $k(s, t) = s \wedge t$. The discussion in Example 3.1 indicates that equally spaced design points provide already an efficient allocation for the new estimator $\hat{\theta}^*_n$. Consequently, we compare the estimator $\hat{\theta}_{\mathrm{DPZ},n}$ (with a corresponding optimal design) proposed in Section 2.5 of Dette et al. (2015) with the BLUE and also with the estimator defined by (3.2) and Lemma 3.2 based on a uniform design. The latter two estimators are denoted by $\hat{\theta}^{\mathrm{uni}}_{\mathrm{BLUE},n}$ and $\hat{\theta}^{*\mathrm{uni}}_n$, respectively, and we consider a uniform design with $n = 5$ points. The corresponding efficiencies are displayed in Table 1.

Table 1: *Efficiencies (in percent) of various estimators in the univariate linear regression model for $n = 5$ observations on the interval $[1, 2]$. $\hat{\theta}^{\mathrm{uni}}_{\mathrm{BLUE},n}$ is the BLUE based on a uniform design, $\hat{\theta}^{*\mathrm{uni}}_n$ is the estimator defined by (3.2) and Lemma 3.2 based on a uniform design and $\hat{\theta}_{\mathrm{DPZ},n}$ (with a corresponding design) proposed in Dette et al. (2015).*

$f(t)$	t^2	$t^2 - 0.5$	t^4
$\hat{\theta}^{\mathrm{uni}}_{\mathrm{BLUE},n}$	99.798	99.783	98.416
$\hat{\theta}^{*\mathrm{uni}}_n$	99.798	99.783	98.416
$\hat{\theta}_{\mathrm{DPZ},n}$	99.582	99.346	92.662

We observe that both $\hat{\theta}^{\mathrm{uni}}_{\mathrm{BLUE},n}$ and $\hat{\theta}^{*\mathrm{uni}}_n$ have very good efficiencies and therefore we did not determine the optimal allocations for the two estimators. A comparison between both estimators shows that $\hat{\theta}^{\text{uni}}_{\text{BLUE},n}$ and $\hat{\theta}^{*\text{uni}}_{n}$ are practically not distinguishable. In all the cases considered, the efficiencies do not differ in the first 5 decimals. For example, for the function $f(t) = t^2 - 0.5$ we have

$$\text{eff}(\hat{\theta}^{\text{uni}}_{\text{BLUE},n}) = 0.99782609\ ,\ \ \text{eff}(\hat{\theta}^{*\text{uni}}_{n}) = 0.99782596\ .$$

The investigation of other one-dimensional examples showed a similar picture and details are omitted for the sake of brevity. Therefore, the new estimator $\hat{\theta}^*_n$ with a uniform design is not only highly efficient (even for small values of n), but most importantly, it is very close to the best achievable. The comparison with the estimator $\hat{\theta}_{\text{DPZ},n}$ proposed in Dette et al. (2015) shows that the new approach still provides an improvement of an estimator which has efficiencies already above 90%, with the difference of efficiencies being small for $f(t) = t^2, t^2 - 0.5$ and large for $f(t) = t^4$.

4.2 Models with $m > 1$ parameters

We now compare the various estimators in the multi-parameter case. In particular, we consider two regression models given by

$$Y_t = (t, t^2, t^3)^T\theta + \varepsilon_t, \quad t \in [a, b] \tag{4.1}$$

$$Y_t = (\sin t, \cos t, \sin 2t, \cos 2t)^T\,\theta + \varepsilon_t, \quad t \in [a, b]. \tag{4.2}$$

For each one of these models we study two cases of the covariance kernel of the error process in model (2.1), namely $K(t, t') = \min\{t, t'\}$ and $K(t, t') = \exp\{-\lambda|t - t'|\}$. The sample size is again $n = 5$ and the design space is the interval $[1, 2]$.

It turns out that for these models and the particularly small sample size the uniform design does not yield similar high efficiencies as in the case $m = 1$ discussed in the previous section. For this reason we also calculate the corresponding optimal designs for the BLUE $\hat{\theta}_{\text{BLUE},n}$ and the estimator $\hat{\theta}^*_n$ proposed in this paper [see (3.10) and Theorem 3.2] using the Particle swarm optimization (PSO) algorithm [see for example Clerc (2006) or Wong et al. (2015) among others].

If the error process is a Brownian motion, the optimal design of $\hat{\theta}^*_n$ is obtained by applying the PSO algorithm on the trace of the mean squared error $\mathbb{E}_\theta[(\hat{\theta}_{\text{BLUE}} - \hat{\theta}_n)(\hat{\theta}_{\text{BLUE}} - \hat{\theta}_n)^T]$ given in (3.14) (or equivalently on the trace of $\mathbb{E}_\theta[(\hat{\theta}_n - \theta)(\hat{\theta}_n - \theta)^T]$), using the optimal weights μ^*_i, $i = 2, \ldots, n$, given in Theorem 3.2. In the case of the exponential kernel $K(t, t') = \exp\{-\lambda|t - t'|\}$ we follow the same procedure as before but for the transformed continuous time model given in (2.9). The optimal design for the initial model with the exponential covariance kernel can then be obtained by the transformation $\tilde{t} = q(t)$ applied on each one of the optimal design points the algorithm will yield (see Remark 2.1(b)). Minimizing (using the PSO method) the trace of $\text{Var}(\hat{\theta}_{\text{WLSE}})$ given in (2.2) for the corresponding variance/covariance matrix $\Sigma = (K(t_i, t_j))_{i,j=1,\ldots,n}$ of the error process gives the optimal design for $\hat{\theta}_{\text{BLUE,n}}$.

For the model and covariance kernel examples under consideration, the optimal designs for the estimators $\hat{\theta}_{BLUE,n}$ and $\hat{\theta}_n^*$ are presented in Table 2. The corresponding designs for the estimator $\hat{\theta}_{\mathrm{DPZ}}$ are chosen as described in Dette et al. (2015). We observe that regardless of the model and the covariance kernel, the optimal designs for the estimators $\hat{\theta}_{\mathrm{BLUE,n}}$ and $\hat{\theta}_n^*$ are very similar. Furthermore, for the specific examples, the choice of covariance kernel does not affect the optimal design since for a given estimator, the two kernels yield the same design (up to 2 d.p.) for both models. In particular, the optimal designs are always supported at both end-points of the design space. For model (4.1), although the uniform design is not optimal, the middle points of the optimal design are somewhat spread in the interval $(1, 2)$, whereas in the case of model (4.2), more points are allocated closer to the lower bound $t = 1$ of the design space.

Table 2: *Optimal five-point designs in the interval* $[1, 2]$ *for the estimators* $\hat{\theta}_{\mathrm{BLUE},n}$ *and* $\hat{\theta}_n^*$ *for models* (4.1) *and* (4.2) *with two covariance kernels.*

		Optimal designs	
Model	Kernel	$\hat{\theta}_{\mathrm{BLUE},n}$	$\hat{\theta}_n^*$
(4.1)	$t \wedge t'$	[1, 1.466, 1.680, 1.852, 2]	[1, 1.444, 1.668, 1.846, 2]
	$\exp\{-\|t-t'\|\}$	[1, 1.474, 1.683, 1.852, 2]	[1, 1.459, 1.674, 1.847, 2]
(4.2)	$t \wedge t'$	[1, 1.111, 1.243, 1.800, 2]	[1, 1.120, 1.264, 1.802,2]
	$\exp\{-\|t-t'\|\}$	[1, 1.113, 1.245, 1.800, 2]	[1, 1.120, 1.263, 1.801, 2]

Table 3 gives the efficiencies of the three estimators $\hat{\theta}_{\mathrm{BLUE},n}$, $\hat{\theta}_n^*$ and $\hat{\theta}_{\mathrm{DPZ},n}$ for the optimal design of each estimator (upper part) and the uniform design (lower part) with $n = 5$ observations. For model (4.1) and any of the two covariance kernels, if the uniform design is used both $\hat{\theta}_{\mathrm{BLUE},n}$ and $\hat{\theta}_n^*$ estimators are very efficient. The efficiencies of course increase when observations are taken according to the optimal instead of the uniform design but remain below 90% when the four-dimensional model (4.2) is considered.

We also observe that the estimator $\hat{\theta}_n^*$ proposed in this paper has substantially larger efficiencies than $\hat{\theta}_{\mathrm{DPZ},n}$ (always well below 90%) and thus the new approach provides a substantial improvement and is additionally much easier to implement for multi-parameter models than that introduced in Dette et al. (2015). Finally, the estimators $\hat{\theta}_{\mathrm{BLUE},n}$ and $\hat{\theta}_n^*$ have similar efficiencies regardless of the underlying design. We therefore conclude that the alternative approach proposed in this paper provides estimators with corresponding optimal designs for finite

Table 3: *Efficiencies (in percent) of the estimators* $\hat{\theta}_{\mathrm{BLUE},n}$, $\hat{\theta}^*_n$ *and* $\hat{\theta}_{\mathrm{DPZ},n}$ *for models* (4.1) *and* (4.2) *and for two covariance kernels of the error process. The design is the uniform or the optimal design for five observations*

			Efficiencies		
	Model	Kernel	$\hat{\theta}_{\mathrm{BLUE},n}$	$\hat{\theta}^*_n$	$\hat{\theta}_{\mathrm{DPZ},n}$
optimal design	(4.1)	$t \wedge t'$	96.77	96.71	82.14
		$\exp\{-\lvert t-t'\rvert\}$	96.72	96.65	79.60
	(4.2)	$t \wedge t'$	83.98	83.40	70.91
		$\exp\{-\lvert t-t'\rvert\}$	83.47	82.95	71.57
uniform design	(4.1)	$t \wedge t'$	94.35	93.82	76.38
		$\exp\{-\lvert t-t'\rvert\}$	94.07	93.46	75.10
	(4.2)	$t \wedge t'$	73.13	73.12	70.91
		$\exp\{-\lvert t-t'\rvert\}$	72.56	72.46	71.57

sample which are practically not distinguishable from the optimal estimator and corresponding design.

5 Degenerate models

So far we have considered the continuous regression model (2.3) with a covariance kernel of the form (2.4) satisfying $u(a) \neq 0$. If $u(a) = 0$, then the variance of the observation at $t = a$ is 0 and all formulas of Section 2 and 3 degenerate in this case. The estimator $\hat{\theta}_{\text{BLUE}}$ in the continuous time model and its discrete approximation (3.10) are not well defined and the results of previous sections cannot be applied. In this section, we indicate how the methodology can be extended to the case $u(a) = 0$. For the sake of brevity we only consider the continuous time model with a Brownian motion as error process, since the transformation (2.10) which reduces any model with the covariance kernel (2.4) to the case of Brownian motion can still be applied. Moreover, the construction of an estimator (with a corresponding design) from the solution for the continuous time model can be obtained by similar arguments as presented in Section 3.
The main idea is to construct the BLUE $\hat{\theta}_{\text{BLUE}}$ in the continuous time model (2.3) on the interval $[0, b]$ by a sequence of estimators $\hat{\theta}_{\text{BLUE},a}$ for the same model on the interval $[a, b]$, where $a \to 0$. For this purpose we make the dependence of some quantities in the following discussion more explicit. For example we write C_a for the matrix C defined in (2.5) and so on. We have to consider three different cases of degeneracy, which will be discussed below.

5.1 Models with no intercept, that is $1 \notin \text{span}\{f_1, \ldots, f_m\}$

By Lemma A.1 in Section A.1, if $1 \notin \text{span}\{f_1, \ldots, f_m\}$ then the matrix

$$M_a = \int_a^b \dot{f}(s)\dot{f}^T(s)ds$$

is non-singular for all $a \in [0, b)$. In particular, M_0^{-1} exists. Additionally, in this case, for any $a > 0$ the inverse of the matrix

$$C_a = \int_a^b \dot{f}(t)\dot{f}^T(t)\,dt + \frac{f(a)f^T(a)}{a} = M_a + \frac{f(a)f^T(a)}{a}$$

can be expressed in the form

$$C_a^{-1} = M_a^{-1} - \frac{M_a^{-1}f(a)f^T(a)M_a^{-1}}{a + f^T(a)M_a^{-1}f(a)}\,. \tag{4.3}$$

We now discuss the cases $f(0) \neq 0$ and $f(0) = 0$ separately.

Theorem 5.1 *Consider the continuous time linear regression model* (2.3) *on the interval* $[0, b]$ *with a continuously differentiable vector* f *of regression functions. If each component of* f *is of bounded variation,* $1 \notin \mathrm{span}\{f_1, \dots, f_m\}$ *and* $f(0) \neq 0 \in \mathbb{R}^m$*, then the estimator*

$$\hat{\theta}_{\mathrm{BLUE}} = \underline{C} \int_0^b \dot{f}(t)\, dY_t + \frac{M_0^{-1} f(0)}{f^T(0) M_0^{-1} f(0)} Y_0 \,, \tag{4.4}$$

is the best linear unbiased estimator, where

$$\underline{C} = \lim_{a \to 0} C_a^{-1} = M_0^{-1} - \frac{M_0^{-1} f(0) f^T(0) M_0^{-1}}{f^T(0) M_0^{-1} f(0)} = \mathrm{Var}(\hat{\theta}_{\mathrm{BLUE}}) \,.$$

Proof. For any $a > 0$ the BLUE $\hat{\theta}_{\mathrm{BLUE},a}$ in the continuous time model (2.3) on the interval $[a, b]$ is given by

$$\hat{\theta}_{\mathrm{BLUE},a} = C_a^{-1} \Big(\int_a^b \dot{f}(t)\, dY_t + \frac{f(a)}{a} Y_a \Big). \tag{4.5}$$

As $a \to 0$,

$$\lim_{a \to 0} C_a^{-1} \int_a^b \dot{f}(t)\, dY_t = \underline{C} \int_0^b \dot{f}(t)\, dY_t$$

and

$$\begin{aligned} \lim_{a \to 0} C_a^{-1} \frac{f(a)}{a} &= \lim_{a \to 0} \Big(M_a^{-1} \frac{f(a)}{a} - \frac{M_a^{-1} f(a) f^T(a) M_a^{-1} f(a)}{a(a + f^T(a) M_a^{-1} f(a))} \Big) \\ &= \lim_{a \to 0} \frac{M_a^{-1} f(a)}{a + f^T(a) M_a^{-1} f(a))} = \frac{M_0^{-1} f(0)}{f^T(0) M_0^{-1} f(0)} \end{aligned}$$

Hence the left-hand side of (4.4) is the limit of the estimators $\hat{\theta}_{\mathrm{BLUE},a}$ as $a \to 0$. The covariance matrix of this estimator is obtained by Ito's formula and the fact that $\varepsilon_0 = 0$, i.e.

$$\mathrm{Var}(\hat{\theta}_{\mathrm{BLUE}}) \;=\; \underline{C} \Big[\int_0^b \dot{f}(t) \dot{f}^T(t)\, dt \Big] \underline{C} = \underline{C} M_0 \underline{C} = I - \frac{M_0^{-1} f(0) f^T(0)}{f^T(0) M_0^{-1} f(0)} \underline{C} = \underline{C} \,.$$

In order to prove that the derived estimator (4.4) is in fact BLUE we use Theorem 2.3 in Näther (1985a), which states that an unbiased estimator of the form $\hat{\theta} = \int_a^b Y_t dG(t)$ with covariance matrix $C = \mathrm{Var}(\hat{\theta})$ is BLUE in model (2.1) if the identity

$$\int_a^b K(s,t) dG(s) = C f(t) \tag{4.6}$$

holds for all $t \in [a, b]$. Here G is a vector measure on the interval $[a, b]$. In the present case $a = 0$ and $K(s,t) = \min(s,t)$, and in order to prove that the estimator (4.4) is indeed BLUE we use the representation

$$\int_0^b \dot{f}(t)\, dY_t = \dot{f}(b) Y_b - \dot{f}(0) Y_0 - \int_0^b Y_t d\dot{f}(t),$$

for the stochastic integral $\int_0^b \dot f(t)\, dY_t$. This defines the vector measure dG in an obvious manner, i.e. it has mass $\underline{C}\dot f(b)$ at the point b, the density $-\underline{C}\ddot f(t)$ for $t \in [0,b]$ and some mass at the point 0. The validity of (4.6) for $\hat\theta_{\mathrm{BLUE}}$ and $\underline{C}$ now follows from

$$\begin{aligned} -\int_0^b \min(s,t) d\dot f(s) &= -\int_0^t s d\dot f(s) - t\int_t^b d\dot f(s) \\ &= -[t\dot f(t) - f(t) + f(0)] - t[\dot f(b) - \dot f(t)] = -f(0) + f(t) - t\dot f(b), \end{aligned}$$

by noting that $\underline{C}f(0) = 0$ and that the weight at b cancels out. □

If $f(0) = 0 \in \mathbb{R}^m$, the observation at $t = 0$ necessarily gives $Y_0 = 0$ and provides no further information about the parameter θ. We obtain the following result.

Theorem 5.2 *Consider the continuous time linear regression model* (2.3) *on the interval* $[0,b]$ *with a continuously differentiable vector f of regression functions. If each component of f is of bounded variation,* $1 \notin \mathrm{span}\{f_1,\ldots,f_m\}$ *and* $f(0) = 0 \in \mathbb{R}^m$, *then*

$$\hat\theta_{\mathrm{BLUE}} = M_0^{-1}\int_0^b \dot f(t)\, dY_t\,, \tag{4.7}$$

and

$$\mathrm{Var}(\hat\theta_{\mathrm{BLUE}}) = M_0^{-1}$$

Proof. Since for any $p = 1,\ldots,m$ the function $f_p(t)$ is continuously differentiable on $[0,b]$, the limit $\lim_{t\to 0} f_p(t)/t$ is necessarily finite, possibly 0. Using this and the fact that $f(0) = 0$, the representation (4.3) gives $\lim_{a\to 0} C_a^{-1} = M_0^{-1}$, and the limit of $\hat\theta_{\mathrm{BLUE},a}$ defined in (4.5) is obviously (4.7). The covariance matrix of this estimator is again obtained by an application of Ito's formula and its optimality follows by similar arguments as given in the proof of Theorem 5.1. □

5.2 Models with an intercept, that is $1 \in \mathrm{span}\{f_1,\ldots,f_m\}$

W.l.o.g. we may assume $f_1(t) = 1$ for all $t \in [0,b]$ and rewrite the original regression model (2.3) as

$$Y_t = \theta_1 + \tilde\theta^T \tilde f(t) + \varepsilon_t, \qquad t \in [0,b],$$

where $\tilde\theta = (\theta_2,\ldots,\theta_m)^T$ and $\tilde f(t) = (f_2(t),\ldots,f_m(t))^T)$. Note that the observation at $t = 0$ is error-free and gives $Y_0 = \theta_1 + \tilde\theta^T \tilde f(0)$. By subtracting we obtain

$$Y_t - Y_0 = \tilde\theta^T(\tilde f(t) - \tilde f(0)) + \varepsilon_t. \tag{4.8}$$

Note that $1 \notin \text{span}\{\tilde{f}_2(t) - \tilde{f}_2(0), \ldots, \tilde{f}_m(t) - \tilde{f}_m(0)\}$ and $\tilde{f}(t) - \tilde{f}(0)$ is obviously 0 at $t = 0$. For computing the BLUE for $\tilde{\theta}$ and its covariance matrix in model (4.8) we can apply Theorem 5.2 and obtain

$$\tilde{\theta}_{\text{BLUE}} = \tilde{M}_0^{-1} \int_0^b \dot{\tilde{f}}(t)\, d(Y_t)\,, \tag{4.9}$$

$$\text{Var}(\tilde{\theta}_{\text{BLUE}}) = \tilde{M}_0^{-1} = \left[\int_0^b \dot{\tilde{f}}(t)\dot{\tilde{f}}^T(t)dt\right]^{-1}. \tag{4.10}$$

Finally, the BLUE for θ_1 is given by $\hat{\theta}_1 = Y_0 - \tilde{\theta}_{\text{BLUE}}^T \tilde{f}(0)$. Noting that Y_0 is a constant, we obtain $\text{cov}(\hat{\theta}_1, \hat{\theta}_p) = -\tilde{f}^T(0) M_0^{-1} e_p \quad (p = 2, \ldots, m)$, where e_p is the p-th coordinate vector. The variance of $\hat{\theta}_1$ is given by $\text{Var}(\hat{\theta}_1) = \tilde{f}^T(0) M_0^{-1} \tilde{f}(0)$.

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A Appendix: More technical details

A.1 An auxiliary result

Lemma A.1 *Let $f(t) = (f_1(t), \dots, f_m(t))^T$ be a vector of continuously differentiable linearly independent functions on the interval $[a,b]$ with $0 \le a < b$ and define $M = \int_a^b \dot{f}(s)\dot{f}^T(s)ds$.*

1. *The matrix M is non-singular if and only if $1 \notin \operatorname{span}\{f_1, \dots, f_m\}$.*
2. *If $1 \in \operatorname{span}\{f_1, \dots, f_m\}$ then $\operatorname{rank}(M) = m - 1$.*

Proof.
(1) Obviously the non-singularity of M implies that $1 \notin \operatorname{span}\{f_1, \dots, f_m\}$. To prove the converse we consider the equation

$$a_1\dot{f}_1(t) + \dots a_m\dot{f}_m(t) = 0, \quad \forall t \in [a,b] \tag{4.11}$$

for scalars $a_1, \dots, a_m$. This equation is satisfied if and only if for some a_0 we have

$$a_0 + a_1 f_1(t) + \dots a_m f_m(t) = 0, \quad \forall t \in [a,b]\,. \tag{4.12}$$

By the assumption, the functions $f_1, \dots, f_m$ are linearly independent on the interval $[a,b]$ and $1 \notin \operatorname{span}\{f_1, \dots, f_m\}$, which implies that the $m+1$ functions $1, f_1, \dots, f_m$ are also linearly independent on $[a,b]$. Consequently the equation (4.12) has only the trivial solution $a_0 = a_1 = \dots = a_m = 0$. which yields that the equation (4.11) has only trivial solution $a_1 = \dots = a_m = 0$. Therefore the functions $\dot{f}_1(t), \dots, \dot{f}_m(t)$ are linearly independent on the interval $[a,b]$ and the non-singularity of M follows from basic results on Gramian matrices [see Akhiezer and Glazman (1981), p. 18].

(2) To prove the second part assume now that $1 \in \operatorname{span}\{f_1, \dots, f_m\}$. Since $f_1, \dots, f_m$ are linearly independent we may assume w.l.o.g. that $f_1(t) = \text{const}$ for all $t \in [a,b]$. In this case, $\dot{f}_1 = 0$ and $1 \notin \operatorname{span}\{f_2, \dots, f_m\}$ and part (1) shows that the $(m-1) \times (m-1)$ submatrix of the matrix $(\int_a^b f_k(s) f_l(s) ds)_{k,l=2,\dots,m}$ has full rank, which implies that $\operatorname{rank}(M) = m - 1$. □

A.2 Proof of Lemma 2.1

If $1 \notin \operatorname{span}\{f_1, \dots, f_m\}$ if follows from Lemma A.1 in Section A.1 that the matrix M is non-singular and hence positive definite, which implies $C > 0$. If $1 \in \operatorname{span}\{f_1, \dots, f_m\}$ we may assume w.l.o.g. that $f_1(t) \equiv 1$. As the functions $f_2, \dots, f_m$ are linearly independent and $1 \notin \operatorname{span}\{f_2, \dots f_m\}$ it follows that

$$M = \int_a^b \dot{f}(t)\dot{f}^T(t)dt = \begin{pmatrix} 0 & 0 \\ 0 & \tilde{M} \end{pmatrix}$$

where (by Lemma A.1) the matrix $\tilde{M} = (\int_a^b \dot{f}_k(t)\dot{f}_l^T(t)dt)_{k,l=2}^m$ has rank $m-1$. Define $f(t) = (1, \tilde{f}(t)^T)$, where $\tilde{f}^T(t) = (f_2, \ldots, f_m)$ and assume that the matrix C is singular. Then there exists a vector $z = (z_1, \tilde{z}^T) \in \mathbb{R}^m \setminus \{0\}$ with $\tilde{z} \in \mathbb{R}^{m-1}$ such that

$$z^T C z = z^T M z + \frac{z^T f(a) f^T(a) z}{a} = \tilde{z}^T \tilde{M} \tilde{z} + (z^T f(a))^2 / a = 0.$$

As both terms in the sum are nonnegative we have $\tilde{z}^T \tilde{M} \tilde{z} = 0$ and $z^T f(a) = 0$. Since $\tilde{M}$ is a positive definite matrix we obtain $\tilde{z} = 0 \in \mathbb{R}^{m-1}$. The equation $z^T f(a) = 0$ then becomes $z_1 f_1(0) = 0$ implying $z_1 = 0$ and hence $z = 0 \in \mathbb{R}^m$. This yields a contradiction to the assumption that the matrix C is singular and proves Lemma 2.1. □

A.3 Proof of Lemma 3.3

Define the random variables

$$X_i = \int_{t_{i-1}}^{t_i} [\dot{f}(s) - \mu_i]\, dY_s, \qquad i = 2, \ldots, n.$$

From the definition of $\hat{\theta}_{\mathrm{BLUE}}$ and $\hat{\theta}_n$ in (2.6) and (3.10), respectively, we have

$$\mathbb{E}_\theta[(\hat{\theta}_{\mathrm{BLUE}} - \hat{\theta}_n)(\hat{\theta}_{\mathrm{BLUE}} - \hat{\theta}_n)^T] = C^{-1} \mathbb{E}_\theta\Big[\sum_{i=2}^n X_i \sum_{j=2}^n X_j^T\Big] C^{-1}.$$

Observing the fact that the random variables $X_2, \ldots, X_n$ are independent we obtain

$$\mathbb{E}_\theta\Big[\sum_{i=2}^n X_i \sum_{i=2}^n X_i^T\Big] = \sum_{i=2}^n \mathbb{E}_\theta\big[(X_i - \mathbb{E}_\theta[X_i])(X_i - \mathbb{E}_\theta[X_i])^T\big] + \sum_{i=2}^n \mathbb{E}_\theta[X_i] \sum_{j=2}^n \mathbb{E}_\theta[X_j^T].$$

Ito's isometry yields

$$\mathbb{E}_\theta[X_i] = \int_{t_{i-1}}^{t_i} [\dot{f}(s) - \mu_i] \dot{f}^T(s) \theta ds, \qquad i = 2, \ldots, n,$$

and

$$\begin{aligned} \mathbb{E}_\theta[(X_i - \mathbb{E}_\theta[X_i])(X_i - \mathbb{E}_\theta[X_i])^T] &= \mathbb{E}_\theta\Big[\int_{t_{i-1}}^{t_i} [\dot{f}(s) - \mu_i]\, d\varepsilon_s \int_{t_{i-1}}^{t_i} [\dot{f}(s) - \mu_i]^T\, d\varepsilon_s\Big] \\ &= \int_{t_{i-1}}^{t_i} [\dot{f}(s) - \mu_i][\dot{f}(s) - \mu_i]^T\, ds. \end{aligned}$$

Therefore,

$$\begin{aligned} \mathbb{E}_\theta\Big[\sum_{i=2}^n X_i \sum_{i=2}^n X_i^T\Big] &= \sum_{i=2}^n \int_{t_{i-1}}^{t_i} [\dot{f}(s) - \mu_i][\dot{f}(s) - \mu_i]^T\, ds \\ &\quad + \sum_{i=2}^n \int_{t_{i-1}}^{t_i} [\dot{f}(s) - \mu_i] \dot{f}^T(s) \theta\, ds \sum_{j=2}^n \int_{t_{j-1}}^{t_j} \theta^T \dot{f}(s) [\dot{f}(s) - \mu_j]^T\, ds, \end{aligned}$$

which proves the assertion. □

A.4 Proof of Theorem 3.1.

Standard calculations show that

$$\mathbb{E}_\theta[\hat{\theta}_n] = C^{-1}\Big[\sum_{i=2}^{n}\mu_i(f(t_i)-f(t_{i-1}))^T + \frac{f(a)f^T(a)}{a}\Big]\theta.$$

Observing the definition of the matrix C in (2.7) it follows that the estimator $\hat{\theta}_n$ defined in (3.1) is unbiased if and only if the identity (3.12) is satisfied. In order to prove the second part of Theorem 3.1 we use the decomposition

$$\mathbb{E}_\theta[(\tilde{\theta}_n-\theta)(\tilde{\theta}_n-\theta)^T] = E_1 + E_2 + E_2^T + E_3, \tag{4.13}$$

where the terms E_1, E_2 and E_3 are defined by

$$\begin{aligned} E_1 &= \mathbb{E}_\theta[(\tilde{\theta}_n-\hat{\theta}_{\text{BLUE}})(\tilde{\theta}_n-\hat{\theta}_{\text{BLUE}})^T], \\ E_2 &= \mathbb{E}_\theta[(\tilde{\theta}_n-\hat{\theta}_{\text{BLUE}})(\hat{\theta}_{\text{BLUE}}-\theta)^T], \\ E_3 &= \mathbb{E}_\theta[(\hat{\theta}_{\text{BLUE}}-\theta)(\hat{\theta}_{\text{BLUE}}-\theta)^T]. \end{aligned}$$

By Theorem 2.1 we have

$$E_3 = C^{-1} = \Big[\int_a^b \dot{f}(s)\dot{f}^T(s)\,ds + \frac{f(a)f^T(a)}{a}\Big]^{-1}.$$

Using the definition of $\tilde{\theta}_n$ and $\hat{\theta}_{\text{BLUE}}$ in (2.6), yields

$$\begin{aligned} C(\tilde{\theta}_n-\hat{\theta}_{\text{BLUE}}) &= C\int_a^b g(s)\,dY_s - \int_a^b \dot{f}(s)\,dY_s - \frac{f(a)}{a}Y_a \\ &= C\int_a^b g(s)\dot{f}^T(s)\theta\,ds + C\int_a^b g(s)\,d\varepsilon_s - \int_a^b \dot{f}(s)\dot{f}^T(s)\theta\,ds - \int_a^b \dot{f}(s)\,d\varepsilon_s \\ &\quad - \frac{f(a)f^T(a)}{a}\theta - \frac{f(a)}{a}\varepsilon_a \\ &= \int_a^b [Cg(s)-\dot{f}(s)]\,d\varepsilon_s - \frac{f(a)}{a}\varepsilon_a, \end{aligned}$$

where the last identity follows from the fact that $\tilde{\theta}_n$ is unbiased, that is,

$$\int_a^b g(s)\dot{f}^T(s)ds = I. \tag{4.14}$$

On the other hand

$$\begin{aligned} C(\hat{\theta}_{\text{BLUE}}-\theta) &= \int_a^b \dot{f}(s)\,dY_s + \frac{f(a)}{a}Y_a - \int_a^b \dot{f}(s)\dot{f}^T(s)\,ds\theta - \frac{f(a)f^T(a)}{a}\theta \\ &= \int_a^b \dot{f}(s)\,d\varepsilon_s + \frac{f(a)}{a}\varepsilon_a. \end{aligned}$$

Therefore we obtain for the term E_2 the representation

$$\begin{aligned} E_2 &= C^{-1}\Big\{\mathbb{E}_\theta\Big[\Big(\int_a^b [Cg(s) - \dot f(s)]\, d\varepsilon_s - \frac{f(a)}{a}\varepsilon_a\Big)\Big(\int_a^b \dot f(s)\, d\varepsilon_s + \frac{f(a)}{a}\varepsilon_a\Big)^T\Big]\Big\}C^{-1} \\ &= C^{-1}\Big\{\mathbb{E}_\theta\Big[\int_a^b [Cg(s) - \dot f(s)]\, d\varepsilon_s \int_a^b \dot f^T(s)\, d\varepsilon_s\Big] - \mathbb{E}_\theta\Big[\frac{f(a)}{a}\varepsilon_a\varepsilon_a^T\frac{f^T(a)}{a}\Big]\Big\}C^{-1} \\ &= C^{-1}\Big[\int_a^b [Cg(s) - \dot f(s)]\dot f^T(s)\, ds - \frac{f(a)f^T(a)}{a}\Big]C^{-1} \\ &= C^{-1}\Big[C - \int_a^b \dot f(s)\dot f^T(s)\, ds - \frac{f(a)f^T(a)}{a}\Big]C^{-1} = 0, \end{aligned}$$

where the last identity is again a consequence of (4.14). Hence it follows from (4.13)

$$\mathbb{E}_\theta[(\tilde\theta_n - \theta)(\tilde\theta_n - \theta)^T] = \mathbb{E}_\theta[(\tilde\theta_n - \hat\theta_{\text{BLUE}})(\tilde\theta_n - \hat\theta_{\text{BLUE}})^T] + C^{-1},$$

which proves the assertion of Theorem 3.1. □