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# Improved error bounds for quantization based numerical schemes for BSDE and nonlinear filtering

GILLES PAGÈS \* ABASS SAGNA † ‡

## Abstract

We take advantage of recent (see [42, 61]) and new results on optimal quantization theory to improve the quadratic optimal quantization error bounds for backward stochastic differential equations (BSDE) and nonlinear filtering problems. For both problems, a first improvement relies on a Pythagoras like Theorem for quantized conditional expectation. While allowing for some locally Lipschitz continuous conditional densities in nonlinear filtering, the analysis of the error brings into play a new robustness result about optimal quantizers, the so-called distortion mismatch property: the  $L^s$ -mean quantization error induced by  $L^r$ -optimal quantizers of size  $N$  converges at the same rate  $N^{-\frac{1}{d}}$  for every  $s \in (0, r + d)$ .

## 1 Introduction

In this work we propose improved error bounds for quantization based numerical schemes introduced in [4] and [59] to solve BSDEs and nonlinear filtering problems. For BSDE, we consider equations where the driver depends on the “ $Z$ ” term (see Equation (1) below) and for nonlinear filtering, we extend existing results to locally Lipschitz continuous densities (see Section 6). For both problems, we also improve the error bounds themselves by using a Pythagoras like theorem for the approximation of conditional expectations introduced in [61] (see also [58]). These problems have a wide range of applications, in particular in Financial Mathematics, when modeling the price of financial derivatives or in stochastic control, in credit risk modeling, etc.

BSDEs were first introduced in [12] but raised a wide interest mostly after their extension in [64]. In this latter paper, the existence and the uniqueness of a solution have been established for the following backward stochastic differential equation with Lipschitz continuous driver  $f$  (valued in  $\mathbb{R}^d$ ) and terminal condition  $\xi$ :

$$Y_t = \xi + \int_t^T f(s, Y_s, Z_s) ds - \int_t^T Z_s dW_s, \quad 0 \leq t \leq T, \quad (1)$$

where  $W$  is a  $q$ -dimensional brownian motion. We mean by a solution a pair  $(Y_t, Z_t)_{t \leq T}$  (valued in  $\mathbb{R}^d \times \mathbb{R}^{d \times q}$ ) of square integrable progressively measurable (with respect to the augmented Brownian filtration  $(\mathcal{F}_t)_{t \geq 0}$ ) and satisfying Equation (1). Extensions of these existence and uniqueness results

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have been investigated in more general situations such as: less regular drivers (locally Lipschitz driver, see [1, 43]; quadratic BSDEs, see [50]; rough integrals instead of Lebesgue integrals, see [27]; super-linear quadratic BSDEs, see [51]); randomized horizon, see [63]; introduction of Poisson random measure component subject to constraints on the jump component, see [49, 48]; extension to second order BSDEs, see [56]); non-smooth terminal conditions, see [31, 30, 37].

Since the pioneering work [29] in which the link between BSDE and hedging portfolio of European (and American) derivatives has been first established, various other applications have been developed, as risk-sensitive control problems, risk measure theory, etc.

However, even if it can be established in many cases that a BSDE has a unique solution, this solution admits no closed form in general. This led to devise tractable approximation schemes of the solution. In the Markovian case (see (2) below) for example, where the terminal condition is of the form  $\xi = h(X_T)$  for some forward diffusion  $X$ , a first numerical method has been proposed in [28] for a class of forward-backward stochastic differential equations, based on a four step scheme developed later on in [54].

Many other approximation methods of the solutions of some classes of BSDEs have been proposed such as BSDEs with possible path-dependent terminal condition, see [70] and [16], coupled BSDE, see [71], Reflected BSDE, see [46], BSDE for quasilinear PDEs, see [26], BSDE applied to control problems or nonlinear PDEs, see [2]. Higher order schemes have also been considered, see [20] or [6]. As for quadratic BSDE – *i.e.* when the generator  $f$  has a quadratic growth with respect to  $z$  – we refer to [21] where the authors consider a slightly modified dynamical programming equation to propose a numerical scheme. They investigate the time discretization error and use optimal quantization to implement their algorithm. However, they do not study the induced quantization error.

In the present work, we consider the following decoupled FBSDE (Forward-Backward SDE),

$$Y_t = \xi + \int_t^T f(s, X_s, Y_s, Z_s) ds - \int_t^T Z_s \cdot dW_s, \quad t \in [0, T], \quad (2)$$

where  $W$  is a  $q$ -dimensional Brownian motion,  $(Z_t)_{t \in [0, T]}$  is a square integrable progressively measurable process taking values in  $\mathbb{R}^q$  and  $f : [0, T] \times \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^q \rightarrow \mathbb{R}$  is a Borel function. We suppose a terminal condition of the form  $\xi = h(X_T)$ , for a given Borel function  $h : \mathbb{R}^d \rightarrow \mathbb{R}$ , where  $X_T$  is the value at time  $T$  of a Brownian diffusion process  $(X_t)_{t \geq 0}$ , strong solution to the SDE:

$$X_t = x + \int_0^t b(s, X_s) ds + \int_0^t \sigma(s, X_s) dW_s, \quad x \in \mathbb{R}^d. \quad (3)$$

In this case, the solution of the BSDE is usually approximated at the points of a time grid  $t_0 = 0, \dots, t_n = T$  and involve in particular the approximation of conditional expectations  $\mathbb{E}(g_{k+1}(X_{t_{k+1}}) | X_{t_k})$ , where the functions  $g_k$  are determined in the recursion. The sequence  $(X_{t_{k+1}})_{0 \leq k \leq n}$  is either a “sampling” of the diffusion  $X$  at times  $(t_k)_{0 \leq k \leq n}$  or, most often, a discretization scheme of  $(X_t)_{t \geq 0}$ , typically the discrete time Euler scheme, when the solution of (3) is not explicit enough to be simulated in an exact way.

In this paper, we consider an *explicit* time discretization scheme where the conditioning is performed *inside* the driver  $f$  (see also [47]). It is recursively defined in a backward way as:

$$\tilde{Y}_{t_n} = h(\bar{X}_{t_n}) \quad (4)$$

$$\tilde{Y}_{t_k} = \mathbb{E}(\tilde{Y}_{t_{k+1}} | \mathcal{F}_{t_k}) + \Delta_n f(t_k, \bar{X}_{t_k}, \mathbb{E}(\tilde{Y}_{t_{k+1}} | \mathcal{F}_{t_k}), \tilde{\zeta}_{t_k}), \quad k = 0, \dots, n-1, \quad (5)$$

$$\text{with} \quad \tilde{\zeta}_{t_k} = \frac{1}{\Delta_n} \mathbb{E}(\tilde{Y}_{t_{k+1}} (W_{t_{k+1}} - W_{t_k}) | \mathcal{F}_{t_k}), \quad k = 0, \dots, n-1. \quad (6)$$

The process  $(\bar{X}_{t_k})_{k=0, \dots, n}$  is the discrete time Euler scheme of the diffusion process  $(X_t)_{t \in [0, T]}$  with

step  $\Delta_n = \frac{T}{n}$ , recursively defined by

$$\bar{X}_{t_k} = \bar{X}_{t_{k-1}} + \Delta_n b(t_{k-1}, \bar{X}_{t_{k-1}}) + \sigma(t_{k-1}, \bar{X}_{t_{k-1}})(W_{t_k} - W_{t_{k-1}}), \quad k = 1, \dots, n, \quad \bar{X}_0 = x.$$

Under some smooth assumptions on the coefficients of the diffusions, there exists (see Theorem 3.1 further on for a precise statement, see also [70, 13]) that there is a real constant  $\tilde{C}_{b,\sigma,f,T} > 0$  such that, for every  $n \geq 1$ ,

$$\max_{k \in \{0, \dots, n\}} \mathbb{E}|Y_{t_k} - \tilde{Y}_{t_k}|^2 + \int_0^T \mathbb{E}|Z_t - \tilde{Z}_t|^2 dt \leq \tilde{C}_{b,\sigma,f,T} \Delta_n,$$

where  $\tilde{Z} = \tilde{Z}^{(n)}$  comes from the martingale representation of  $\sum_{k=1}^n \tilde{Y}_{t_k} - \mathbb{E}(\tilde{Y}_{t_k} | \mathcal{F}_{t_{k-1}})$ .

At this stage, since the scheme (4)-(5) involves the computation of conditional expectations for which no analytical expression is available, its solution  $(\tilde{Y}, \tilde{\zeta})$  has in turn to be approximated. A possible approach is to rely on regression methods involving the Monte Carlo simulations, see *e.g.* [13, 34, 36, 35]. Other methods using on line Monte Carlo simulations have been developed in a Malliavin calculus framework (conditional expectations are “regularized” by integration by parts from which “Malliavin” weights come out, see [13, 23, 39, 45, 69]). Among alternative approaches let us cite the least-squares regression methods, the multistep schemes methods (see [8, 40]), the primal-dual approach (see [9]). New approaches have been proposed recently: a combination of Picard iterates and a decomposition in Wiener chaos (see [15]), a “forward” approach in connection with the semi-linear PDE associated to the BSDE (see [44]), an analytic approach in [38].

In this paper, we go back to the *optimal quantization tree* approach originally introduced in [5] (in fact for *Reflected BSDEs*) and developed in [4, 3, 7]. This approach is based on an optimally fitting approximation of the Markovian dynamics of the discrete time Markov chain  $(\bar{X}_{t_k})_{0 \leq k \leq n}$  (or a sampling of  $X$  at discrete times  $(t_k)_{k=0, \dots, n}$ ) with random variables having a finite support. However, we consider a different quantization tree (or quantized scheme) defined recursively by mimicking (4)-(5) as follows:

$$\hat{Y}_{t_n} = h(\hat{X}_{t_n}) \tag{7}$$

$$\hat{Y}_{t_k} = \hat{\mathbb{E}}_k(\hat{Y}_{t_{k+1}}) + \Delta_n f(t_k, \hat{X}_{t_k}, \hat{\mathbb{E}}_k(\hat{Y}_{t_{k+1}}), \hat{\zeta}_{t_k}) \tag{8}$$

with 
$$\hat{\zeta}_{t_k} = \frac{1}{\Delta_n} \hat{\mathbb{E}}_k(\hat{Y}_{t_{k+1}} \Delta W_{t_{k+1}}), \quad k = 0, \dots, n-1, \tag{9}$$

where  $\Delta W_{t_{k+1}} = W_{t_{k+1}} - W_{t_k}$ ,  $\hat{\mathbb{E}}_k = \mathbb{E}(\cdot | \hat{X}_{t_k})$ , and  $\hat{X}_{t_k}$  is a quantization of  $\bar{X}_{t_k}$  on a finite grid  $\Gamma_k \subset \mathbb{R}^d$ , *i.e.*,  $\hat{X}_{t_k} = \pi_k(\bar{X}_{t_k})$ , where  $\pi_k : \mathbb{R}^d \rightarrow \Gamma_k$  is a Borel “projection” on  $\Gamma_k$ ,  $k = 0, \dots, n$ . At this stage the function  $\pi_k$  might be any  $\Gamma_k$ -valued Borel functions. In order to derive better theoretical rates as well as for practical implementation, we will first consider Borel *nearest neighbor projections*  $\pi_k = \text{Proj}_{\Gamma_k}$  at every time step and then search for grids optimally “fitting” the distribution of  $X_{t_k}$  *i.e.* minimizing the resulting error  $\|X_{t_k} - \text{Proj}_{\Gamma_k}(X_{t_k})\|_2$  among all grids  $\Gamma_k$  of a prescribed size  $N_k$ , see Section 4 for details. This is an *explicit inner* scheme in the sense that the conditioning is performed inside the driver  $f$  in contrast with what is usually done in the literature (where implicit or *outer* explicit schemes are in force). This scheme, though quite natural, seems not to have been extensively analyzed (see however [47] where a first analysis is carried out in the spirit of [4, 3]). It turns out to be well designed to establish our improved rates and shows quite satisfactory numerical performances. Our objective here is two-fold: first include the  $Z$  term in the driver and to dramatically improve the error bounds in [3, 7], especially its dependence in the size  $n+1$  of the time discretization mesh.

So, the question of interest will be to estimate the quadratic quantization error  $(\mathbb{E}|\tilde{Y}_{t_k} - \hat{Y}_{t_k}|^2)^{1/2}$  induced by the approximation of  $\tilde{Y}_{t_k}$  by  $\hat{Y}_{t_k}$ , for every  $k = 0, \dots, n$ , where  $\hat{Y}_{t_k}$  is the quantized version

of  $\tilde{Y}_{t_k}$  given by (7)-(8). Under more general assumptions than [4, 5], we show in Theorem 3.2(a) that, at every step  $k$  of the procedure,

$$\|\tilde{Y}_{t_k} - \hat{Y}_{t_k}\|_2^2 \leq \sum_{i=k}^n \tilde{K}_i \|\bar{X}_{t_i} - \hat{X}_{t_i}\|_2^2, \quad (10)$$

for positive real constants  $\tilde{K}_i$  depending on  $t_i$  and  $T$  and on the regularity of the coefficients of  $b, \sigma$  and the driver  $f$  which remain bounded as  $n \uparrow +\infty$ . The presence of the squared quadratic norms on both sides of (10) improves the control of the time discretization effect, compared with [4, 5] in which error bounds of the form  $\|\tilde{Y}_{t_k} - \hat{Y}_{t_k}\|_p \leq \sum_{i=k}^n K_i \|\bar{X}_{t_i} - \hat{X}_{t_i}\|_p$  are established for  $p \in [1, +\infty)$ . In fact, we switch from a global error (at  $t = 0$ ) of order  $n \times \max_{0 \leq k \leq n} \|X_{t_k} - \hat{X}_{t_k}\|_2$  to  $\sqrt{n} \times \max_{0 \leq k \leq n} \|X_{t_k} - \hat{X}_{t_k}\|_2$ . This theoretical improvement confirms the results of numerical experiments first carried out in [7] though it was in a less favorable framework (with reflection) or in [18, 17] for American options.

For the  $Z$  part which is approximated first by  $\tilde{\zeta}$  in (6) and whose quantization version  $\hat{\zeta}$  is given by (9), we get the following approximation error (see Theorem 3.2(b))

$$\Delta_n \sum_{k=0}^{n-1} \|\tilde{\zeta}_k - \hat{\zeta}_k\|_2^2 \leq \sum_{k=0}^{n-1} \tilde{K}'_k \|\bar{X}_k - \hat{X}_k\|_2^2 + \sum_{k=0}^{n-1} \|\tilde{Y}_{k+1} - \hat{Y}_{k+1}\|_2^2$$

where  $\tilde{K}'_i$  are positive constants depending on  $t_i$  and  $T$  and on the regularity of the coefficients of  $b, \sigma$  and the driver  $f$ . So, we switch from  $n^{\frac{3}{2}} \times \max_{0 \leq k \leq n} \|\bar{X}_{t_k} - \hat{X}_{t_k}\|_2$  to  $n \times \max_{0 \leq k \leq n} \|\bar{X}_{t_k} - \hat{X}_{t_k}\|_2$ .

We notice here that other quantization based discretization schemes have been devised, especially for *Forward-Backward* SDEs (see [25]) where the diffusion and the BSDE are fully coupled (including the  $Z$  in the driver) where the grids  $\Gamma_k$  are the trace of  $\delta \mathbb{Z}^d$  ( $\delta > 0$ ) on an expanding compact as  $t_k$  grows. In contrast the Brownian increments are replaced by optimal quantization of the  $\mathcal{N}(0; I_d)$ -distribution. But the obtained resulting error bound for the scheme are not of the improved from (10). A multistep approach based on two reference ODEs from the computation of conditional expectation has been developed in a similar framework (coupled and uncoupled) in [71].

In the second part of the paper, we first propose (Section 4) a short background on optimal vector quantization, enriched by a new result, namely Theorem 4.3, which essentially solves the-called *distortion mismatch* problem. By distortion mismatch we mean the robustness of optimal quantization grids. An optimal (quadratic) quantization grid  $\Gamma_N$  at level  $N$  for the distribution of a random vector  $X$  is such that  $\|X - \text{Proj}_{\Gamma_N}(X)\|_2 = e_{N,2}(X) := \inf \{\|X - q(X)\|_2, q : \mathbb{R}^d \rightarrow \Gamma, \text{Borel}, \Gamma \subset \mathbb{R}^d, \text{card}(\Gamma_N) \leq N\}$  where  $\text{Proj}_{\Gamma_N}$  denotes a (Borel) nearest neighbor projection on  $\Gamma_N$ . It exists for every size (or level)  $N \geq 1$  as soon as  $X \in L^2$  and it follows from Zador's Theorem that  $e_{N,2}(X) \sim c(X)N^{-\frac{1}{d}}$  as  $N \rightarrow +\infty$  (see Section 4 for details). The distortion mismatch property established in Theorem 4.3 states that, for every  $s \in (0, d + 2)$ ,  $\overline{\lim}_N N^{\frac{1}{d}} \|X - \text{Proj}_{\Gamma_N}(X)\|_s < +\infty$ . This result holds whenever  $X \in L^s$  with a distribution satisfying mild additional property. This theorem extends first results established in [42] for various classes of absolutely continuous distributions. Note that all the above properties depend on the distribution  $\mathbb{P}_X$  of  $X$  rather than on the random vector  $X$  itself. This robustness property is the key of the second kind of improvement proposed in this paper, this time for quantization based schemes for non-linear filtering investigated in the third part. In Section 5 we propose numerical illustrations using optimal quantization based schemes for various types of BSDEs which confirm that the improved rates established in the first part are the true ones.

In this third part of the paper (Section 6), we consider a (discrete time) nonlinear filtering problem and improve (in the quadratic setting) the results obtained in [59]. Firstly, we relax the Lipschitz assumption made on the conditional densities then we provide new improved error bounds for the

quantization based scheme introduced in [59] to numerically solve a discrete filter by optimal quantization.

In fact, we consider a discrete time nonlinear filtering problem where the signal process  $(X_k)_{k \geq 0}$  is an  $\mathbb{R}^d$ -valued discrete time Markov process and the observation process  $(Y_k)_{k \geq 0}$  is an  $\mathbb{R}^q$ -valued random vector, both defined on a probability space  $(\Omega, \mathcal{A}, \mathbb{P})$ . The distribution  $\mu$  of  $X_0$  is given, as well as the transition probabilities  $P_k(x, dx') = \mathbb{P}(X_k \in dx' | X_{k-1} = x)$  of the process  $(X_k)_{k \geq 0}$ . We also suppose that the process  $(X_k, Y_k)_{k \geq 0}$  is a Markov chain and that for every  $k \geq 1$ , the conditional distribution of  $Y_k$ , given  $(X_{k-1}, Y_{k-1}, X_k)$  has a density  $g_k(X_{k-1}, Y_{k-1}, X_k, \cdot)$ . Having a fixed observation  $Y := (Y_0, \dots, Y_n) = (y_0, \dots, y_n)$ , for  $n \geq 1$ , we aim at computing the conditional distribution  $\Pi_{y,n}$  of  $X_n$  given  $Y = (y_0, \dots, y_n)$ . It is well-known that for any bounded and measurable function  $f$ ,  $\Pi_{y,n}f$  is given by the celebrated Kallianpur-Striebel formula (see *e.g.* [59])

$$\Pi_{y,n}f = \frac{\pi_{y,n}f}{\pi_{y,n}\mathbf{1}} \quad (11)$$

where the so-called un-normalized filter  $\pi_{y,n}$  is defined for every bounded or non-negative Borel function  $f$  by

$$\pi_{y,n}f = \mathbb{E}(f(X_n)L_{y,n})$$

with

$$L_{y,n} = \prod_{k=1}^n g_k(X_{k-1}, y_{k-1}, X_k, y_k).$$

Defining the family of transition kernels  $H_{y,k}$ ,  $k = 1, \dots, n$ , by

$$H_{y,k}f(x) = \mathbb{E}(f(X_k)g_k(x, y_{k-1}, X_k, y_k) | X_{k-1} = x) \quad (12)$$

for every bounded or non-negative Borel function  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  and setting

$$H_{y,0}f(x) = \mathbb{E}(f(X_0)),$$

one shows that the un-normalized filter may be computed by the following *forward* induction formula:

$$\pi_{y,k}f = \pi_{y,k-1}H_{y,k}f, \quad k = 1, \dots, n, \quad (13)$$

with  $\pi_{y,0} = H_{y,0}$ . A useful formulation, especially to establish error bound for the quantization based approximate filter is its *backward* counterpart defined by setting

$$\pi_{y,n}f = u_{y,-1}(f)$$

where  $u_{y,-1}$  is the final value of the backward recursion:

$$u_{y,n}(f)(x) = f(x), \quad u_{y,k-1}(f) = H_{y,k}u_{y,k}(f), \quad k = 0, \dots, n. \quad (14)$$

In order to compute the normalized filter  $\Pi_{y,n}$ , we just have to compute the transition kernels  $H_{y,k}$  and to use the recursive formulas (13) or (14). However these kernels have no closed formula in general so that we have to approximate them. Optimal quantization based algorithms for non linear filtering has been introduced in [59] (see also [66, 19, 59, 68] for further developments and contributions). It turned out to be an efficient alternative approach to particle methods (we refer *e.g.* to [24] and the references therein which rely on Monte Carlo simulation of interacting particles) owing to its tractability. For a survey and comparisons between optimal quantization and particle methods, we refer to [68].

The quantization based approximate filter is designed as follows: denoting for every  $k = 0, \dots, n$  by  $\hat{X}_k$  a quantization of  $X_k$  at level  $N_k$  by the grid  $\Gamma_k = \{x_k^1, \dots, x_k^{N_k}\}$ , we will formally replace

$X_k$  in (13) or (14) by  $\hat{X}_k$ . As a consequence the (optimally) quantized approximation  $\hat{\pi}_{y,n}$  of  $\pi_{y,n}$  is defined simply by the quantized counterpart of the Kallianpur-Striebel formula: we introduce for every bounded or non-negative Borel function  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  the family of quantized transition kernels  $\hat{H}_{y,k}$ ,  $k = 0, \dots, n$ , by  $\hat{H}_{y,0}f(x) = \mathbb{E}(f(\hat{X}_0))$  and

$$\hat{H}_{y,k}f(x_{k-1}^i) = \mathbb{E}(f(\hat{X}_k)g_k(x_{k-1}^i, y_{k-1}, \hat{X}_k, y_k) | X_{k-1} = x_{k-1}^i), \quad k = 1, \dots, n. \quad (15)$$

$$= \sum_{j=1}^{N_k} \hat{H}_{y,k}^{ij} f(x_k^j), \quad i = 1, \dots, N_{k-1} \quad (16)$$

$$\text{with} \quad \hat{H}_{y,k}^{ij} = g_k(x_{k-1}^i, y_{k-1}; x_k^j, y_k) \hat{p}_k^{ij} \quad (17)$$

$$\text{and} \quad \hat{p}_k^{ij} = \mathbb{P}(\hat{X}_k = x_k^j | \hat{X}_{k-1} = x_{k-1}^i) \quad i = 1, \dots, N_{k-1}, j = 1, \dots, N_k. \quad (18)$$

Then set

$$\hat{\pi}_{y,k} = \hat{\pi}_{y,k-1} \hat{H}_{y,k}, \quad k = 1, \dots, n, \quad \text{and} \quad \hat{\pi}_{y,0} = \hat{H}_{y,0} \quad (19)$$

or, equivalently,

$$\hat{\pi}_{y,k} = \sum_{i=1}^{N_k} \hat{\pi}_{y,k}^i \delta_{x_k^i} \quad \text{with} \quad \hat{\pi}_{y,k}^i = \sum_{j=1}^{N_{k-1}} \hat{\pi}_{y,k-1}^j \hat{H}_{y,k}^{ij}, \quad k = 1, \dots, n$$

and  $\hat{\pi}_0 = \sum_{i=1}^{N_0} \hat{p}_0^i \delta_{x_0^i}$  with  $\hat{p}_0^i = \mathbb{P}(\hat{X}_0 = x_0^i)$ ,  $i = 1, \dots, N_0$ . As a final step, we approximate the normalized filter  $\Pi_{y,n}$  by  $\hat{\Pi}_{y,n}$  given by

$$\hat{\Pi}_{y,n}f = \frac{\hat{\pi}_{y,n}f}{\hat{\pi}_{y,n}\mathbf{1}} = \sum_{i=1}^{N_n} \hat{\Pi}_{y,n}^i f(x_n^i) \quad \text{with} \quad \hat{\Pi}_{y,n}^i = \frac{\hat{\pi}_{y,n}^i}{\sum_{j=1}^{N_n} \hat{\pi}_{y,n}^j}, \quad i = 1, \dots, N_n.$$

One shows (see [59]) that the un-normalized quantized filter may also be computed by the following *backward* induction formula, defined by

$$\hat{\pi}_{y,n}f = \hat{u}_{y,-1}(f)$$

where  $\hat{u}_{y,-1}$  is the final value of the backward recursion:

$$\hat{u}_{y,n}(f) = f \text{ on } \Gamma_n, \quad \hat{u}_{y,k-1}(f) = \hat{H}_{y,k} \hat{u}_{y,k}(f) \text{ on } \Gamma_k, \quad k = 0, \dots, n. \quad (20)$$

Our aim is then to estimate the quantization error induced by the approximation of  $\Pi_{y,n}$  by  $\hat{\Pi}_{y,n}$ . Note that this problem has been considered in [59] where it has been shown that, for every bounded Borel function  $f$ , the absolute error  $|\Pi_{y,n}f - \hat{\Pi}_{y,n}f|$  is bounded (up to a constant depending in particular on  $n$ ) by the cumulated sum of the  $L^r$ -quantization errors  $\|X_k - \hat{X}_k\|_r$ ,  $k = 0, \dots, n$ . In this work, we improve this result in the particular case of the quadratic quantization framework (*i.e.*  $r = 2$ ) in two directions. In fact, we first show that, for every bounded Borel function  $f$ , the squared-absolute error  $|\Pi_{y,n}f - \hat{\Pi}_{y,n}f|^2$  is bounded by the cumulated square-quadratic quantization errors  $\|X_k - \hat{X}_k\|_2^2$  from  $k = 0$  to  $n$ , similarly to what we did for BSDEs inducing a similar improvement for dependence in  $n$  of the error bounds (*i.e.* the time discretization step  $1/n$  if  $(X_k)_{k \geq 0}$  is a discretization step of a diffusion). Once again, this confirms numerical evidences observed in [59, 7]. Secondly, we show that these improved error bounds hold under local Lipschitz continuity assumptions on the conditional density functions  $g_k$  (instead of Lipschitz conditions in [59]). The distortion mismatch property established in Theorem 4.3 is the key of this extension.

The paper is divided into three parts. The first part is devoted to the analysis of the optimal quantization error associated to the BSDE algorithm under consideration. We recall first, in Section 2, the

discretization scheme we consider for the BSDE. Then, in Section 3, we investigate the error analysis for the time discretization and the quantization scheme. In the second part, some results about optimal quantization are recalled in Section 4 and a new distortion mismatch theorem is established about the robustness of  $L^r$ -optimal quantization in  $L^s$  for  $s \in (r, r + d)$ . Some numerical tests confirm and illustrate these improved error bonds in Section 5. The final part, Section 6, is devoted to the nonlinear filtering problem analysis when estimating the nonlinear filter by optimal quantization with new improved error bounds obtained under less than stringent – local – Lipschitz assumptions than in the existing literature.

NOTATIONS:  $\bullet \|\cdot\|$  denotes the canonical Euclidean norm on  $\mathbb{R}^d$ .

- For every  $f : \mathbb{R}^d \rightarrow \mathbb{R}$ , set  $\|f\|_\infty = \sup_{x \in \mathbb{R}^d} |f(x)|$  and  $[f]_{\text{Lip}} = \sup_{x \neq y} \frac{|f(x) - f(y)|}{|x - y|} \leq +\infty$ .
- If  $A \in \mathcal{M}(d, q)$  we define the Fröbenius norm of  $A$  by  $\|A\| = \sqrt{\text{Tr}(AA^*)}$ .

## 2 Discretization of the BSDE

Let  $(W_t)_{t \geq 0}$  be a  $q$ -dimensional Brownian motion defined on a probability space  $(\Omega, \mathcal{A}, \mathbb{P})$  and let  $(\mathcal{F}_t)_{t \geq 0}$  be its augmented natural filtration. We consider the following stochastic differential equation:

$$X_t = x + \int_0^t b(s, X_s) ds + \int_0^t \sigma(s, X_s) dW_s, \quad (21)$$

where the drift coefficient  $b : [0, T] \times \mathbb{R}^d \rightarrow \mathbb{R}^d$  and the matrix diffusion coefficient  $\sigma : [0, T] \times \mathbb{R}^d \rightarrow \mathcal{M}(d, q)$  are Lipschitz continuous in  $(t, x)$ . For a fixed horizon (the maturity)  $T > 0$ , we consider the following Markovian Backward Stochastic Differential Equation (BSDE):

$$Y_t = h(X_T) + \int_t^T f(s, X_s, Y_s, Z_s) ds - \int_t^T Z_s \cdot dW_s, \quad t \in [0, T], \quad (22)$$

where the function  $h : \mathbb{R}^d \rightarrow \mathbb{R}$  is  $[h]_{\text{Lip}}$ -Lipschitz continuous, the driver  $f(t, x, y, z) : [0, T] \times \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^q \rightarrow \mathbb{R}$  is Lipschitz continuous with respect to  $(x, y, z)$ , uniformly in  $t \in [0, T]$ , *i.e.* satisfies

$$(\text{Lip}_f) \equiv |f(t, x, y, z) - f(t, x', y', z')| \leq [f]_{\text{Lip}}(|x - x'| + |y - y'| + |z - z'|). \quad (23)$$

Under the previous assumptions on  $b, \sigma, h, f$ , the BSDE (22) has a unique  $\mathbb{R} \times \mathbb{R}^q$ -valued,  $\mathcal{F}_t$ -adapted solution  $(Y, Z)$  satisfying (see [64], see also [55])

$$\mathbb{E} \left( \sup_{t \in [0, T]} |Y_t|^2 + \int_0^T |Z_s|^2 ds \right) < +\infty.$$

Let us consider now  $(\bar{X}_{t_k})_{k=0, \dots, n}$ , the discrete time Euler scheme with step  $\Delta_n = \frac{T}{n}$  of the diffusion process  $(X_t)_{t \in [0, T]}$ :

$$\bar{X}_{t_k} = \bar{X}_{t_{k-1}} + \Delta_n b(t_{k-1}, \bar{X}_{t_{k-1}}) + \sigma(t_{k-1}, \bar{X}_{t_{k-1}})(W_{t_k} - W_{t_{k-1}}), \quad k = 1, \dots, n, \quad \bar{X}_0 = x$$

where  $t_k := \frac{kT}{n}$ ,  $k = 0, \dots, n$  and its continuous time counterpart, sometimes called *genuine Euler scheme* (we drop the dependence in  $n$  when no ambiguity) defined as an Itô process by

$$d\bar{X}_t = b(t, \bar{X}_t) dt + \sigma(t, \bar{X}_t) dW_t, \quad \bar{X}_0 = x \quad (24)$$

where  $\underline{t} = \frac{kT}{n}$  when  $t \in [t_k, t_{k+1})$ . In particular  $(\bar{X}_t)_{t \in [0, T]}$  is an  $\mathcal{F}_t$ -adapted Itô process satisfying under the above assumptions made on  $b$  and  $\sigma$  (see *e.g.* [14]):

$$\forall p \in (0, +\infty), \quad \left\| \sup_{t \in [0, T]} |X_t| \right\|_p + \sup_{n \geq 1} \left\| \sup_{t \in [0, T]} |\bar{X}_t^n| \right\|_p \leq C_{b, \sigma, p, T} (1 + |x|)$$



and

$$\forall p \in (0, +\infty), \forall n \geq 1, \quad \left\| \sup_{t \in [0, T]} |X_t - \bar{X}_t^n| \right\|_p \leq C_{b, \sigma, p, T} \sqrt{\Delta_n} (1 + |x|)$$

for a positive constant  $C_{b, \sigma, p, T}$ .

As a consequence, general existence-uniqueness results for BSDEs entail (see [65]) the existence of a unique solution  $(\bar{Y}, \bar{Z})$  to the Markovian BSDE having the genuine Euler scheme  $\bar{X}$  instead of  $X$  as a forward process. Then, we can apply the classical comparison result (Proposition 2.1 from [29]) with  $f^1(\omega, t, y, z) = f(t, \bar{X}_t(\omega), y, z)$  and  $f^2(\omega, t, x, y, z) = f(t, X_t(\omega), y, z)$  which immediately yields the existence of real constants  $C_{b, \sigma, f, T}^{(i)} > 0, i = 1, 2$ , such that

$$\begin{aligned} \mathbb{E} \left[ \sup_{t \in [0, T]} |Y_t - \bar{Y}_t|^2 + \int_0^T |Z_t - \bar{Z}_t|^2 dt \right] &\leq C^{(1)} \left[ \mathbb{E} (h(X_T) - h(\bar{X}_T))^2 + [f]_{\text{Lip}}^2 \mathbb{E} \int_0^T |X_t - \bar{X}_t^n|^2 dt \right] \\ &\leq C_{b, \sigma, f, T}^{(2)} \Delta_n. \end{aligned}$$

Unfortunately, at this stage, the couple  $(\bar{Y}_t, \bar{Z}_t)_{t \in [0, T]}$  is still “intractable” for numerical purposes (it satisfies no Dynamic Programming Principle due to its continuous time nature and there is no possible exact simulation, etc). This is mainly due to  $\bar{Z}$  about which little is known. By contrast with  $Z$  which is *e.g.* closely connected to a PDE. So we will need to go deeper in the time discretization, by discretizing the  $Z$  term itself. Consequently, we need to perform a second time discretization on the Euler scheme based BSDE, only involving discrete instants  $t_k, k = 0, \dots, n$ .

We consider an *explicit inner* scheme recursively defined in a backward way as follows:

$$\tilde{Y}_{t_n} = h(\bar{X}_{t_n}) \tag{25}$$

$$\tilde{Y}_{t_k} = \mathbb{E}(\tilde{Y}_{t_{k+1}} | \mathcal{F}_{t_k}) + \Delta_n f(t_k, \bar{X}_{t_k}, \mathbb{E}(\tilde{Y}_{t_{k+1}} | \mathcal{F}_{t_k}), \tilde{\zeta}_{t_k}) \tag{26}$$

$$\tilde{\zeta}_{t_k} = \frac{1}{\Delta_n} \mathbb{E}(\tilde{Y}_{t_{k+1}} (W_{t_{k+1}} - W_{t_k}) | \mathcal{F}_{t_k}), \quad k = 0, \dots, n-1 \tag{27}$$

It slightly differs from the other explicit schemes analyzed in the literature to our knowledge, since the conditioning is applied directly to  $\tilde{Y}_{t_{k+1}}$  *inside the driver function* rather than outside. Note that in many situations, one uses the following more symmetric alternative formula

$$\tilde{\zeta}_{t_k} = \frac{1}{\Delta_n} \mathbb{E}((\tilde{Y}_{t_{k+1}} - \tilde{Y}_{t_k})(W_{t_{k+1}} - W_{t_k}) | \mathcal{F}_{t_k}),$$

which is clearly quite natural when thinking of a hedging term as a derivative (*e.g.* computed in a binomial tree). It also has virtues in terms of variance reduction (see *e.g.* [7]). One easily shows by a backward induction that, for every  $k \in \{0, \dots, n\}$ ,  $\tilde{Y}_{t_k} \in L^2(\Omega, \mathcal{A}, \mathbb{P})$  since  $\sup_{t \in [0, T]} |\bar{X}_t| \in L^2(\mathbb{P})$ .

Our first aim is to adapt standard comparison theorems to compare the above purely discrete scheme  $(\tilde{Y}_{t_k}, \tilde{Z}_{t_k})$  with the original BSDE to derive error bounds similar to those recalled above between  $(Y, Z)$  and  $(\bar{Y}, \bar{Z})$ . To this end, like for the Euler scheme, we need to extend  $\tilde{Y}$  into a continuous time process by an appropriate interpolation. We proceed as follows: let

$$M_T = \sum_{k=1}^n \tilde{Y}_{t_k} - \mathbb{E}(\tilde{Y}_{t_k} | \mathcal{F}_{t_{k-1}}).$$

This random variable is in  $L^2(\mathbb{P})$ . Hence, by the martingale representation theorem, there exists an  $(\mathcal{F}_t)$ -progressively measurable  $\tilde{Z} \in L^2([0, T] \times \Omega, \mathbb{P} \otimes dt)$  such that

$$M_T = \int_0^T \tilde{Z}_t dW_t.$$

Then  $\tilde{Y}_{t_k} - \mathbb{E}(\tilde{Y}_{t_k} | \mathcal{F}_{t_{k-1}}) = \int_{t_{k-1}}^{t_k} \tilde{Z}_s dW_s$ . In particular

$$\tilde{\zeta}_{t_k} = \frac{1}{\Delta_n} \mathbb{E}(\tilde{Y}_{t_{k+1}}(W_{t_{k+1}} - W_{t_k}) | \mathcal{F}_{t_k}) = \frac{1}{\Delta_n} \mathbb{E}\left(\int_{t_k}^{t_{k+1}} \tilde{Z}_s ds | \mathcal{F}_{t_k}\right), \quad k = 0, \dots, n-1,$$

so that we may define a continuous extension of  $(\tilde{Y}_{t_k})_{0 \leq k \leq n}$  as follows:

$$\tilde{Y}_t = \tilde{Y}_{t_k} - (t - t_k)f(t_k, \bar{X}_{t_k}, \mathbb{E}(\tilde{Y}_{t_{k+1}} | \mathcal{F}_{t_k}), \tilde{\zeta}_{t_k}) + \int_{t_k}^t \tilde{Z}_s dW_s, \quad t \in [t_k, t_{k+1}]. \quad (28)$$

### 3 Error analysis

#### 3.1 The time discretization error

We provide in the theorem below the quadratic error bound for the inside explicit time discretization scheme  $(\tilde{Y}, \tilde{Z})$  defined by (25)-(43) and (28). Claim (b) comes from [70]. The detailed proof of Claim (a) is given in the appendix. Like for most results of this type, the proof of (a) follows the lines of that devised for comparison theorems in [29]. In particular, though slightly more technical at some places, it is close to its counterpart for the standard outer explicit scheme originally established in [3] (in  $L^p$  for reflected BSDEs, but without  $Z$  on the driver) or in [70] (in the quadratic case, see also [33] for an extension error bounds in  $L^p$  or [13] for implicit scheme).

**Theorem 3.1.** (a) *Assume the functions  $f : [0, T] \times \mathbb{R} \times \mathbb{R}^d \times \mathbb{R}^q \rightarrow \mathbb{R}$  is Lipschitz continuous in  $(t, x, y, z)$  and that  $h : \mathbb{R}^d \rightarrow \mathbb{R}^d$  is Lipschitz continuous. Then, there exists a real constant  $C_{b,\sigma,f,T} > 0$  such that, for every  $n \geq 1$ ,*

$$\max_{k=0,\dots,n} \mathbb{E}|Y_{t_k} - \tilde{Y}_{t_k}|^2 + \int_0^T \mathbb{E}|Z_t - \tilde{Z}_t|^2 dt \leq C_{b,\sigma,f,T} \left( \Delta_n + \int_0^T \mathbb{E}|Z_s - Z_{\underline{s}}|^2 ds \right).$$

where  $\underline{s} = t_k$  if  $s \in [t_k, t_{k+1})$ .

(b) *Assume that the functions  $b, \sigma, f$  are continuously differentiable in their spatial variables  $(x$  and  $(x, y, z)$  respectively) with bounded partial derivatives and  $\frac{1}{2}$ -Hölder continuous with respect to  $t$ , that  $d = q$  and  $\sigma\sigma^*$  is uniformly elliptic. Assume  $h$  is Lipschitz continuous. Then, the process  $(Z_t)_{t \in [0, T]}$  admits a càdlàg modification and*

$$\int_0^T \mathbb{E}|Z_s - Z_{\underline{s}}|^2 ds \leq C'_{b,\sigma,f,T} \Delta_n, \quad (29)$$

so that there exists a real constant  $\tilde{C}_{b,\sigma,f,T} > 0$  such that, for every  $n \geq 1$ ,

$$\max_{k=0,\dots,n} \mathbb{E}|Y_{t_k} - \tilde{Y}_{t_k}|^2 + \int_0^T \mathbb{E}|Z_t - \tilde{Z}_t|^2 dt \leq \tilde{C}_{b,\sigma,f,T} \Delta_n. \quad (30)$$

Claim (b) as stated comes from [70] (Theorem 3.1 and Lemma 2.5(i)). It admits several variants (see [13]) or improvements in the literature. Thus, in [37] (Theorem 20) it is obtained under a still lighter assumption on the terminal value  $h$  of fractional type, provided this time  $b$  and  $\sigma$  are bounded,  $\mathcal{C}^{2+\gamma}$ ,  $\gamma \in (0, 1]$ , in space, uniformly  $\frac{1}{2}$ -Hölder in time (and  $\sigma$  uniformly elliptic) and the driver  $f$  is in  $\mathcal{C}^1$  in its spatial variable with bounded partial derivatives and  $f(\cdot, 0, 0, 0) \in L^1([0, T], dt)$ . Then, the resulting bound is  $O(\Delta_n^\gamma)$  for a uniform mesh (but can attain  $O(\Delta_n)$  for a tailored mesh). See

also [26] for a PDE based extension to general forward-backward system *i.e.* when the both forward and backward equations are coupled.

NOTATIONS (CHANGE OF). The previous schemes (25)-(26) involve some quantities and operators which will be the core of what follows and are of discrete time nature. So, in order to simplify the proofs and alleviate the notations, we will identify every time step  $t_k^n$  by  $k$  and we will denote  $\mathbb{E}_k = \mathbb{E}(\cdot | \mathcal{F}_{t_k})$ . Thus, we will switch to

$$\bar{X}_k := \bar{X}_{t_k}, \quad \tilde{Y}_k := \tilde{Y}_{t_k}, \quad f_k(x, y, z) = f(t_k, x, y, z).$$

### 3.2 Error bound for the quantization scheme

In this section, we consider the quantization scheme (7)-(8) and compute the quadratic quantization error  $(\mathbb{E}|\tilde{Y}_{t_k} - \hat{Y}_{t_k}|^2)^{1/2}$  induced by the approximation of  $\tilde{Y}_{t_k}$  by  $\hat{Y}_{t_k}$ , for every  $k = 0, \dots, n$ . This leads to the following theorem which is the first main result of this paper.

**Theorem 3.2.** *Assume that the drift  $b$  and the diffusion coefficient  $\sigma$  of the diffusion  $(X_t)_{t \in [0, T]}$  defined by (21) are Lipschitz continuous, that the driver function  $f$  satisfies  $(\text{Lip}_f)$  (Assumption(23)) and that the function  $h$  is  $[h]_{\text{Lip}}$ -Lipschitz continuous. Assume that  $n \geq n_0$  (in order to provide sharper constants depending on  $n_0 \geq 1$ ).*

(a) For every  $k = 0, \dots, n$ ,

$$\|\tilde{Y}_k - \hat{Y}_k\|_2^2 \leq \sum_{i=k}^n e^{(1+[f]_{\text{Lip}})(t_i - t_k)} K_i(b, \sigma, T, f) \|\bar{X}_i - \hat{X}_i\|_2^2, \quad (31)$$

where  $K_n(b, \sigma, T, f) := [h]_{\text{Lip}}^2$  and, for every  $k = 0, \dots, n-1$ ,

$$K_k(b, \sigma, T, f) := \kappa_1^2 e^{2\kappa_0(T-t_k)} + (1 + \Delta_{n_0}) (C_{1,k}(b, \sigma, T, f) \Delta_{n_0} + C_{2,k}(b, \sigma, T, f)),$$

with  $\kappa_0 = C_{b, \sigma, T} + [f]_{\text{Lip}} \left(1 + \frac{[f]_{\text{Lip}}}{2}\right)$ ,  $\kappa_1 = \frac{[f]_{\text{Lip}}}{\kappa_0} + [h]_{\text{Lip}}$ ,

$$C_{2,k}(b, \sigma, T, f) = q \kappa_1^2 [f]_{\text{Lip}}^2 e^{2\Delta_{n_0} C_{b, \sigma, T} + 2\kappa_0(T-t_{k+1})} \text{ and } C_{1,k}(b, \sigma, T, f) = [f]_{\text{Lip}}^2 + \frac{C_{2,k}(b, \sigma, T, f)}{q}$$

and

$$C_{b, \sigma, T} = [b]_{\text{Lip}} + \frac{1}{2} \left( [\sigma]_{\text{Lip}}^2 + \frac{T}{n_0} [b]_{\text{Lip}}^2 \right). \quad (32)$$

(b) For every  $k = 0, \dots, n$ ,

$$\Delta_n \sum_{k=0}^{n-1} \|\tilde{\zeta}_k - \hat{\zeta}_k\|_2^2 \leq \sum_{k=0}^{n-1} \frac{C_{2,k}(b, \sigma, T, f)}{[f]_{\text{Lip}}^2} \|\bar{X}_k - \hat{X}_k\|_2^2 + \sum_{k=0}^{n-1} \|\tilde{Y}_{k+1} - \hat{Y}_{k+1}\|_2^2.$$

The proof is divided in two main steps: in the first one we establish the propagation of the Lipschitz property through the functions  $\tilde{y}_k$  and  $\tilde{z}_k$  involved in the Markov representation (25)-(26) of  $\tilde{Y}_k$  and  $\tilde{\zeta}_k$ , namely  $\tilde{Y}_k = \tilde{y}_k(\bar{X}_k)$  and  $\tilde{\zeta}_k = \tilde{z}_k(\bar{X}_k)$ , and to control precisely the propagation of their Lipschitz coefficients (an alternative to this phase can be to consider the Lipschitz properties of the flow of the SDE like in [47]). As a second step, we introduce the quantization based scheme which is the counterpart of (25) and (26) for which we establish a backward recursive inequality satisfied by  $\|\tilde{Y}_k - \hat{Y}_k\|_2^2$ .

**Remark 3.1.** (About the relationship between the temporal and the spatial partitions) Owing to the non-asymptotic bound for the quantization (see Theorem 4.1 further), we deduce from the upper bound of Equation (31) that there exists some constants  $c_i, i = 1, \dots, n$  (only depending on the coefficients  $b$  and  $\sigma$  of the diffusion  $X$ ) such that for every  $k = 1, \dots, n$ ,

$$\|\tilde{Y}_k - \hat{Y}_k\|_2^2 \leq \sum_{i=k}^n c_i N_i^{-2/d}. \quad (33)$$

So, a natural question is to determine how to dispatch optimally the sizes  $N_1, \dots, N_n$  (for a fixed mesh of length  $n$ , given that  $X_0$  is deterministic and, as such, perfectly quantized with  $N_0 = 1$ ) of the quantization grids under the total “budget” constraint  $N_1 + \dots + N_n \leq N$  of elementary quantizers (with  $N \geq n$  and  $N_k \geq 1$ , for every  $k = 1, \dots, n$ ). This amounts (at least at time  $k = 0$ ) to solving the constrained minimization problem

$$\min_{N_1 + \dots + N_n \leq N} \sum_{i=1}^n c_i N_i^{-2/d},$$

whose solution reads  $N_i = \left\lfloor \frac{c_i^{\frac{d}{d+2}}}{\sum_{k=1}^n c_k^{\frac{d}{d+2}}} N \right\rfloor \vee 1, i = 1, \dots, n$ . Coming back to (33), and using the Hölder inequality (to get the second inequality below) yields

$$\|\tilde{Y}_0 - \hat{Y}_0\|_2 \leq N^{-1/d} \left( \sum_{i=1}^n c_i^{\frac{d}{d+2}} \right)^{1/2+1/d} \leq \left( \frac{n}{N} \right)^{1/d} \left( \sum_{i=1}^n c_i \right)^{\frac{1}{2}} \leq \left[ \max_{i=1, \dots, n} c_i^{\frac{1}{2}} \right] \frac{n^{1/2+1/d}}{N^{\frac{1}{d}}}. \quad (34)$$

Notice that for the standard (“non-improved”) error bounds (see the introduction), the same optimal allocation procedure would yield (starting from  $\|\tilde{Y}_0 - \hat{Y}_0\|_2 \leq \sum_{i=0}^n c'_i N_i^{-1/d}$ ),

$$\|\tilde{Y}_0 - \hat{Y}_0\|_2 \leq \left( \frac{n}{N} \right)^{1/d} \sum_{i=1}^n c'_i \leq \left[ \max_{i=1, \dots, n} c'_i \right] \frac{n^{1+1/d}}{N^{\frac{1}{d}}}$$

which emphasizes the improvement of the error bound as concerns the dependence in the time mesh size  $n$ .

### 3.2.1 First step toward the proof of Theorem 3.2: Lipschitz operators

As a first step we introduce several operators which appear naturally when representing  $Y_k$ . We will show that these operators propagate Lipschitz continuity. It is a classical step when establishing *a priori error bounds* going back to [4, 3], see also more recently [34] (Proposition 3.4). However we do not skip it since it emphasizes the technical specificities induced by our choice of an inner explicit scheme.

To be more precise, we set for every  $k \in \{0, \dots, n-1\}$  and every Borel function  $g : \mathbb{R}^d \rightarrow \mathbb{R}$  with polynomial growth

$$\mathcal{E}_k(x, u) = x + \Delta_n b(t_k, x) + \sqrt{\Delta_n} \sigma(t_k, x) u, \quad x \in \mathbb{R}^d, \quad u \in \mathbb{R}^q \quad (35)$$

$$P_{k+1}g(x) = \mathbb{E}g(\mathcal{E}_k(x, \varepsilon)) \quad \text{where } \varepsilon \sim \mathcal{N}(0; I_q) \quad (36)$$

$$Q_{k+1}g(x) = \frac{1}{\sqrt{\Delta_n}} \mathbb{E} \left( g(\mathcal{E}_k(x, \varepsilon)) \varepsilon \right). \quad (37)$$

One immediately checks that for every  $k \in \{0, \dots, n-1\}$ ,

$$\mathbb{E}_k g(\bar{X}_{k+1}) = P_{k+1}g(\bar{X}_k) \quad \text{and} \quad \mathbb{E}_k (g(\bar{X}_{k+1})(W_{t_{k+1}}^n - W_{t_k}^n)) = \Delta_n Q_{k+1}g(\bar{X}_k).$$

Note that the process  $(\bar{X}_k)_{0 \leq k \leq n}$  is an  $(\mathcal{F}_k)_{0 \leq k \leq n}$ -Markov chain with transitions  $P_k(x, dy) = \mathbb{P}(\bar{X}_k \in dy \mid \bar{X}_{k-1} = x)$ ,  $k = 1, \dots, n$ . Moreover, it shares the property to propagate the Lipschitz property as established in the Lemma below.

**Lemma 3.3.** *For every  $k = 0, \dots, n-1$ , the transition operator  $P_{k+1}$  is Lipschitz in the sense that its Lipschitz coefficient defined by  $[P_{k+1}]_{\text{Lip}} := \sup_{f, [f]_{\text{Lip}} \leq 1} [P_{k+1}f]_{\text{Lip}}$  is finite. More precisely, it satisfies:*

$$[P_{k+1}]_{\text{Lip}} \leq e^{\Delta_n C_{b, \sigma, T}} \quad (38)$$

where  $C_{b, \sigma, T}$  is given by (32) (see also the comment that follows).

**Proof.** We have for every  $x, x' \in \mathbb{R}^d$ , and for every Lipschitz continuous function  $g$

$$\begin{aligned} |P_{k+1}g(x) - P_{k+1}g(x')|^2 &\leq \mathbb{E} |g(\mathcal{E}_k(x, \varepsilon)) - g(\mathcal{E}_k(x', \varepsilon))|^2 \\ &\leq [g]_{\text{Lip}}^2 \mathbb{E} |\mathcal{E}_k(x, \varepsilon) - \mathcal{E}_k(x', \varepsilon)|^2 \end{aligned}$$

and elementary computations, already carried out in [4], show that

$$\begin{aligned} \mathbb{E} |\mathcal{E}_k(x, \varepsilon) - \mathcal{E}_k(x', \varepsilon)|^2 &\leq (1 + \Delta_n (2[b(t_k^n, \cdot)]_{\text{Lip}} + [\sigma(t_k^n, \cdot)]_{\text{Lip}}^2) + \Delta_n^2 [b(t_k^n, \cdot)]_{\text{Lip}}^2) |x - x'|^2 \\ &\leq (1 + \Delta_n (2[b]_{\text{Lip}} + [\sigma]_{\text{Lip}}^2) + \Delta_n^2 [b]_{\text{Lip}}^2) |x - x'|^2 \\ &\leq (1 + \Delta_n C_{b, \sigma, T})^2 |x - x'|^2 \\ &\leq e^{2\Delta_n C_{b, \sigma, T}} |x - x'|^2 \end{aligned}$$

where  $C_{b, \sigma, T}$  can be e.g. taken equal to  $[b]_{\text{Lip}} + \frac{1}{2}([\sigma]_{\text{Lip}}^2 + \frac{T}{n_0}[b]_{\text{Lip}}^2)$  provided  $n \geq n_0$ . It follows that  $P_{k+1}$  is Lipschitz with Lipschitz constant  $[P_{k+1}]_{\text{Lip}} \leq e^{\Delta_n C_{b, \sigma, T}}$ .  $\square$

**Proposition 3.4.** (see [4]) (a) *The functions  $y_k$ ,  $k = 0, \dots, n$ , defined by the backward induction*

$$y_n = h, \quad y_k = P_{k+1}y_{k+1} + \Delta_n f_k(\cdot, P_{k+1}y_{k+1}, Q_{k+1}y_{k+1}), \quad k = 0, \dots, n-1,$$

satisfies  $\tilde{Y}_k = y_k(\bar{X}_k)$  for every  $k \in \{0, \dots, n\}$ . Moreover,  $\tilde{\zeta}_k = \frac{z_k(\bar{X}_k)}{\sqrt{\Delta_n}}$  where, for every  $k \in \{0, \dots, n-1\}$ ,

$$z_k(x) = \mathbb{E}(y_{k+1}(\mathcal{E}_k(x, \varepsilon)) \mid \varepsilon), \quad k = 0, \dots, n-1.$$

(b) *Furthermore, assume that the function  $h$  is  $[h]_{\text{Lip}}$ -Lipschitz continuous and that the function  $f(t, x, y, z)$  is  $[f]_{\text{Lip}}$ -Lipschitz continuous in  $(x, y, z)$ , uniformly in  $t \in [0, T]$ . Then, for every  $k \in \{0, \dots, n\}$ , the function  $y_k$  is  $[y_k]_{\text{Lip}}$ -Lipschitz continuous and there exists real constants  $\kappa_0 = C_{b, \sigma, T} + [f]_{\text{Lip}}(1 + \frac{1}{2}[f]_{\text{Lip}})$ , and  $\kappa_1 = \frac{[f]_{\text{Lip}}}{\kappa_0} + [h]_{\text{Lip}}$  (where  $C_{b, \sigma, T}$  is given by (32)), such that  $[y_k]_{\text{Lip}} = [h]_{\text{Lip}}$  and*

$$[y_k]_{\text{Lip}} \leq \frac{\Delta_n}{e^{\kappa_0 \Delta_n} - 1} (e^{\kappa_0(T-t_k^n)} - 1) [f]_{\text{Lip}} + e^{\kappa_0(T-t_k^n)} [h]_{\text{Lip}} e^{\kappa_0(T-t_k^n)} \kappa_1, \quad k = 0, \dots, n-1. \quad (39)$$

In particular,  $\sup_{n \geq 1} \max_{k=0, \dots, n} [y_k]_{\text{Lip}} \leq e^{\kappa_0 T} \kappa_1 < +\infty$ . Moreover the functions  $z_k$  are Lipschitz too and

$$[z_k]_{\text{Lip}} \leq \sqrt{q} e^{\Delta_n C_{b, \sigma, T}} \kappa_1 e^{\kappa_0(T-t_{k+1}^n)}, \quad k = 0, \dots, n-1. \quad (40)$$

*Proof.* (a) We proceed by a backward induction using (25) and (26), relying on the fact that  $(\bar{X}_k)_{k=0, \dots, n}$  is a Markov chain which propagates Lipschitz continuity. In fact,  $\tilde{Y}_n = h(\bar{X}_n) := y_n(\bar{X}_n)$ . Assuming that  $\tilde{Y}_{k+1} = y_{k+1}(\bar{X}_{k+1})$  and using Equation (26) and the Markov property, we get

$$\begin{aligned} \tilde{Y}_k &= \mathbb{E}(y_{k+1}(\bar{X}_{k+1}) \mid \bar{X}_k) + \Delta_n f_k(\bar{X}_k, \mathbb{E}(y_{k+1}(\bar{X}_{k+1}) \mid \bar{X}_k), \zeta_{t_k^n}) \\ &= P_{k+1}y_{k+1}(\bar{X}_k) + \Delta_n f_k(\bar{X}_k, P_{k+1}y_{k+1}(\bar{X}_k), Q_{k+1}y_{k+1}(\bar{X}_k)) = y_k(\bar{X}_k). \end{aligned}$$

One shows likewise that  $\zeta_k = Q_{k+1}(y_{k+1})(\bar{X}_k) = \frac{z_k(\bar{X}_k)}{\sqrt{\Delta_n}}$ ,  $k = 0, \dots, n-1$ .

(b) We also show this claim by a backward induction. In fact,  $\tilde{Y}_n = h(\bar{X}_n) := y_n(\bar{X}_n)$  and  $h$  is  $[h]_{\text{Lip}}$ -Lipschitz. Suppose that  $y_{k+1}$  is  $[y_{k+1}]_{\text{Lip}}$ -Lipschitz continuous. Then, for every  $x, x' \in \mathbb{R}^d$ , we can write

$$\begin{aligned} y_k(x) - y_k(x') &= \mathbb{E}(y_{k+1}(\mathcal{E}_k(x, \varepsilon)) - y_{k+1}(\mathcal{E}_k(x', \varepsilon))) \\ &\quad + \Delta_n \left[ A_{x,x'}(x - x') + B_{x,x'} \mathbb{E}(y_{k+1}(\mathcal{E}_k(x, \varepsilon)) - y_{k+1}(\mathcal{E}_k(x', \varepsilon))) \right. \\ &\quad \left. + C_{x,x'} \mathbb{E} \left( (y_{k+1}(\mathcal{E}_k(x, \varepsilon)) - y_{k+1}(\mathcal{E}_k(x', \varepsilon))) \frac{\varepsilon}{\sqrt{\Delta_n}} \right) \right] \end{aligned}$$

where  $\varepsilon \sim \mathcal{N}(0, I_q)$  and

$$\begin{aligned} A_{x,x'} &= \frac{f_k(x, P_{k+1}y_{k+1}(x), Q_{k+1}y_{k+1}(x)) - f_k(x', P_{k+1}y_{k+1}(x), Q_{k+1}y_{k+1}(x))}{x - x'} \mathbf{1}_{\{x \neq x'\}}, \\ B_{x,x'} &= \frac{f_k(x', P_{k+1}y_{k+1}(x), Q_{k+1}y_{k+1}(x)) - f_k(x', P_{k+1}y_{k+1}(x'), Q_{k+1}y_{k+1}(x))}{P_{k+1}y_{k+1}(x) - P_{k+1}y_{k+1}(x')} \mathbf{1}_{P_{x,x'}}, \\ C_{x,x'} &= \frac{f_k(x', P_{k+1}y_{k+1}(x'), Q_{k+1}y_{k+1}(x)) - f_k(x', P_{k+1}y_{k+1}(x'), Q_{k+1}y_{k+1}(x'))}{Q_{k+1}y_{k+1}(x) - Q_{k+1}y_{k+1}(x')} \mathbf{1}_{Q_{x,x'}}, \end{aligned}$$

with  $P_{x,x'} = \{P_{k+1}y_{k+1}(x) \neq P_{k+1}y_{k+1}(x')\}$  and  $Q_{x,x'} = \{Q_{k+1}y_{k+1}(x) \neq Q_{k+1}y_{k+1}(x')\}$ . The function  $f_k$  being Lipschitz continuous, one clearly has  $|A_{x,x'}|, |B_{x,x'}|, |C_{x,x'}| \leq [f]_{\text{Lip}}$ . Now, taking advantage of the linearity of expectation, we get

$$y_k(x) - y_k(x') = \mathbb{E} \left[ (y_{k+1}(\mathcal{E}(x, \varepsilon)) - y_{k+1}(\mathcal{E}(x', \varepsilon))) \left( 1 + \Delta_n \left( B_{x,x'} + C_{x,x'} \frac{\varepsilon}{\sqrt{\Delta_n}} \right) \right) \right] + A_{x,x'}(x - x').$$

Then Schwarz's Inequality yields

$$|y_k(x) - y_k(x')| \leq \|y_{k+1}(\mathcal{E}(x, \varepsilon)) - y_{k+1}(\mathcal{E}(x', \varepsilon))\|_2 \left\| 1 + \Delta_n \left( B_{x,x'} + C_{x,x'} \frac{\varepsilon}{\sqrt{\Delta_n}} \right) \right\|_2 + \Delta_n [f]_{\text{Lip}} |x - x'|.$$

Now,

$$\|y_{k+1}(\mathcal{E}_k(x, \varepsilon)) - y_{k+1}(\mathcal{E}_k(x', \varepsilon))\|_2 \leq [y_{k+1}]_{\text{Lip}} \|\mathcal{E}_k(x, \varepsilon) - \mathcal{E}_k(x', \varepsilon)\|_2 \leq [y_{k+1}]_{\text{Lip}} e^{\Delta_n C_{b,\sigma,T}} |x - x'|$$

by Lemma 3.3. On the other hand, using that  $|B_{x,x'}|, |C_{x,x'}| \leq [f]_{\text{Lip}}$  and  $\mathbb{E}(\varepsilon) = 0$ ,

$$\begin{aligned} \left\| 1 + \Delta_n \left( B_{x,x'} + C_{x,x'} \frac{\varepsilon}{\sqrt{\Delta_n}} \right) \right\|_2^2 &= (1 + \Delta_n B_{x,x'})^2 + \Delta_n C_{x,x'}^2 \\ &\leq 1 + \Delta_n (2[f]_{\text{Lip}} + [f]_{\text{Lip}}^2) + \Delta_n^2 [f]_{\text{Lip}}^2 \\ &\leq e^{2\Delta_n [f]_{\text{Lip}} (1 + \frac{1}{2} [f]_{\text{Lip}})}. \end{aligned}$$

Finally, owing to the definition of  $\kappa_0$ , we get

$$|y_k(x) - y_k(x')| \leq (e^{\Delta_n \kappa_0} [y_{k+1}]_{\text{Lip}} + \Delta_n [f]_{\text{Lip}}) |x - x'|$$

*i.e.*  $y_k$  is Lipschitz continuous with Lipschitz coefficient  $[y_k]_{\text{Lip}}$  satisfying

$$[y_k]_{\text{Lip}} \leq e^{\kappa_0 \Delta_n} [y_{k+1}]_{\text{Lip}} + \Delta_n [f]_{\text{Lip}}.$$

The conclusion follows by induction. As for the functions  $z_k$ , we get for every  $k = 0, \dots, n-1$ ,

$$z_k(x) - z_k(x') = \mathbb{E} \left( (y_{k+1}(\mathcal{E}_k(x, \varepsilon)) - y_{k+1}(\mathcal{E}_k(x', \varepsilon))) \varepsilon \right).$$

Hence, using that  $\varepsilon \sim \mathcal{N}(0; I_q)$  combined with Schwartz's Inequality, we get

$$\begin{aligned}
|z_k(x) - z_k(x')| &\leq [y_{k+1}]_{\text{Lip}} \mathbb{E} \left| \left( (x - x') + \Delta_n(b(x) - b(x')) + \sqrt{\Delta_n}(\sigma(x) - \sigma(x'))\varepsilon \right) \varepsilon \right| \\
&\leq [y_{k+1}]_{\text{Lip}} \left\| \left( (x - x') + \Delta_n(b(x) - b(x')) + \sqrt{\Delta_n}(\sigma(x) - \sigma(x'))\varepsilon \right) \varepsilon \right\|_2 \\
&\leq [y_{k+1}]_{\text{Lip}} e^{\Delta_n C_{b,\sigma,T}} \sqrt{q} |x - x'| \\
&\leq \sqrt{q} e^{\Delta_n C_{b,\sigma,T}} \kappa_1 e^{\kappa_0(T-t_{k+1}^n)} |x - x'|. \quad \square
\end{aligned}$$

### 3.2.2 Second step of the proof of Theorem 3.2

Let  $(\hat{X}_k)_{k=0,\dots,n}$  be the quantization of the Markov chain  $\bar{X}$ , where every quantizer  $\hat{X}_k$  is of size  $N_k$ , for every  $k \in \{0, \dots, n\}$ . Recall that the discrete time quantized BSDE process  $(\hat{Y}_k)_{k=0,\dots,n}$  is defined by the following recursive algorithm:

$$\begin{aligned}
\hat{Y}_n &= h(\hat{X}_n) \\
\hat{Y}_k &= \hat{\mathbb{E}}_k(\hat{Y}_{k+1}) + \Delta_n f_k(\hat{X}_k, \hat{\mathbb{E}}_k(\hat{Y}_{k+1}), \hat{\zeta}_k) \\
\text{with} \quad \hat{\zeta}_k &= \frac{1}{\Delta_n} \hat{\mathbb{E}}_k(\hat{Y}_{k+1} \Delta W_{t_{k+1}}), k = 0, \dots, n-1,
\end{aligned}$$

where  $\hat{\mathbb{E}}_k = \mathbb{E}(\cdot | \hat{X}_k)$ . Owing to the previous section, we are now in position to prove Theorem 3.2.

**Proof of Theorem 3.2.** (a) Using the fact that, for every  $k \in \{0, \dots, n\}$ ,  $\sigma(\hat{X}_k) \subset \sigma(\bar{X}_k)$ , we have

$$\tilde{Y}_k - \hat{Y}_k = \tilde{Y}_k - \hat{\mathbb{E}}_k(\tilde{Y}_k) + \hat{\mathbb{E}}_k(\tilde{Y}_k - \hat{Y}_k) \quad (41)$$

where  $\tilde{Y}_k - \hat{\mathbb{E}}_k(\tilde{Y}_k)$  and  $\hat{\mathbb{E}}_k(\tilde{Y}_k - \hat{Y}_k)$  are square integrable and orthogonal in  $L^2(\sigma(\bar{X}_k))$ . As a consequence, using the Pythagoras theorem for conditional expectation yields

$$\|\tilde{Y}_k - \hat{Y}_k\|_2^2 = \|\tilde{Y}_k - \hat{\mathbb{E}}_k(\tilde{Y}_k)\|_2^2 + \|\hat{\mathbb{E}}_k(\tilde{Y}_k - \hat{Y}_k)\|_2^2.$$

On the other hand, it follows from the definition of the conditional expectation  $\hat{\mathbb{E}}_k(\cdot)$  as the best approximation in  $L^2$  among square integrable  $\sigma(\hat{X}_k)$ -measurable random vectors that

$$\|\tilde{Y}_k - \hat{\mathbb{E}}_k(\tilde{Y}_k)\|_2^2 = \|y_k(\bar{X}_k) - \hat{\mathbb{E}}_k(y_k(\bar{X}_k))\|_2^2 \leq \|y_k(\bar{X}_k) - y_k(\hat{X}_k)\|_2^2 \leq [y_k]_{\text{Lip}}^2 \|\bar{X}_k - \hat{X}_k\|_2^2.$$

Let us consider now the last term of the equality (41). We have,

$$\begin{aligned}
\hat{\mathbb{E}}_k(\tilde{Y}_k - \hat{Y}_k) &= \hat{\mathbb{E}}_k[\tilde{Y}_{k+1} - \hat{Y}_{k+1} + \Delta_n (f_k(\bar{X}_k, \mathbb{E}_k(\tilde{Y}_{k+1}), \tilde{\zeta}_k) - f_k(\hat{X}_k, \hat{\mathbb{E}}_k(\hat{Y}_{k+1}), \hat{\zeta}_k))] \\
&= \hat{\mathbb{E}}_k[\tilde{Y}_{k+1} - \hat{Y}_{k+1} + \Delta_n (f_k(\bar{X}_k, \mathbb{E}_k(\tilde{Y}_{k+1}), \tilde{\zeta}_k) - f_k(\hat{X}_k, \hat{\mathbb{E}}_k(\tilde{Y}_{k+1}), \hat{\mathbb{E}}_k(\tilde{\zeta}_k))] \\
&\quad + \Delta_n (f_k(\hat{X}_k, \hat{\mathbb{E}}_k(\tilde{Y}_{k+1}), \hat{\mathbb{E}}_k(\tilde{\zeta}_k)) - f_k(\hat{X}_k, \hat{\mathbb{E}}_k(\hat{Y}_{k+1}), \hat{\zeta}_k)] \\
&= \hat{\mathbb{E}}_k[\tilde{Y}_{k+1} - \hat{Y}_{k+1} + \Delta_n \hat{B}_k \hat{\mathbb{E}}_k(\tilde{Y}_{k+1} - \hat{Y}_{k+1}) + \Delta_n \hat{C}_k \hat{\mathbb{E}}_k(\tilde{\zeta}_k - \hat{\zeta}_k)] \\
&\quad + \Delta_n \hat{\mathbb{E}}_k (f_k(\bar{X}_k, \mathbb{E}_k(\tilde{Y}_{k+1}), \tilde{\zeta}_k) - f_k(\hat{X}_k, \hat{\mathbb{E}}_k(\tilde{Y}_{k+1}), \hat{\mathbb{E}}_k(\tilde{\zeta}_k)))
\end{aligned}$$

$$\text{where} \quad \hat{B}_k := \frac{f_k(\hat{X}_k, \hat{\mathbb{E}}_k(\tilde{Y}_{k+1}), \hat{\mathbb{E}}_k(\tilde{\zeta}_k)) - f_k(\hat{X}_k, \hat{\mathbb{E}}_k(\hat{Y}_{k+1}), \hat{\mathbb{E}}_k(\tilde{\zeta}_k))}{\hat{\mathbb{E}}_k(\tilde{Y}_{k+1}) - \hat{\mathbb{E}}_k(\hat{Y}_{k+1})} \mathbf{1}_{\{\hat{\mathbb{E}}_k(\tilde{Y}_{k+1}) \neq \hat{\mathbb{E}}_k(\hat{Y}_{k+1})\}}$$

$$\text{and} \quad \hat{C}_k := \frac{f_k(\hat{X}_k, \hat{\mathbb{E}}_k(\hat{Y}_{k+1}), \hat{\mathbb{E}}_k(\tilde{\zeta}_k)) - f_k(\hat{X}_k, \hat{\mathbb{E}}_k(\hat{Y}_{k+1}), \hat{\zeta}_k)}{\hat{\mathbb{E}}_k(\tilde{\zeta}_k) - \hat{\mathbb{E}}_k(\hat{\zeta}_k)} \mathbf{1}_{\{\hat{\mathbb{E}}_k(\tilde{\zeta}_k) \neq \hat{\mathbb{E}}_k(\hat{\zeta}_k)\}}.$$

As

$$\hat{\mathbb{E}}_k(\tilde{\zeta}_k) - \hat{\mathbb{E}}_k(\hat{\zeta}_k) = \frac{1}{\Delta_n} \hat{\mathbb{E}}_k((\tilde{Y}_{k+1} - \hat{Y}_{k+1})\Delta W_{t_{k+1}}),$$

we deduce that

$$\begin{aligned} \hat{\mathbb{E}}_k(\tilde{Y}_k - \hat{Y}_k) &= \hat{\mathbb{E}}_k[(\tilde{Y}_{k+1} - \hat{Y}_{k+1})(1 + \Delta_n \hat{B}_k + \hat{C}_k \Delta W_{t_{k+1}})] \\ &\quad + \Delta_n (f_k(\bar{X}_k, \mathbb{E}_k(\tilde{Y}_{k+1}), \tilde{\zeta}_k) - f_k(\hat{X}_k, \hat{\mathbb{E}}_k(\tilde{Y}_{k+1}), \hat{\mathbb{E}}_k(\tilde{\zeta}_k))). \end{aligned} \quad (42)$$

So, it remains to control each term of the above equality. Considering its last term, it follows from the Lipschitz assumption on the driver  $f_k$  that

$$\begin{aligned} \|f_k(\bar{X}_k, \mathbb{E}_k(\tilde{Y}_{k+1}), \tilde{\zeta}_k) - f_k(\hat{X}_k, \hat{\mathbb{E}}_k(\tilde{Y}_{k+1}), \hat{\mathbb{E}}_k(\tilde{\zeta}_k))\|_2^2 &\leq [f]_{\text{Lip}}^2 (\|\bar{X}_k - \hat{X}_k\|_2^2 \\ &\quad + \|\mathbb{E}_k(\tilde{Y}_{k+1}) - \hat{\mathbb{E}}_k(\mathbb{E}_k(\tilde{Y}_{k+1}))\|_2^2 \\ &\quad + \|\tilde{\zeta}_k - \hat{\mathbb{E}}_k(\tilde{\zeta}_k)\|_2^2). \end{aligned}$$

First, from the very definition of conditional expectation operator  $\hat{\mathbb{E}}_k$  as the best quadratic approximation by a Borel function of  $\hat{X}_k$  (or, equivalently, the orthogonal projection on  $L^2(\sigma(\hat{X}_k), \mathbb{P})$ ), we derive that

$$\begin{aligned} \|\mathbb{E}_k(\tilde{Y}_{k+1}) - \hat{\mathbb{E}}_k(\mathbb{E}_k(\tilde{Y}_{k+1}))\|_2^2 &\leq \|P_{k+1}y_{k+1}(\bar{X}_k) - P_{k+1}y_{k+1}(\hat{X}_k)\|_2^2 \\ &\leq [P_{k+1}]_{\text{Lip}}^2 [y_{k+1}]_{\text{Lip}}^2 \|\bar{X}_k - \hat{X}_k\|_2^2. \end{aligned}$$

On the other hand, starting from  $\tilde{\zeta}_k = \frac{1}{\Delta_n} \mathbb{E}_k(\tilde{Y}_{k+1} \Delta W_{t_{k+1}}) = \frac{z_k(\bar{X}_k)}{\sqrt{\Delta_n}}$ ,  $k = 0, \dots, n-1$  (see Proposition 3.4(a)), we get, using again the above characterization of the conditional expectation operator  $\hat{\mathbb{E}}_k$ ,

$$\begin{aligned} \|\tilde{\zeta}_k - \hat{\mathbb{E}}_k \tilde{\zeta}_k\|_2^2 &= \frac{1}{\Delta_n} \|z_k(\bar{X}_k) - \hat{\mathbb{E}}_k(z_k(\bar{X}_k))\|_2^2 \\ &\leq \frac{1}{\Delta_n} \|z_k(\bar{X}_k) - z_k(\hat{X}_k)\|_2^2 \leq \frac{1}{\Delta_n} [z_k]_{\text{Lip}}^2 \|\bar{X}_k - \hat{X}_k\|_2^2. \end{aligned} \quad (43)$$

Finally, using the upper-bound for  $[z_k]_{\text{Lip}}$  established in Proposition 3.4(b), we deduce that

$$\begin{aligned} \|f_k(\bar{X}_k, \mathbb{E}_k(\tilde{Y}_{k+1}), \tilde{\zeta}_k) - f_k(\hat{X}_k, \hat{\mathbb{E}}_k(\tilde{Y}_{k+1}), \hat{\mathbb{E}}_k(\tilde{\zeta}_k))\|_2 \\ \leq \left( C_{1,k}(b, \sigma, T, f) + \frac{C_{2,k}(b, \sigma, T, f)}{\Delta_n} \right)^{\frac{1}{2}} \|\bar{X}_k - \hat{X}_k\|_2 \end{aligned} \quad (44)$$

since, owing to (39) and (40), we have

$$[f]_{\text{Lip}}^2 (1 + [P_{k+1}]_{\text{Lip}}^2 [y_{k+1}]_{\text{Lip}}^2) \leq C_{1,k}(b, \sigma, T, f) \quad \text{and} \quad [f]_{\text{Lip}}^2 [z_k]_{\text{Lip}}^2 \leq C_{2,k}(b, \sigma, T, f),$$

$k = 0, \dots, n-1$ , where

$$C_{2,k}(b, \sigma, T, f) = q\kappa_1^2 [f]_{\text{Lip}}^2 e^{2\Delta_n C_{b,\sigma,T} + 2\kappa_0(T-t_{k+1})} \quad \text{and} \quad C_{1,k}(b, \sigma, T, f) = [f]_{\text{Lip}}^2 + \frac{C_{2,k}(b, \sigma, T, f)}{q}. \quad (45)$$

To complete the proof, it suffices to control the remaining terms in Equation (42). Using the (conditional) Schwarz inequality yields

$$\left| \hat{\mathbb{E}}_k[(\tilde{Y}_{k+1} - \hat{Y}_{k+1})(1 - \Delta_n \hat{B}_k - \hat{C}_k \Delta W_{t_{k+1}})] \right| \leq [\hat{\mathbb{E}}_k(\tilde{Y}_{k+1} - \hat{Y}_{k+1})^2]^{\frac{1}{2}} [\hat{\mathbb{E}}_k(1 - \Delta_n \hat{B}_k - \hat{C}_k \Delta W_{t_{k+1}})^2]^{\frac{1}{2}}.$$



Furthermore, using the fact that  $\hat{\mathbb{E}}_k(\Delta W_{t_{k+1}}) = \hat{\mathbb{E}}_k(\mathbb{E}_k(\Delta W_{t_{k+1}})) = 0$  and owing to the measurability of  $\hat{B}_k$  and  $\hat{C}_k$  with respect to  $\sigma(\hat{X}_k)$ , we get

$$\begin{aligned}\hat{\mathbb{E}}_k[(1 - \Delta_n \hat{B}_k - \hat{C}_k \Delta W_{t_{k+1}})^2] &= (1 - \Delta_n \hat{B}_k)^2 + \hat{C}_k^2 \hat{\mathbb{E}}_k((\Delta W_{t_{k+1}})^2) \\ &= (1 - \Delta_n \hat{B}_k)^2 + \hat{C}_k^2 \Delta_n \\ &\leq (1 + \Delta_n [f]_{\text{Lip}})^2 + (\Delta_n [f]_{\text{Lip}})^2 \leq e^{2\Delta_n [f]_{\text{Lip}}}.\end{aligned}$$

Then, using the conditional Schwarz inequality and again the contraction property of conditional expectation, we get

$$\left\| \hat{\mathbb{E}}_k[(\tilde{Y}_{k+1} - \hat{Y}_{k+1})(1 - \Delta_n \hat{B}_k - \hat{C}_k \Delta W_{t_{k+1}})] \right\|_2 \leq e^{\Delta_n [f]_{\text{Lip}}} \|\tilde{Y}_{k+1} - \hat{Y}_{k+1}\|_2. \quad (46)$$

Using Schwarz's Inequality for the  $L^2$ -norm, we derive from (41), (42), (44) and (46) that

$$\begin{aligned}\|\tilde{Y}_k - \hat{Y}_k\|_2^2 &= \|\tilde{Y}_k - \hat{\mathbb{E}}_k(\tilde{Y}_k)\|_2^2 + \|\hat{\mathbb{E}}_k(\tilde{Y}_k - \hat{Y}_k)\|_2^2 \\ &\leq [y_k]_{\text{Lip}}^2 \|\bar{X}_k - \hat{X}_k\|_2^2 + \left( e^{\Delta_n [f]_{\text{Lip}}} \|\tilde{Y}_{k+1} - \hat{Y}_{k+1}\|_2 + \Delta_n \|f_k(\bar{X}_k, \mathbb{E}_k(\tilde{Y}_{k+1}), \tilde{\zeta}_k) \right. \\ &\quad \left. - f_k(\hat{X}_k, \hat{\mathbb{E}}_k(\tilde{Y}_{k+1}), \hat{\mathbb{E}}_k(\tilde{\zeta}_k)) \right)_2^2 \\ &\leq [y_k]_{\text{Lip}}^2 \|\bar{X}_k - \hat{X}_k\|_2^2 + \left( e^{\Delta_n [f]_{\text{Lip}}} \|\tilde{Y}_{k+1} - \hat{Y}_{k+1}\|_2 \right. \\ &\quad \left. + \Delta_n \left( C_{1,k}(b, \sigma, T, f) + \frac{C_{2,k}(b, \sigma, T, f)}{\Delta_n} \right)^{\frac{1}{2}} \|\bar{X}_k - \hat{X}_k\|_2 \right)^2.\end{aligned} \quad (47)$$

We first deal with the second term on the right hand side of the above inequality. Using the classical inequality

$$(a + b)^2 \leq a^2(1 + \Delta_n) + b^2(1 + \Delta_n^{-1}),$$

we derive that

$$\begin{aligned}&\left( e^{\Delta_n [f]_{\text{Lip}}} \|\tilde{Y}_{k+1} - \hat{Y}_{k+1}\|_2 + \Delta_n \left( C_{1,k}(b, \sigma, T, f) + \frac{C_{2,k}(b, \sigma, T, f)}{\Delta_n} \right)^{\frac{1}{2}} \|\bar{X}_k - \hat{X}_k\|_2 \right)^2 \\ &\leq e^{\Delta_n [f]_{\text{Lip}}} (1 + \Delta_n) \|\tilde{Y}_{k+1} - \hat{Y}_{k+1}\|_2^2 \\ &\quad + \left( 1 + \frac{1}{\Delta_n} \right) \Delta_n^2 \left( C_{1,k}(b, \sigma, T, f) + \frac{C_{2,k}(b, \sigma, T, f)}{\Delta_n} \right) \|\bar{X}_k - \hat{X}_k\|_2^2 \\ &\leq e^{\Delta_n (1 + [f]_{\text{Lip}})} \|\tilde{Y}_{k+1} - \hat{Y}_{k+1}\|_2^2 + \left( 1 + \Delta_n \right) \left( C_{1,k}(b, \sigma, T, f) \Delta_n + C_{2,k}(b, \sigma, T, f) \right) \|\bar{X}_k - \hat{X}_k\|_2^2.\end{aligned}$$

Hence (using that  $\Delta_n \leq T/n_0$ , if  $n \geq n_0$ ), we obtain, for every  $k \in \{0, \dots, n-1\}$ ,

$$\|\tilde{Y}_k - \hat{Y}_k\|_2^2 \leq e^{\Delta_n (1 + [f]_{\text{Lip}})} \|\tilde{Y}_{k+1} - \hat{Y}_{k+1}\|_2^2 + \tilde{K}_k(b, \sigma, T, f) \|\bar{X}_k - \hat{X}_k\|_2^2 \quad (48)$$

where

$$\begin{aligned}\tilde{K}_k(b, \sigma, T, f) &:= [y_{k+1}]_{\text{Lip}}^2 + \left( 1 + \frac{T}{n} \right) \left( C_{1,k}(b, \sigma, T, f) \frac{T}{n} + C_{2,k}(b, \sigma, T, f) \right), \quad k = 0, \dots, n-1, \\ &\leq K_k(b, \sigma, T, f)\end{aligned}$$

It follows that, for every  $k \in \{0, \dots, n-1\}$ ,

$$e^{\Delta_n k (1 + [f]_{\text{Lip}})} \|\tilde{Y}_k - \hat{Y}_k\|_2^2 \leq e^{\Delta_n (k+1) (1 + [f]_{\text{Lip}})} \|\tilde{Y}_{k+1} - \hat{Y}_{k+1}\|_2^2 + e^{\Delta_n k (1 + [f]_{\text{Lip}})} K_k(b, \sigma, T, f) \|\bar{X}_k - \hat{X}_k\|_2^2.$$

Keeping in mind that  $\|\tilde{Y}_n - \hat{Y}_n\|_2^2 \leq [h]_{\text{Lip}}^2 \|\bar{X}_n - \hat{X}_n\|_2^2$ , we finally derive by a backward induction that

$$\|\tilde{Y}_k - \hat{Y}_k\|_2^2 \leq \sum_{i=k}^n e^{\Delta_n (i-k) (1 + [f]_{\text{Lip}})} K_i(b, \sigma, T, f) \|\bar{X}_i - \hat{X}_i\|_2^2.$$

(b) We derive from the very definition of  $\tilde{\zeta}_k$  and  $\hat{\zeta}_k$  that

$$\tilde{\zeta}_k - \hat{\zeta}_k = (\tilde{\zeta}_k - \hat{\mathbb{E}}_k(\tilde{\zeta}_k)) \perp\!\!\!\perp (\hat{\mathbb{E}}_k(\tilde{\zeta}_k) - \hat{\zeta}_k)$$

where  $\perp\!\!\!\perp$  means that both random variables are  $L^2$ -orthogonal. We know from (43) that

$$\|\hat{\mathbb{E}}_k(\tilde{\zeta}_k - \hat{\mathbb{E}}_k(\tilde{\zeta}_k))\|_2^2 \leq \frac{[z_k]_{\text{Lip}}^2}{\Delta_n} \|\bar{X}_k - \hat{X}_k\|_2^2.$$

On the other hand, as  $\sigma(\hat{X}_k) \subset \sigma(\bar{X}_k) \subset \mathcal{F}_k$ , it is clear that  $\hat{\mathbb{E}}_k(\tilde{\zeta}_k) = \frac{1}{\Delta_n} \hat{\mathbb{E}}_k(\tilde{Y}_{k+1} \Delta W_{t_{k+1}})$  so that

$$\|\hat{\mathbb{E}}_k(\tilde{\zeta}_k) - \hat{\zeta}_k\|_2^2 = \frac{1}{\Delta_n^2} \|\hat{\mathbb{E}}_k((\tilde{Y}_{k+1} - \hat{Y}_{k+1}) \Delta W_{t_{k+1}})\|_2^2.$$

Conditional Schwarz's Inequality applied with  $\hat{\mathbb{E}}_k$  implies that

$$\hat{\mathbb{E}}_k((\tilde{Y}_{k+1} - \hat{Y}_{k+1}) \Delta W_{t_{k+1}})^2 \leq (\hat{\mathbb{E}}_k(\tilde{Y}_{k+1} - \hat{Y}_{k+1})^2) \Delta_n$$

which in turn implies that

$$\|\hat{\mathbb{E}}_k(\tilde{\zeta}_k) - \hat{\zeta}_k\|_2^2 = \frac{1}{\Delta_n} \|\tilde{Y}_{k+1} - \hat{Y}_{k+1}\|_2^2$$

so that, finally,

$$\Delta_n \|\hat{\mathbb{E}}_k(\tilde{\zeta}_k) - \hat{\zeta}_k\|_2^2 \leq \frac{C_{2,k}(b, \sigma, T, f)}{[f]_{\text{Lip}}^2} \|\bar{X}_k - \hat{X}_k\|_2^2 + \|\tilde{Y}_{k+1} - \hat{Y}_{k+1}\|_2^2. \quad \square$$

**Remark 3.2.** The key property leading to Theorem 3.2 and allowing to improve the existing results for similar problems (see *e.g.* [4]) is the Pythagoras like equality (47) which is true only for the quadratic norm. This equality is the key to get the sharp constant equal to 1 before the term  $\|\hat{\mathbb{E}}_k(\tilde{Y}_k - \hat{Y}_k)\|_2^2$ .

### 3.3 Computing the $\hat{\zeta}_k$ terms

Recall that for every  $k \in \{0, \dots, n-1\}$ , the  $\mathbb{R}^q$ -valued random vector  $\hat{\zeta}_k = (\hat{\zeta}_k^1, \dots, \hat{\zeta}_k^q)$  reads

$$\hat{\zeta}_k = \frac{1}{\Delta_n} \hat{z}_k(\hat{X}_k) \quad \text{where} \quad \hat{z}_k(\hat{X}_k) = \hat{\mathbb{E}}_k(\hat{Y}_{k+1} \Delta W_{t_{k+1}})$$

with  $\hat{z}_k : \Gamma_k \rightarrow \mathbb{R}^q$  is a Borel function ( $\Gamma_k$  is the grid used to quantize  $\bar{X}_k$ ). As  $\hat{Y}_{k+1} = \hat{y}_{k+1}(\hat{X}_{k+1})$  we easily derive that the function  $\hat{z}_k$  is defined on  $\Gamma_k = \{x_1^k, \dots, x_{N_k}^k\}$  by the ( $\mathbb{R}^q$ -valued) weighted sum

$$\hat{z}_k(x_i^k) = \sum_{j=1}^{N_{k+1}} \hat{y}_{k+1}(x_j^{k+1}) \pi_{ij}^{W,k}$$

where, for every  $(i, j) \in \{1, \dots, N_k\} \times \{1, \dots, N_{k+1}\}$ ,  $\pi_{ij}^{W,k}$  is an  $\mathbb{R}^q$ -valued vector given by

$$\pi_{ij}^{W,k} = \frac{1}{\mathbb{P}(\hat{X}_k = x_i^k)} \times \mathbb{E} \left( \Delta W_{t_{k+1}} \mathbf{1}_{\{\hat{X}_{k+1} = x_j^{k+1}, \hat{X}_k = x_i^k\}} \right).$$

These vector valued "weights" appear as new companion parameters (as well as the original weights  $\pi_{ij}^k$  of the quantized transition matrices) which can be computed *on line* when simulating the Euler scheme of the diffusion by a Monte Carlo simulation.

Note that, for every  $k \in \{0, \dots, n-1\}$  and every  $i \in \{1, \dots, N_k\}$ ,

$$\begin{aligned} \sum_{j=1}^{N_{k+1}} \pi_j^{W,k} &= \hat{\mathbb{E}}_k(\Delta W_{t_{k+1}}^n \mathbf{1}_{\{\hat{X}_k = x_i^k\}}) = \hat{\mathbb{E}}_k\left(\mathbb{E}_k(\Delta W_{t_{k+1}}^n \mathbf{1}_{\{\hat{X}_k = x_i^k\}})\right) \\ &= \hat{\mathbb{E}}_k\left(\mathbb{E}_k(\Delta W_{t_{k+1}}^n) \mathbb{P}(\hat{X}_k = x_i^k)\right) = \hat{\mathbb{E}}_k 0 = 0. \end{aligned}$$

As a consequence, an alternative formula for  $\hat{z}_k$  can be

$$\hat{z}_k(x_i^k) = \sum_{j=1}^{N_{k+1}} \pi_{ij}^{W,k} (\hat{y}_{k+1}(x_j^{k+1}) - \hat{y}_k(x_i^k)).$$

## 4 Background and new results on optimal vector quantization

It is important to have in mind that all what precedes holds true for any quantizations  $\hat{X}_{t_k}$  of the Euler scheme  $\bar{X}_{t_k}$  *i.e.* for any sequence of the form  $\hat{X}_{t_k} = \pi_k(\bar{X}_{t_k})$  where  $\pi_k : \mathbb{R}^d \rightarrow \mathbb{R}$  is Borel and  $\pi_k(\mathbb{R}^d)$  is finite. In fact the theory of optimal vector quantization starts when tackling the problem of minimizing the  $L^2$  (and more generally the  $L^r$ )-mean quantization error induced by this substitution, namely  $\|\bar{X}_{t_k} - \hat{X}_{t_k}\|_2$ , which in turn will provide the lowest possible error bounds for quantization based numerical schemes. This question is in fact a very old question that goes back to the 1940's, motivated by Signal transmission and processing. These techniques have been imported in Numerical Probability, originally for numerical integration by cubature formulas, in the 1990's (see [57] or [22]).

### 4.1 Short background

Let  $X : (\Omega, \mathcal{A}, \mathbb{P}) \rightarrow \mathbb{R}^d$  be a random vector lying in  $L^r(\mathbb{P})$ ,  $r \in (0, +\infty)$ . The  $L^r$ -optimal quantization problem of size  $N$  for  $X$  (or equivalently for its distribution  $\mathbb{P}_X$ ) consists in finding the best  $L^r(\mathbb{P})$ -approximation of  $X$  by a random variable  $\pi(X)$  taking at most  $N$  values. The integer  $N$  is called the *quantization level*.

First, we associate to every Borel function  $\pi : \mathbb{R}^d \rightarrow \mathbb{R}$  taking at most  $N$  values the induced  $L^r(\mathbb{P})$ -mean error  $\|X - \pi(X)\|_r$  (where  $\|X\|_r := (\mathbb{E}|X|^r)^{1/r}$  is the usual  $L^r(\mathbb{P})$ -norm on  $(\Omega, \mathcal{A})$  induced by the norm  $|\cdot|$  on  $\mathbb{R}^d$  (*a priori* any norm, but always the canonical Euclidean norm in this paper and in most applications). Note that when  $r \in (0, 1)$ , the terms “norm” is an abuse of language since  $L^r(\mathbb{P})$  is only a metric space metrized by  $\|X - Y\|_r$ . As a consequence, finding the best approximation of  $X$  in the earlier described sense boils down to solve the following minimization problem:

$$e_{N,r}(X) = \inf \left\{ \|X - \pi(X)\|_r, v : \mathbb{R}^d \rightarrow \Gamma, \Gamma \subset \mathbb{R}^d, \text{card}(\Gamma) \leq N \right\}$$

where  $\text{card}(\Gamma)$  denotes the cardinality of the set  $\Gamma$  (commonly called *grid* or *codebook* depending on the field of application. It is clear that for every grid  $\Gamma = \{x_1, \dots, x_N\} \subset \mathbb{R}^d$ , for any Borel function  $\pi : \mathbb{R}^d \rightarrow \Gamma$ ,

$$|\xi - \pi(\xi)| \geq \text{dist}(\xi, \Gamma) = \min_{1 \leq i \leq N} |\xi - x_i|.$$

Equality holds if and only if  $\pi$  is a Borel nearest neighbor projection  $\pi_\Gamma$  defined by

$$\pi_\Gamma(\xi) = \sum_{i=1}^N x_i \mathbf{1}_{C_i(\Gamma)}(\xi)$$

where  $(C_i(\Gamma))_{i=1,\dots,N}$  is a Borel partition of  $\mathbb{R}^d$  satisfying

$$\forall i \in \{1, \dots, N\}, \quad C_i(\Gamma) \subset \left\{ \xi \in \mathbb{R}^d : |\xi - x_i| = \min_{j=1,\dots,N} |\xi - x_j| \right\}.$$

Such a Borel partition is called a *Voronoi partition* (induced by  $\Gamma$ ). The random variable  $\hat{X}^\Gamma$  is called a *Voronoi quantization* of  $X$  induced by  $\Gamma$ . It follows that for every  $r > 0$ ,  $\|X - \hat{X}^\Gamma\|_r = \|\text{dist}(X, \Gamma)\|_r$  does not depend on the choice of the Voronoi projection. Thus, we may denote  $e_r(X, \Gamma) = \|X - \hat{X}^\Gamma\|_r$  the  *$L^r$ -mean quantization error* induced by the grid  $\Gamma$  (under  $\mathbb{P}_X$ ). As a consequence, the optimal  $L^r$ -mean quantization error finally reads

$$e_{N,r}(X) = \inf \left\{ \|X - \hat{X}^\Gamma\|_r, \Gamma \subset \mathbb{R}^d, \text{card}(\Gamma) \leq N \right\}. \quad (49)$$

Note that for every level  $N \geq 1$ , the infimum in (49) is in fact a minimum, *i.e.*, it is attained at least at one grid  $\Gamma_N$ , see *e.g.* [41] or [57]. Any such grid is called an  *$L^r$ -optimal  $N$ -quantizer* and the resulting Borel nearest neighbor projection is called an  *$L^r$ -optimal  $N$ -quantization*. It should be noticed as well that  $e_{N,r}(X)$  is entirely characterized by the distribution  $\mathbb{P}_X$  of  $X$ , hence will be often denoted by  $e_{N,r}(\mathbb{P}_X)$ .

One shows that if  $\text{card}(\text{supp}(\mathbb{P}_X)) \geq N$  then any optimal  $N$ -quantizer is of full size  $N$ . Furthermore (see again [41] or [57]), the optimal  $L^r$ -mean quantization error  $e_{N,r}(X)$  at level  $N$  decreases to 0 as  $N$  goes to infinity. Its rate of convergence is ruled by the so-called Zador Theorem recalled below, in which,  $|\cdot|$  temporarily may denote any norm on  $\mathbb{R}^d$ .

**Theorem 4.1. Zador's Theorem** (a) *Sharp asymptotic rate (see [41]):* Let  $X : (\Omega, \mathcal{A}, \mathbb{P}) \rightarrow \mathbb{R}^d$  be a random vector such that  $X \in L^{r+\delta}(\mathbb{P})$  for some real number  $\delta > 0$  and let  $\mathbb{P}_X = \varphi \cdot \lambda_d + \mathbb{P}_X^s$  denote the canonical Lebesgue decomposition of  $\mathbb{P}_X$  where  $\mathbb{P}_X^s$  stands for the singular part of  $\mathbb{P}_X$ . Then

$$\lim_{N \rightarrow +\infty} N^{r/d} (e_{N,r}(\mathbb{P}_X))^r = J_{r,d} \|\varphi\|_{\frac{d}{d+r}} \in [0, +\infty) \quad (50)$$

with  $\|\varphi\|_{\frac{d}{d+r}} = \left( \int_{\mathbb{R}^d} \varphi^{\frac{d}{d+r}} d\lambda_d \right)^{\frac{d+r}{d}}$  and  $J_{r,d,|\cdot|} = \inf_{N \geq 1} N^{r/d} e_{N,r}^r(U([0, 1]^d)) \in (0, +\infty)$  (51)

( $U([0, 1]^d)$  denotes the uniform distribution on the hypercube  $[0, 1]^d$ ).

(b) *Non-asymptotic bound (see [41, 52]):* Let  $r' > r$ . There exists a universal real constant  $C_{r,r',d} \in (0, +\infty)$  such that, for every  $\mathbb{R}^d$ -valued random vector  $X$ ,

$$\forall N \geq 1, \quad e_{N,r}(\mathbb{P}_X) \leq C_{r,r',d} \sigma_{r'}(X) N^{-\frac{1}{d}}$$

where  $\sigma_{r'}(X) := \inf_{a \in \mathbb{R}^d} \|X - a\|_{r'} \leq +\infty$  is the  $L^{r'}$ -(pseudo)-standard deviation of  $X$ .

**Numerical aspects (few words about).** From the numerical probability viewpoint, finding an optimal  $N$ -quantizer  $\Gamma$  is a challenging task, especially in higher dimension ( $d \geq 2$ ). In this paper as in many applications we will mainly focus on the quadratic case  $r = 2$ . Note that, in practice,  $|\cdot|$  will be the canonical Euclidean norm on  $\mathbb{R}^d$  for numerical implementations.

The key property to devise procedures to search for optimal quantizers rely on the following differentiability property of the squared quadratic quantization error (also known as quadratic distortion function) for a fixed level  $N$  (and with respect to the canonical Euclidean norm). First, we define the distortion function  $D_{N,2}$  (which is defined on  $(\mathbb{R}^d)^N$  and not on the set of grids of size at most  $N$ ) by:

$$\forall x = (x_1, \dots, x_N) \in (\mathbb{R}^d)^N, \quad D_{N,2}^X(x) = \int_{\mathbb{R}^d} \min_{1 \leq i \leq N} |\xi - x_i|^2 d\mathbb{P}_X(\xi). \quad (52)$$

To an  $N$ -tuple  $x = (x_1, \dots, x_N) \in (\mathbb{R}^d)^N$  we associate its grid of values  $\Gamma^x = \{x_1, \dots, x_N\}$  so that  $D_{N,2}^X(x) = \|X - \hat{X}^{\Gamma^x}\|_2^2$ . In particular, it is clear that

$$e_{N,2}(\mathbb{P}_X) = \inf_{x \in (\mathbb{R}^d)^N} D_{N,2}(x)$$

since an  $N$ -tuples can contain repeated values.

**Proposition 4.2** (see Theorem 4.2 in [41]). (a) *The function  $D_{N,2}$  is differentiable at any  $N$ -tuple  $x \in (\mathbb{R}^d)^N$  having pairwise distinct components and satisfying the following boundary negligibility assumption:*

$$\mathbb{P}_X \left( \bigcup_{1 \leq i \leq N} \partial C_i(\Gamma^x) \right) = 0.$$

*Its gradient is given by*

$$\nabla D_{N,2}^X(x) = 2 \left( \int_{C_i(\Gamma^x)} (x_i - \xi) d\mathbb{P}_X(\xi) \right)_{i=1, \dots, N}. \quad (53)$$

(b) *The above negligibility assumption on the Voronoi partition boundaries does not depend on the selected partition. It holds in particular when the distribution of  $X$  is strongly continuous i.e. assigns no mass to hyperplanes and, for any distribution  $\mathbb{P}_X$  such that  $\text{card}(\text{supp}(\mathbb{P}_X)) \geq N$ , when  $x \in \text{argmin} D_{N,2}$ .*

The result is a consequence of the interchange of the differentiation and the integral leading to (53) when formally differentiating (52) (see [41, 57]). Consequently, any  $N$ -tuple  $x \in \text{argmin} D_{N,2}$  satisfies

$$\nabla D_{N,2}(x) = 0.$$

Note that this equality also reads, still under the assumption  $\text{card}(\text{supp}(\mathbb{P}_X)) \geq N$ ,

$$\mathbb{E} \left( X | \hat{X}^\Gamma \right) = \hat{X}^\Gamma.$$

All numerical methods to compute optimal quadratic quantizers are based on this result: recursive procedures like Newton's algorithm (when  $d = 1$ ), randomized fixed point procedures like Lloyd's I algorithms (see e.g. [32, 62]) or recursive stochastic gradient descent like the Competitive Learning Vector Quantization (CLVQ) algorithm (see [32, 57] or [60]) in the multidimensional framework. However note that in higher dimension this equation has several solutions (called *stationary quantizers*) possibly sub-optimal. Optimal quantization grids associated to the multivariate Gaussian random vector can be downloaded from the website [www.quantize.math-fi.com](http://www.quantize.math-fi.com). For more details about numerical methods we refer to the recent survey [58] and the references therein.

## 4.2 Distortion mismatch: $L^s$ -robustness of $L^r$ -optimal quantizers

The distortion mismatch problem is the following: when does an  $L^r$ -optimal sequence of quantizers  $(\Gamma_N)_{N \geq 1}$  for a random variable  $X$  remain  $L^s$ -rate optimal for some  $s > r$  (if  $X \in L^s$ )? Or in more mathematical terms, if  $X \in L^s$ ,  $s > r$ , when do we have for such a sequence of  $L^r$ -optimal quantizers

$$\limsup_N N^{\frac{1}{d}} e_s(\Gamma_N, X) < +\infty ?$$

This problem has obvious applications in numerical probability since, for algorithmic reasons, one usually has access to optimal quadratic quantizers (see e.g. the website [www.quantize.maths-fi.com](http://www.quantize.maths-fi.com)) whereas they are currently used in a non quadratic framework. What will be done in Section 6

for nonlinear filtering is precisely to take advantage of this result to strongly relax some growth assumptions on the conditional densities involved in the Kallianpur-Striebel formula.

The distortion mismatch problem was first addressed in [42] for various classes of distributions on  $\mathbb{R}^d$ , in particular for distributions having a *radial density* satisfying (an almost necessary) moment assumption of order higher than  $s$ . In the theorem below we extend this result to *all random vectors satisfying this moment condition*.

**Theorem 4.3** ( *$L^r$ - $L^s$ -distortion mismatch*). *Let  $X : (\Omega, \mathcal{A}, \mathbb{P}) \rightarrow \mathbb{R}^d$  be a random vector and let  $r \in (0, +\infty)$ . Assume that the distribution  $\mathbb{P}_X$  of  $X$  has a non-zero absolutely continuous component with density  $\varphi$ . Let  $(\Gamma_N)_{N \geq 1}$  be a sequence of  $L^r$ -optimal grids and let  $s \in (r, r + d)$ . If*

$$X \in L^{\frac{sd}{d+r-s} + \delta}(\Omega, \mathcal{A}, \mathbb{P}) \quad (54)$$

for some  $\delta > 0$ , then

$$\limsup_N N^{\frac{1}{d}} e_s(\Gamma_N, X) < +\infty. \quad (55)$$

**Definition 4.1.** Let  $r \in (0, +\infty)$  and  $s \in (r, r + d)$ . A random vector  $X \in L^r(\Omega, \mathcal{A}, \mathbb{P})$  has an  $(r, s)$ -distribution (or its distribution  $\mathbb{P}_X$  is an  $(r, s)$ -distribution) if (55) is satisfied.

Note that if  $X$  has an  $(r, s)$ -distribution, then it has an  $(r, s')$  distribution for any  $s' \in (r, s)$  since the  $L^s$ -norm is increasing in  $s$ .

Thus, the integrability condition (54) appears as a criterion to have an  $(r, s)$ -distribution (see also the first remark after the proof of the theorem). Note that, as expected,  $\frac{sd}{d+r-s} > s$  so that the preservation of the  $(r, s)$ -property for  $s > r$  requires more than  $L^s$ -integrability. Finally, if  $X$  has polynomial moment at any order, then the  $(r, s)$ -property holds for every  $s \in (r, r + d)$ .

*Proof of Theorem 4.3. STEP 1 (Control of the distance to the quantizers):* Let  $(\Gamma_N)_{N \geq 1}$  be a sequence of  $L^r$ -optimal quantizers. It is clear that, for every  $\xi \in \mathbb{R}^d$ ,

$$d(\xi, \Gamma_N) \leq |\xi| + d(0, \Gamma_N).$$

The sequence  $(d(0, \Gamma_N))_{N \geq 1}$  is bounded since  $d(\Gamma_N, \text{supp}(\mathbb{P}_X)^c) \rightarrow 0$  as  $N \rightarrow +\infty$  and  $d(0, \text{supp}(\mathbb{P}_X)^c) < +\infty$ . Then there exists a real constant  $A_X \geq 0$  such that for every  $\xi \in \mathbb{R}^d$ ,

$$d(\xi, \Gamma_N) \leq |\xi| + A_X.$$

*STEP 2 (Micro-macro inequality):* The optimality of the grids  $\Gamma_N$ ,  $N \geq 1$ , allow to apply to the micro-macro inequality (see Equation (3.2) in the proof of Theorem 2 in [42]), namely : for every real constant  $c \in (0, \frac{1}{2})$  and every  $y \in \mathbb{R}^d$ ,

$$e_r(\Gamma_N, X)^r - e_r(\Gamma_{N+1}, X)^r \geq ((1-c)^r - c^r) \mathbb{P}_X(B(y; cd(y, \Gamma_N))) d(y, \Gamma_N)^r. \quad (56)$$

Let  $\nu$  be an auxiliary Borel probability measure on  $\mathbb{R}^d$  to be specified further on. Set  $C(r) = (1-c)^r - c^r$ . Integrating the above inequality with respect to  $\nu(dy)$  yields, owing to Fubini's Theorem,

$$\begin{aligned} e_r(\Gamma_N, X)^r - e_r(\Gamma_{N+1}, X)^r &\geq C(r) \iint (B(y; cd(y, \Gamma_N))) d(y, \Gamma_N)^r \mathbb{P}_X(d\xi) \nu(dy) \\ &= C(r) \iint \mathbf{1}_{\{|y-\xi| \leq cd(y, \Gamma_N)\}} d(y, \Gamma_N)^r \nu(dy) \mathbb{P}_X(d\xi) \\ &\geq C(r) \iint \mathbf{1}_{\{|y-\xi| \leq cd(y, \Gamma_N), d(y, \Gamma_N) \geq \frac{1}{c+1} d(\xi, \Gamma_N)\}} d(y, \Gamma_N)^r \nu(dy) \mathbb{P}_X(d\xi). \end{aligned}$$

Now using that  $\xi \mapsto d(\xi, \Gamma_N)$  is Lipschitz continuous with coefficient 1, one derives that

$$\left\{ (\xi, y) : |y - \xi| \leq \frac{c}{c+1} d(\xi, \Gamma_N) \right\} \subset \left\{ (\xi, y) : |y - \xi| \leq cd(y, \Gamma_N), d(y, \Gamma_N) \geq \frac{1}{c+1} d(\xi, \Gamma_N) \right\}$$

and, still by Fubini's Theorem,

$$e_r(\Gamma_N, X)^r - e_r(\Gamma_{N+1}, X)^r \geq \frac{C(r)}{(1+c)^r} \int \nu\left(B(\xi; cd(y, \Gamma_N))\right) d(\xi, \Gamma_N)^r \mathbb{P}_X(d\xi). \quad (57)$$

Let  $\varepsilon \in (0, 1/2)$ . We set  $\nu = f_{\varepsilon, \delta} \cdot \lambda_d$  where  $f_{\varepsilon, \delta}$  is a probability density given by

$$f_{\varepsilon, \delta}(\xi) = \frac{\kappa_{\varepsilon, \delta}}{(|x| + 1 + \varepsilon)^{d+\delta}} \quad \text{with } \delta > 0.$$

The density  $f_{\varepsilon, \delta}$  shares the following property on balls: let  $\xi \in \mathbb{R}^d$  and  $t \in \mathbb{R}_+$ . If  $t \leq \varepsilon(|\xi| + 1)$ , then

$$\nu(B(\xi, t)) \geq g_{\varepsilon, \delta}(\xi) t^d \quad \text{with} \quad g_{\varepsilon, \delta}(\xi) = \frac{1}{(1+\varepsilon)^{d+\delta}} \frac{\kappa_{\varepsilon, \delta}}{(|\xi| + 1)^{d+\delta}} V_d$$

and  $V_d = \lambda_d(B(0; 1))$ . Now let  $c = c(\varepsilon) \in (0, 1)$  such that  $\frac{c}{c+1} = \varepsilon(A_X^{-1} \wedge 1)$ . As  $d(\xi, \Gamma_N) \leq |\xi| + A_X$ , this in turn implies that  $\frac{c}{c+1} d(\xi, \Gamma_N) \leq \varepsilon(|\xi| + 1)$ . As a consequence

$$e_r(\Gamma_N, X)^r - e_r(\Gamma_{N+1}, X)^r \geq \frac{C(r)}{(c+1)^r} \int g_{\varepsilon, \delta}(\xi) d(\xi, \Gamma_N)^{r+d} \mathbb{P}_X(d\xi).$$

Let  $s \in [r, r+d)$ . It follows from Equation (57) and the reverse Hölder inequality applied with  $p = \frac{s}{r+d} \in (0, 1)$  and  $q = -\frac{s}{d+r-s} \in (-\infty, 0)$  that

$$\int g_{\varepsilon, \delta}(\xi) d(\xi, \Gamma_N)^{r+d} \mathbb{P}_X(d\xi) \geq \left[ \int_{\mathbb{R}^d} d(\xi, \Gamma_N)^s \mathbb{P}_X(d\xi) \right]^{\frac{r+d}{s}} \left[ \int g_{\varepsilon, \delta, a}(\xi)^{-\frac{s}{d+r-s}} \mathbb{P}_X(d\xi) \right]^{-\frac{d+r-s}{s}}.$$

It follows from the assumption made on  $X$  (or  $\mathbb{P}_X$ ) that, for small enough  $\delta > 0$ ,

$$\left[ \int_{\mathbb{R}^d} g_{\varepsilon, \delta}^{-\frac{s}{d+r-s}}(\xi) \mathbb{P}_X(d\xi) \right]^{-\frac{d+r-s}{s}} = \frac{\kappa_{\varepsilon, \delta} V_d}{(1+\varepsilon)^{d+\delta}} \left[ \mathbb{E} \left[ (1 + |X|)^{\frac{(d+\delta)s}{d+r-s}} \right] \right]^{-\frac{d+r-s}{s}} < +\infty.$$

As a consequence

$$e_r(\Gamma_N, X)^r - e_r(\Gamma_{N+1}, X)^r \geq C_{X, r, s, \varepsilon, \delta} e_s(\Gamma_N, X)^{r+d} \quad (58)$$

where  $C_{X, r, s, \varepsilon, \delta} = \frac{(1-c)^r - c^r}{(1+c)^r (1+\varepsilon)^{d+\delta}} \kappa_{\varepsilon, \delta} \|1 + |X|\|_{\frac{(d+\delta)s}{d+r-s}}^{-\frac{(d+\delta)s}{d+r-s}}$ .

**STEP 3 (Upper-bound for the quantization error increments):** Since the distribution of  $X$  is absolutely continuous  $X$  (*i.e.* admits a density), one derives following the lines of the proof of Theorem 2 in [42] this upper-bound for the increments of the  $L^r$ -quantization error: there exists a real constant  $\kappa_{X, r} > 0$  such that

$$e_r(\Gamma_N, X)^r - e_r(\Gamma_{N+1}, X)^r \leq \kappa_{X, r} N^{-1-\frac{r}{d}}.$$

Combining this inequality with (58) yields

$$\left[ e_s(\Gamma_N, X)^s \right]^{\frac{r+d}{s}} \leq \tilde{C}_{X, r, s, \varepsilon, \delta} N^{-\frac{r+d}{d}}$$

where  $\tilde{C}_{X,r,s,\varepsilon,\delta} = \frac{\kappa_{X,r}}{C_{X,r,s,\varepsilon,\delta}}$ . This completes the proof by considering the  $(d+r)^{th}$  root of the inequality.  $\square$

**Remarks.** • If  $\varphi$  is radial, more precisely if  $\varphi = \tilde{\varphi}(|x|_0)$  where  $\tilde{\varphi} : \mathbb{R}_+ \rightarrow \mathbb{R}_+$  is bounded and non-increasing on  $[R_0, +\infty)$  and  $|\cdot|_0$  denotes any norm on  $\mathbb{R}^d$  the above result holds true even if  $\delta = 0$  (see [53]).

• Criterion (54) is close to optimality for the following reason. It has been established in [42] (Theorem 1) that if  $X \in L^{r+}(\Omega, \mathcal{A}, \mathbb{P})$ , and if  $(\Gamma_N)_{N \geq 1}$  is a sequence of  $L^r$ -asymptotically optimal quantization grids, then

$$\lim_N N^{\frac{1}{d}} e_s(\Gamma_N, X) \geq J_{r,d,|\cdot|}^{\frac{1}{s}} \left[ \int_{\mathbb{R}^d} \varphi^{\frac{d}{r+d}} d\lambda_d \right]^{\frac{1}{d}} \left[ \int_{\mathbb{R}^d} \varphi^{\frac{d+r-s}{r+d}} d\lambda_d \right]^{\frac{1}{s}}$$

where  $J_{r,d,|\cdot|}^{\frac{1}{s}}$  is given by (51). Since  $X \in L^{r+}(\Omega, \mathcal{A}, \mathbb{P})$ ,  $\int_{\mathbb{R}^d} \varphi^{\frac{d}{r+d}} d\lambda_d < +\infty$  by an elementary application of the reverse Hölder inequality (see Equation (2.11) from [42]). On the other hand,

$$\int_{\mathbb{R}^d} \varphi^{\frac{d+r-s}{r+d}} d\lambda_d = +\infty \implies X \notin L^{\frac{ds}{d+r-s}}(\Omega, \mathcal{A}, \mathbb{P}).$$

## 5 Numerical experiments for the BSDE scheme

To illustrate empirically the improved theoretical rate obtained in the previous section, we deal here with two toy examples: a bull-call spread option (in a market where the risk free returns for the borrower and the lender are different) and a multidimensional example with the Brownian motion. Note that our aim is not to make an extensive numerical test with a complete description (or a complexity analysis) of several used algorithms for the optimal grid search. These subjects have extensively been considered in the past and we refer for example to [60] for more details.

Numerical tests are performed using our quantized BSDE algorithm. At each discretization instant  $t_k$ , we associate a quantization grid  $\Gamma_k = \{x_i^k, i = 1, \dots, N_k\}$  of size  $N_k$ , possibly not optimal *a priori*, and  $\hat{X}_k = \text{Proj}_{\Gamma_k}(\bar{X}_k)$  the resulting Voronoi quantization of  $\bar{X}_k$ . Then, we set for every  $k = 0, \dots, n-1, i = 1, \dots, N_k, j = 1, \dots, N_{k+1}$ , the *transition weights* (or probabilities)

$$p_{ij}^k = \mathbb{P}(\hat{X}_{k+1} = x_j^{k+1} | \hat{X}_k = x_i^k), \quad k = 0, \dots, n-1.$$

and, for  $k = 0, \dots, n, i = 1, \dots, N_k$ , the *marginal weights*  $p_i^k = \mathbb{P}(\hat{X}_k = x_i^k), k = 0, \dots, n$ .

Setting  $\hat{Y}_k = \hat{y}_k(\hat{X}_k)$ , for every  $k \in \{0, \dots, n\}$ , the quantized BSDE scheme reads as

$$\begin{cases} \hat{y}_n(x_i^n) = h(x_i^n) & i = 1, \dots, N_n \\ \hat{y}_k(x_i^k) = \hat{\alpha}_k(x_i^k) + \Delta_n f(t_k, x_i^k, \hat{\alpha}_k(x_i^k), \hat{\beta}_k(x_i^k)) & i = 1, \dots, N_k \end{cases}$$

where for  $k = 0, \dots, n-1$ ,

$$\hat{\alpha}_k(x_i^k) = \sum_{j=1}^{N_{k+1}} \hat{y}_{k+1}(x_j^{k+1}) p_{ij}^k \quad \text{and} \quad \hat{\beta}_k(x_i^k) = \frac{1}{\Delta_n} \sum_{j=1}^{N_{k+1}} \hat{y}_{k+1}(x_j^{k+1}) \pi_{ij}^{W,k} \quad (59)$$

with

$$\pi_{ij}^{W,k} = \frac{1}{p_i^k} \times \mathbb{E} \left( \Delta W_{t_{k+1}} \mathbf{1}_{\{\hat{X}_{k+1} = x_j^{k+1}, \hat{X}_k = x_i^k\}} \right).$$



We use a time discretization mesh of length  $n = 20$  for the first example and of length  $n = 10$  for all dimensions in the second example. In both examples below, the quantizers  $\hat{X}_k$ ,  $k = 1, \dots, n$  (with  $\hat{X}_0 = X_0$ ) are computed from a scaling of the optimal grid of  $\mathcal{N}(0, I_d)$  Gaussian distributions available on the website devoted to quantization

[www.quantize.maths-fi.com](http://www.quantize.maths-fi.com).

The transition probabilities are approximated using a Monte Carlo simulation of size  $10^7$  for all examples (keep in mind that we may have the same precision with a smaller size of Monte Carlo trials but our aim is not to optimize these sizes of the trials). For simplicity reasons, we use a uniform dispatching across the time layers for the quantizers by assigning the same grid size  $N_k$  to all  $\hat{X}_k$  at every discretization step  $t_k$ ,  $k = 1, \dots, n$ . Once the optimal quantization grids are computed offline, the complexity of our procedure depends on the grid sizes and varies from less than 1 second in lower dimension up to a few minutes in dimension 5, almost entirely devoted to the computation by Monte Carlo simulation of the transition weights. By contrast, the (quantized) dynamic programming descent itself is instantaneous.

## 5.1 Bid-ask spread for interest rate

Let us consider a model with two interest rates introduced in [11]: a borrowing rate  $R$  and a lending rate  $r \leq R$  where the stock price  $(X_t)_{t \in [0, T]}$  evolves following the Black-Scholes dynamics

$$dX_t = \mu X_t dt + \sigma X_t dW_t, \quad X_0 = x_0 > 0.$$

Let  $\varphi_t$  be the amount of assets held at time  $t$ . Then, the dynamics of the replicating portfolio is given by

$$Y_t = Y_T + \int_t^T f(Y_s, Z_s) ds - \int_t^T Z_s dW_s \quad (60)$$

where  $Z_t = \sigma \varphi_t X_t$  and the driver function  $f$  is given by

$$f(y, z) = -ry - \frac{\mu - r}{\sigma} z - (R - r) \min\left(y - \frac{z}{\sigma}, 0\right).$$

As in [10], we consider a bull-call spread comprising a long call with strike  $K_1 = 95$  and two short call with strike  $K_2 = 105$ , with payoff function

$$(X_T - K_1)^+ - 2(X_T - K_2)^+ = Y_T.$$

Furthermore, we consider the set of parameters:

$$X_0 = 100, \quad R = 0.06, \quad r = 0.01, \quad \mu = 0.05, \quad \sigma = 0.2, \quad T = 0.25.$$

The BSDE (60) has no analytical solution. We refer to the reference prices given in [10, 67] where  $(Y_0, Z_0)$  is approximated by  $(2.96, 0.55)$ . We put  $n = 20$  and, for every  $k = 1, \dots, n$ , the grid sizes  $N_k = \bar{N} = \frac{N}{n}$  is constant (keep in mind that  $N = N_1 + \dots + N_n$ ). The quantizers  $\hat{X}_{t_k}$  have been obtained by using dilations of optimal Gaussian quantization grids that we substitute to  $W_{t_k}$  into the formula  $X_{t_k} = x_0 e^{(\mu - \frac{\sigma^2}{2})t_k + \sigma W_{t_k}}$ .

The numerical convergence rate of the error  $\bar{N} \mapsto |Y_0 - \hat{Y}_0^{\bar{N}}|$ ,  $\bar{N} = 5\ell$ ,  $\ell = 1, \dots, 30$ , is depicted in Figure 1, including a polynomial regression which emphasizes the empirical order of the convergence rate, namely  $\bar{N}^{-1}$ .

## 5.2 Multidimensional example

We consider the following non linear BSDE (example due to J.-F. Chassagneux):

$$dX_t = dW_t, \quad -dY_t = f(t, Y_t, Z_t)dt - Z_t \cdot dW_t, \quad Y_T = \frac{e_T}{1 + e_T}$$

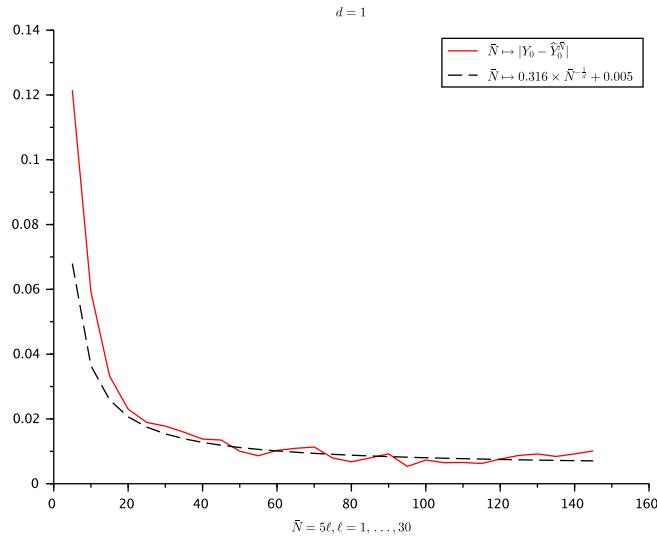
where

$$e_t = \exp(t + W_t^1 + \dots + W_t^d), \quad t \in [0, T],$$

$f(t, y, z) = (z_1 + \dots + z_d)(y - \frac{2+d}{2d})$  and  $W$  is a  $d$ -dimensional Brownian motion. The solution of this BSDE is

$$Y_t = \frac{e_t}{1 + e_t}, \quad Z_t = \frac{e_t}{(1 + e_t)^2}. \quad (61)$$

For the numerical experiments, we use the (regular) time discretization mesh with  $n = 10$ . We choose  $t = 0.5$ ,  $d = 2, 3, 4, 5$ , so that  $Y_0 = 0.5$  and  $Z_0^i = 0.24$ , for every  $i = 1, \dots, d$ . We depict in Figures 2 and 3, the rates of convergence of  $|\hat{Y}_0^{\bar{N}} - 0.5|$  towards 0, for the (constant) layer grid sizes  $N_k = \bar{N} = \frac{N}{n} = 5, \dots, 150$ . The graphics in Figures 2 and 3 confirm a rate of convergence of order  $N^{-1/d}$ .



**Figure 1:** Convergence rate of the quantization error for the Bid-ask spread in the Black-Scholes model. Abscissa axis: the size  $\bar{N} = 5\ell, \ell = 1, \dots, 30$  of the quantization. Ordinate axis: The error  $|Y_0 - \hat{Y}_0^{\bar{N}}|$  and the graph  $\bar{N} \mapsto \hat{a}/\bar{N} + \hat{b}$ , where  $\hat{a}$  and  $\hat{b}$  are the regression coefficients.

## 6 Nonlinear filtering problem

We consider in this section the discrete time nonlinear filtering model and the quantization based numerical scheme presented in the introduction. Our aim is two-fold: improving the error bounds like for BSDE on the one hand and, on the other hand, relaxing the Lipschitz continuity on the conditional densities  $g_k$  (in favor of a local Lipschitz continuity assumption with polynomial growth). In particular, these new error bounds confirm the results obtained in the survey [68] devoted to a comparison between quantization and particle based numerical methods for non-linear filtering.

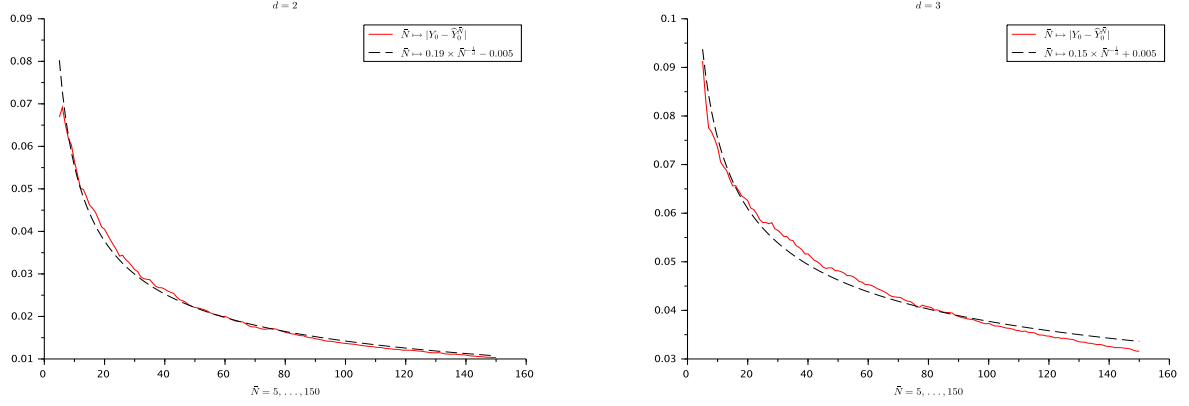


Figure 2: Convergence rate of the quantization error for the multidimensional example. Abscissa axis: the size  $\bar{N} = 5, \dots, 150$  of the quantization. Ordinate axis: The error  $|Y_0 - \hat{Y}_0^{\bar{N}}|$  and the graph  $\bar{N} \mapsto \hat{a}\bar{N}^{-1/d} + \hat{b}$ , where  $\hat{a}$  and  $\hat{b}$  are the regression coefficients. The left hand side graphic corresponds to the dimension  $d = 2$  and the right hand side to  $d = 3$ .

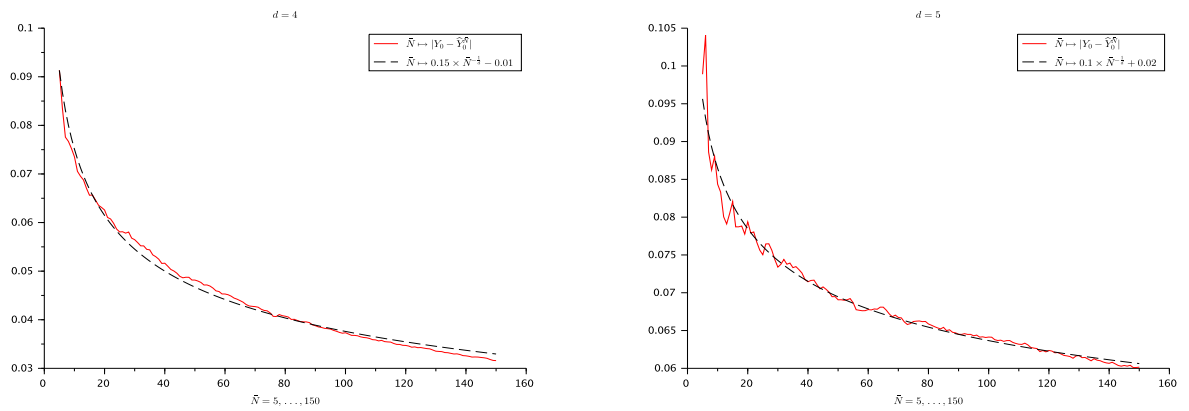


Figure 3: Convergence rate of the quantization error for the multidimensional example. Abscissa axis: the size  $\bar{N} = 5, \dots, 150$  of the quantization. Ordinate axis: The error  $|Y_0 - \hat{Y}_0^{\bar{N}}|$  and the graph  $\bar{N} \mapsto \hat{a}\bar{N}^{-1/d} + \hat{b}$ , where  $\hat{a}$  and  $\hat{b}$  are the regression coefficients. The left hand side graphic corresponds to the dimension  $d = 4$  and the right hand side to  $d = 5$ .

## 6.1 Error analysis

Let us first recall the assumptions made in [59] on the conditional transition density functions  $g_k$  and the Markov transitions  $P_k$ :

( $\mathcal{H}_0$ ) For every  $k \in \{1, \dots, n\}$  there exists  $[g_k^1]_{\text{Lip}}, [g_k^2]_{\text{Lip}} : \mathbb{R}^q \times \mathbb{R}^q \mapsto \mathbb{R}_+$  such that

$$|g_k(x, y, x', y') - g_k(\hat{x}, y, \hat{x}', y')| \leq [g_k^1]_{\text{Lip}}(y, y')|x - \hat{x}| + [g_k^2]_{\text{Lip}}(y, y')|x' - \hat{x}'|.$$

( $\mathcal{A}_1$ ) (i) The Markov transition operators  $P_k(x, dx')$ ,  $k = 1, \dots, n$  propagate Lipschitz continuity (in the sense of Lemma 3.3) and

$$[P]_{\text{Lip}} := \max_{k=1, \dots, n} [P_k]_{\text{Lip}} < +\infty.$$

(ii) For every  $k = 1, \dots, n$ , the functions  $g_k$  are bounded on  $\mathbb{R}^d \times \mathbb{R}^q \times \mathbb{R}^d \times \mathbb{R}^q$  and we set

$$K_g := \max_{k=1, \dots, n} \|g_k\|_\infty < +\infty.$$

We will relax these Lipschitz assumptions into controlled Lipschitz assumptions. Let us consider, for a fixed *non-negative* function  $\theta : \mathbb{R}^d \mapsto \mathbb{R}_+$  satisfying,

( $\mathcal{I}_\theta$ )  $\forall k \in \{1, \dots, n\}, \quad \mathbb{E}(\theta(X_k)) < +\infty.$

We make the following  $\theta$ -local Lipschitz continuity assumption (which is weaker than ( $\mathcal{H}_0$ )) on the growth of the conditional transition density functions  $g_k$ :

( $\mathcal{H}_{\text{Liploc}}$ ) There exists  $[g_k^1]_{\text{Liploc}}, [g_k^2]_{\text{Liploc}} : \mathbb{R}^q \times \mathbb{R}^q \mapsto \mathbb{R}_+$  such that, for every  $k \in \{1, \dots, n\}$ ,

$$|g_k(x, y, x', y') - g_k(\hat{x}, y, \hat{x}', y')| \leq [g_k^1]_{\text{Liploc}}(y, y')(1 + \theta(x) + \theta(\hat{x}) + \theta(x') + \theta(\hat{x}'))|x - \hat{x}| \\ + [g_k^2]_{\text{Liploc}}(y, y')(1 + \theta(x) + \theta(\hat{x}) + \theta(x') + \theta(\hat{x}'))|x' - \hat{x}'|.$$

A standard situation is the sometimes called  $\text{Li}(1, \alpha)$  framework when the  $g_k$  satisfy ( $\mathcal{H}_{\text{Liploc}}$ ) with the function  $\theta : x \mapsto \theta(x) = |x|^\alpha$  for an  $\alpha \geq 0$ , namely

( $\mathcal{H}_\alpha$ ) For every  $k \in \{1, \dots, n\}$  there exists  $[g_k^1]_{\text{pol}}, [g_k^2]_{\text{pol}} : \mathbb{R}^q \times \mathbb{R}^q \mapsto \mathbb{R}_+$  such that

$$|g_k(x, y, x', y') - g_k(\hat{x}, y, \hat{x}', y')| \leq [g_k^1]_{\text{pol}}(y, y')(1 + |x|^\alpha + |\hat{x}|^\alpha + |x'|^\alpha + |\hat{x}'|^\alpha)|x - \hat{x}| \\ + [g_k^2]_{\text{pol}}(y, y')(1 + |x|^\alpha + |\hat{x}|^\alpha + |x'|^\alpha + |\hat{x}'|^\alpha)|x' - \hat{x}'|.$$

When  $\theta \equiv 0$ , this framework coincides with the Lipschitz one. To simplify some statement we will introduce

$$[g^i]_{\text{Liploc}}(y, y') = \max_{k=1, \dots, n} [g_k^i]_{\text{Liploc}}(y, y'), \quad i = 1, 2. \quad (62)$$

**Example.** We may consider a model in which the signal process  $X$  is a discrete time real valued (Markov) process and that the observation process evolves as

$$Y_k = Y_{k-1} + \varphi(X_{k-1}) + \sigma \varepsilon_k, \quad \sigma > 0, \quad \varepsilon_k \stackrel{i.i.d.}{\sim} \mathcal{N}(0, 1), \quad k = 1, \dots, n.$$

where the function  $\varphi$  is bounded, locally Lipschitz continuous but possibly not Lipschitz. In this case, the conditional density functions  $g_k$  do not depend on  $k$  and read (where  $\Phi_0$  denotes the c.d.f. of the  $\mathcal{N}(0; 1)$ )

$$g_k(x, y, x', y') = \Phi_0\left(\frac{y - y' - \varphi(x)}{\sigma}\right).$$

Thus, if  $\varphi(x) = \sin(x^3)$ , then  $g_k$  will be of  $\text{Li}(1, 2)$ -type. This situation extend to any locally Lipschitz bounded function  $\varphi$  whose derivative has a “ $\theta$ -growth” at infinity.

Then we ask the transitions  $P_k(x, dy)$  to propagate this  $\theta$ -local Lipschitz property as a counterpart of  $(\mathcal{A}_1)$ . Let  $f : \mathbb{R}^d \rightarrow \mathbb{R}$  be  $\theta$ -locally Lipschitz with a local Lipschitz coefficient  $[f]_{\text{Liploc}}$  defined by

$$[f]_{\text{Liploc}} = \sup_{x \neq x'} \frac{|f(x) - f(x')|}{(1 + \theta(x) + \theta(x')) |x - x'|} < +\infty. \quad (63)$$

$$(\mathcal{A}_{1,\text{loc}}) \quad [P]_{\text{Liploc}} = \max_{k=1, \dots, n} [P_k]_{\text{Liploc}} < +\infty \quad \text{where} \quad [P_k]_{\text{Liploc}} = \sup_{[f]_{\text{Liploc}} \leq 1} [P_k f]_{\text{Liploc}}.$$

**Remark 6.1.** One easily checks that the transition kernels of the Euler scheme with step  $\frac{T}{n}$  (and Brownian increments) of a diffusion with Lipschitz continuous drift  $b$  and diffusion coefficient  $\sigma$  have the  $\theta$ -local Lipschitz property when  $\theta_\alpha(x) = |x|^\alpha$ ,  $\alpha > 0$ .

The following classical lemma is borrowed (and straightforwardly adapted) from [59] (Lemma 3.1).

**Lemma 6.1.** *Let  $\mu_y$  and  $\vartheta_y$  be two families of finite and positive measures on a measurable space  $(E, \mathcal{E})$ . Suppose that there exist two symmetric functions  $R$  and  $S$  defined on the set of positive finite measures such that, for every bounded  $\theta$ -Lipschitz function  $f$ ,*

$$\left| \int f d\mu_y - \int f d\vartheta_y \right|^2 \leq \|f\|_\infty^2 R(\mu_y, \vartheta_y) + [f]_{\text{Liploc}}^2 S(\mu_y, \vartheta_y). \quad (64)$$

Then,

$$\left| \frac{\int f d\mu_y}{\mu_y(E)} - \frac{\int f d\vartheta_y}{\vartheta_y(E)} \right| \leq 4 \frac{\|f\|_\infty^2 R(\mu_y, \vartheta_y) + \frac{1}{2} [f]_{\text{Liploc}}^2 S(\mu_y, \vartheta_y)}{\mu_y(E) \vee \vartheta_y(E)}. \quad (65)$$

In Theorem 6.3 below we will consider Assumption  $(\mathcal{H}_{\text{Liploc}})$  in place of Assumption  $(\mathcal{H}_0)$  (considered in [59]) to derive an error bound. This less stringent assumption is compensated by taking advantage of the *distortion mismatch* property established in Theorem 4.3. More precisely, we will need that the  $L^s$ -mean quantization error, for an  $s \in (2, 2 + d)$ , associated to any sequence of optimal quadratic quantizers at level  $N$  still goes to zero at the optimal rate  $N^{-\frac{1}{d}}$ .

The following lemma provides a control of the  $\theta$ -local Lipschitz coefficients of the functions  $u_{y,k}(f)$  defined recursively by (14).

Note that we drop the subscript related to the observations  $y$  in the conditional densities  $g_k$  as well as the function  $f$  in  $u_{y,k}(f)$  to alleviate notations in what follows.

**Proposition 6.2.** (a) *Assume that  $(\mathcal{I}_\theta)$ ,  $(\mathcal{H}_{\text{Liploc}})$  and  $(\mathcal{A}_{1,\text{loc}})$  hold and that, for every  $k = 1, \dots, n$ ,*

$$\mathbb{E}(\theta(X_k) | X_{k-1} = x) \leq C_{\theta, X}(1 + \theta(x)). \quad (66)$$

Let  $f : \mathbb{R}^d \rightarrow \mathbb{R}^d$  be  $\theta$ -locally Lipschitz function. Then, the functions  $u_k$  defined by (14) satisfy

$$[u_k]_{\text{Liploc}} \leq K_g^{n-k} \left[ \kappa_{g, X} \frac{[P]_{\text{Liploc}}^{n-k} - 1}{[P]_{\text{Liploc}} - 1} \|f\|_\infty + [P]_{\text{Liploc}}^{n-k} [f]_{\text{Liploc}} \right] \quad (\text{Convention: } \frac{1^n - 1}{1 - 1} = n) \quad (67)$$

where  $\kappa_{g, X} = 2C_{\theta, X}[g^1]_{\text{Liploc}} + [P]_{\text{Liploc}}[g^2]_{\text{Liploc}}$  and  $\|u\|_\infty \leq (K_g)^n \|f\|_\infty$ .

(b) Let  $(X_k)_{k=0, \dots, n}$  be the Markov chain defined as an iterated random map of the form

$$X_k = F_k(X_{k-1}, \varepsilon_k), \quad k = 1, \dots, n \quad (68)$$

where  $(\varepsilon_k)_{k=1,\dots,n}$  is an i.i.d sequence of random variables independent of  $X_0$ .

(i) If there exists some  $p \in (0, +\infty)$  such that

$$\theta(X_0) \in L^p \quad \text{and} \quad \|\theta(F_k(x, \varepsilon_1))\|_p \leq C'_{\theta, X}(1 + \theta(x)) \quad (69)$$

then  $\max_{k=0,\dots,n} \|\theta(X_k)\|_p < +\infty$ .

In particular, for  $p = 1$ , the chain satisfies the integrability assumption  $(\mathcal{I}_\theta)$  and (66).

(ii) If  $F_k(0, \varepsilon_1), \theta(X_0) \in L^2$  and, for every  $k \in \{1, \dots, n\}$ ,  $x, x' \in \mathbb{R}^d$ ,

$$\|\theta(F_k(x, \varepsilon_1))\|_2 \leq C'_{\theta, X}(1 + \theta(x)) \quad \text{and} \quad \|F_k(x, \varepsilon_1) - F_k(x', \varepsilon_1)\|_2 \leq [F_k]_{2, \text{Lip}}|x - x'|, \quad (70)$$

then both  $(\mathcal{I}_\theta)$  and  $(\mathcal{H}_{\text{Liploc}})$  are satisfied. To be more precise

$$\forall k = 1, \dots, n, \quad [P_k]_{\text{Liploc}} \leq \max(1, C'_{\theta, X})[F_k]_{2, \text{Lip}}.$$

**Remark 6.2.** Once again the Euler scheme with step  $\frac{T}{n}$  satisfies Assumption (66) with functions  $\theta_\alpha(x) = |x|^\alpha$ ,  $\alpha > 0$ .

*Proof.* (a) By the Markov property, we have for every  $k = 0, \dots, n-1$  and every  $x \in \mathbb{R}^d$ ,

$$u_k(x) = \mathbb{E}(u_{k+1}(X_{k+1})g_{k+1}(X_k, X_{k+1}) | X_k = x) = (P_{k+1}u_{k+1}g_{k+1}(x, \cdot))(x). \quad (71)$$

It follows that, for every  $k = 0, \dots, n-1$ ,  $\|u_k\|_\infty \leq K_g \|u_{k+1}\|_\infty$ , so that,

$$\|u_k\|_\infty \leq K_g^{n-k} \|f\|_\infty$$

since  $\|u_n\|_\infty = \|f\|_\infty$ . Let  $k \in \{0, \dots, n-1\}$ ; for every  $x, x' \in \mathbb{R}^d$ ,

$$\begin{aligned} |u_k(x) - u_k(x')| &\leq [g_{k+1}^1]_{\text{Liploc}} \|u_{k+1}\|_\infty (1 + \theta(x) + \theta(x') + \mathbb{E}(\theta(X_{k+1}) | X_k = x)) |x - x'| \\ &\quad + [P_{k+1}]_{\text{Liploc}} [u_{k+1}g_{k+1}(x', \cdot)]_{\text{Liploc}} (1 + \theta(x) + \theta(x')) |x - x'|. \end{aligned}$$

Now, still for every  $k = 0, \dots, n-1$ ,

$$\begin{aligned} |u_{k+1}(z)g_{k+1}(x', z) - u_{k+1}(z')g_{k+1}(x', z')| &\leq |u_{k+1}(z) - u_{k+1}(z')|g_{k+1}(x', z) \\ &\quad + |g_{k+1}(x', z) - g_{k+1}(x', z')| |u_{k+1}(z')| \\ &\leq K_g [u_{k+1}]_{\text{Liploc}} (1 + \theta(z) + \theta(z')) |z - z'| \\ &\quad + \|u_{k+1}\|_\infty [g_{k+1}^2]_{\text{Liploc}} (1 + \theta(z) + \theta(z')) |z - z'| \end{aligned}$$

so that

$$[u_{k+1}g_{k+1}(x', \cdot)]_{\text{Liploc}} \leq K_g [u_{k+1}]_{\text{Liploc}} + \|u_{k+1}\|_\infty [g_{k+1}^2]_{\text{Liploc}}.$$

Finally, collecting these inequalities, we deduce from Assumption (66) that, for every  $k = 0, \dots, n-1$ ,

$$\begin{aligned} [u_k]_{\text{Liploc}} &\leq (2C_{\theta, X} [g_{k+1}^1]_{\text{Liploc}} + [P_{k+1}]_{\text{Liploc}} [g_{k+1}^2]_{\text{Liploc}}) \|u_{k+1}\|_\infty + K_g [P_{k+1}]_{\text{Liploc}} [u_{k+1}]_{\text{Liploc}} \\ &\leq \kappa_{g, X} \|u_{k+1}\|_\infty + K_g [P]_{\text{Liploc}} [u_{k+1}]_{\text{Liploc}}. \end{aligned}$$

The conclusion follows by a backward induction (discrete time Gronwall's Lemma) having in mind that  $u_n = f$ .

(b) Claim (i) is obvious. As for claim (ii), let  $f$  be a  $\theta$ -locally Lipschitz with constant  $[f]_{\text{Liploc}}$ . Then, for every  $x, x' \in \mathbb{R}^d$  and every  $k = 1, \dots, n$ ,

$$\begin{aligned} |P_k f(x) - P_k f(x')| &= |\mathbb{E}f(F_k(x, \varepsilon_1)) - \mathbb{E}f(F_k(x', \varepsilon_1))| \\ &\leq [f]_{\text{Liploc}} \mathbb{E} \left( |F_k(x, \varepsilon_1) - F_k(x', \varepsilon_1)| (1 + \theta(F_k(x, \varepsilon_1)) + \theta(F_k(x', \varepsilon_1))) \right) \\ &\leq [f]_{\text{Liploc}} \|F_k(x, \varepsilon_1) - F_k(x', \varepsilon_1)\|_2 (1 + \|\theta(F_k(x, \varepsilon_1))\|_2 + \|\theta(F_k(x', \varepsilon_1))\|_2) \\ &\leq [f]_{\text{Liploc}} [F_k]_{2, \text{Lip}} |x - x'| (1 + C'_{\theta, X} \theta(x) + C'_{\theta, X} \theta(x')) \end{aligned}$$

where we used Schwarz's Inequality in the third line, and (70) and (69) in the last line. We deduce that  $[P_k]_{\text{Liploc}} \leq (1 \vee C'_{\theta, X})$ , for every  $k = 1, \dots, n$ .  $\square$

Notice that assumptions (66) and (69) hold when  $\theta$  is a polynomial convex function and when  $(X_k)_{0 \leq k \leq n}$  is the Euler scheme (with step  $\frac{T}{n}$  and horizon  $T$ ) associated with a stochastic differential equation of the form (21).

**Theorem 6.3.** *Let  $(\mathcal{H}_{\text{Liploc}})$  hold and assume that  $(\mathcal{A}_{1, \text{loc}})$  is fulfilled, as well as assumptions of Proposition 6.2. Suppose that for every  $k = 0, \dots, n$ ,  $X_k$  has an  $(2, 2 + \nu_k)$ -distribution (in the sense of Definition 4.1) for some  $\nu_k \in (0, d)$ , and set  $\bar{\nu}_n = \min_{k=0, \dots, n} \nu_k/2$ . Then for every  $\nu \in (0, \bar{\nu}_n)$ ,*

$$|\Pi_{y, n} f - \hat{\Pi}_{y, n} f|^2 \leq \frac{4(M_{n, \nu} K_g^n)^2}{\phi_n^2(y) \vee \hat{\phi}_n^2(y)} \sum_{k=0}^n B_k^n(f, y) \|X_k - \hat{X}_k\|_{2(1+\nu)}^2 \quad (72)$$

where

$$\phi_n(y) = \pi_{y, n} \mathbf{1} \quad \text{and} \quad \hat{\phi}_n(y) = \hat{\pi}_{y, n} \mathbf{1}$$

and

$$B_k^n(f, y) := 2^k \left( 2\kappa_{g, X}^2 \left( \frac{[P]_{\text{Liploc}}^{n-k} - 1}{[P]_{\text{Liploc}} - 1} \right)^2 + \frac{2[g^1]_{\text{Liploc}}^2 + [g^2]_{\text{Liploc}}^2}{K_g^2} + [P]_{\text{Liploc}}^{2(n-k)} \right)$$

with  $\kappa_{g, X} = 2C_{\theta, X}[g^1]_{\text{Liploc}} + [P]_{\text{Liploc}}[g^2]_{\text{Liploc}}$  and

$$M_{n, \nu} := 1 + \max_{k=0, \dots, n-1} \left( \|\theta(X_k)\|_{2(1+\frac{1}{\nu})} + \|\theta(\hat{X}_k)\|_{2(1+\frac{1}{\nu})} + \|\theta(X_{k+1})\|_{2(1+\frac{1}{\nu})} + \|\theta(\hat{X}_{k+1})\|_{2(1+\frac{1}{\nu})} \right).$$

Let us make few remarks about the assumptions of the theorem before dealing with the proof.

**Remark 6.3.** (a) If  $\theta$  is convex and if all  $\hat{X}_k$  are quadratic optimal quantizers, then it is stationary *i.e.* satisfies  $\hat{X}_k = \mathbb{E}(X_k | \hat{X}_k)$  so that, for every  $k = 0, \dots, n$ , we have, owing to the convexity of  $\theta^{2(1+\frac{1}{\nu})}$  and Jensen's Inequality,

$$\|\theta(\hat{X}_k)\|_{2(1+\frac{1}{\nu})} \leq \|\theta(X_k)\|_{2(1+\frac{1}{\nu})} < +\infty.$$

(b) Suppose that  $(X_k)_{k=0, \dots, n}$  is a Markov chain of iterated random maps

$$X_k = F_k(X_{k-1}, \varepsilon_k), \quad k = 1, \dots, n,$$

under the assumptions of Proposition 6.2. Assume it satisfies the  $\theta$ -local Lipschitz assumption with a function  $\theta(y) \geq C|y|^a$  for some real constants  $C, a > 0$ . If  $a > \frac{1}{2} \frac{(2+\nu)d}{d-\nu}$  for some  $\nu \in (0, d)$ , and the distributions of  $X_k$  are absolutely continuous, then, all  $X_k$  have an  $(2, 2 + \nu)$ -distribution.

*Proof.* Like in [59], the proof relies on the backward formulas (14) and (20) involving the functions  $u_{y, k}(f)$  and their quantized counterpart  $\hat{u}_{y, k}(f)$  whose final values  $u_{-1}$  and  $\hat{u}_{-1}$  define the unnormalized filter  $\pi_{y, n}(f)$  (applied to the function  $f$ ) and its quantized counterpart, respectively.

Following the lines of the proof of Theorem 3.1 in [59], one shows by a backward induction taking advantage of the Markov property that the functions  $u_k : \mathbb{R}^d \rightarrow \mathbb{R}$ ,  $k = 0, \dots, n$ , defined recursively by (14) satisfy  $u_n = f$  and

$$u_k(X_k) = \mathbb{E}_k(\varphi_{k+1}(X_k, X_{k+1})) = \mathbb{E}(\varphi_{k+1}(X_k, X_{k+1}) | X_k), \quad k = 0, \dots, n-1 \quad (73)$$

where

$$\varphi_{k+1}(x_k, x_{k+1}) := g_{k+1}(x_k, x_{k+1})u_{k+1}(x_{k+1}), \quad x_k, x_{k+1} \in \mathbb{R}^d.$$

Finally  $u_{-1} = \mathbb{E}(u_0(X_0)) = \pi_{y,n}(f)$  (un-normalized filter applied to  $f$ ). One shows likewise that the functions  $\hat{u}_k$  defined by (20) satisfy  $\hat{u}_n = f$  (on the grid  $\Gamma_n$ ) and

$$\hat{u}_k(\hat{X}_k) = \hat{\mathbb{E}}_k(\hat{u}_{k+1}(\hat{X}_{k+1})g_{k+1}(\hat{X}_k, \hat{X}_{k+1})), \quad k = 0, \dots, n-1, \quad (74)$$

so that finally  $\hat{u}_{-1}(f) = \mathbb{E}\hat{u}_0(\hat{X}_0) = \hat{\pi}_{y,n}(f)$  (quantized un-normalized filter). One shows like for the functions  $u_k$  in Proposition 6.2 that  $\|\hat{u}_k\|_\infty \leq K_g^{n-k}\|f\|_\infty$ . Now, using the definition of conditional expectation  $\hat{\mathbb{E}}_k$  as an orthogonal projection (hence an  $L^2$ -contraction as well), we have

$$\begin{aligned} \|u_k(X_k) - \hat{u}_k(\hat{X}_k)\|_2^2 &= \|u_k(X_k) - \hat{\mathbb{E}}_k(u_k(X_k))\|_2^2 + \|\hat{\mathbb{E}}_k(u_k(X_k)) - \hat{u}_k(\hat{X}_k)\|_2^2 \\ &\leq \|u_k(X_k) - \hat{\mathbb{E}}_k(u_k(X_k))\|_2^2 \\ &\quad + \|\varphi_{k+1}(X_k, X_{k+1}) - \hat{u}_{k+1}(\hat{X}_{k+1})g_{k+1}(\hat{X}_k, \hat{X}_{k+1})\|_2^2 \end{aligned} \quad (75)$$

where we used in the second line the tower property for conditional expectation to show that  $\hat{\mathbb{E}}_k(u_k(X_k)) = \hat{\mathbb{E}}_k(\varphi_{k+1}(X_k, X_{k+1}))$  (the  $\sigma$ -field  $\sigma(\hat{X}_k) \subset \mathcal{F}_k$ ) and the contraction property of  $\hat{\mathbb{E}}_k$ .

It follows now from the definition of the conditional expectation  $\hat{\mathbb{E}}_k(\cdot)$  as the best approximation in  $L^2$  among square integrable  $\sigma(\hat{X}_k)$ -measurable random vectors that

$$\|u_k(X_k) - \hat{\mathbb{E}}_k(u_k(X_k))\|_2^2 \leq \|u_k(X_k) - u_k(\hat{X}_k)\|_2^2 \leq [u_k]_{\text{Liploc}}^2 \|(1 + \theta(X_k) + \theta(\hat{X}_k))(X_k - \hat{X}_k)\|_2^2.$$

Let  $\nu \in (0, \bar{\nu}_n)$ , so that for every  $k = 0, \dots, n$ ,  $2(1 + \nu) \leq 2 + \nu_k$ . Hölder's inequality with conjugate exponents  $p_\nu = 1 + \nu$  and  $q_\nu = 1 + \frac{1}{\nu}$  gives

$$\|u_k(X_k) - \hat{\mathbb{E}}_k(u_k(X_k))\|_2^2 \leq [u_k]_{\text{Liploc}}^2 \|1 + \theta(X_k) + \theta(\hat{X}_k)\|_{2q_\nu}^2 \|X_k - \hat{X}_k\|_{2(1+\nu)}^2.$$

Let us deal now with the second term on the right hand side of (75) and set for convenience

$$\Delta_k := \varphi_{k+1}(X_k, X_{k+1}) - \hat{u}_{k+1}(\hat{X}_{k+1})g_{k+1}(\hat{X}_k, \hat{X}_{k+1}).$$

By the triangle inequality and the boundedness of  $g_{k+1}$ , we get

$$\begin{aligned} |\Delta_k| &\leq |(u_{k+1}(X_{k+1}) - \hat{u}_{k+1}(\hat{X}_{k+1}))g_{k+1}(X_k, X_{k+1})| \\ &\quad + |\hat{u}_{k+1}(\hat{X}_{k+1})(g_{k+1}(X_k, X_{k+1}) - g_{k+1}(\hat{X}_k, \hat{X}_{k+1}))| \\ &\leq K_g |u_{k+1}(X_{k+1}) - \hat{u}_{k+1}(\hat{X}_{k+1})| + \|\hat{u}_{k+1}\|_\infty |g_{k+1}(X_k, X_{k+1}) - g_{k+1}(\hat{X}_k, \hat{X}_{k+1})| \end{aligned}$$

so that

$$\|\Delta_k\|_2^2 \leq 2K_g^2 \|u_{k+1}(X_{k+1}) - \hat{u}_{k+1}(\hat{X}_{k+1})\|_2^2 + 2\|\hat{u}_{k+1}\|_\infty^2 \|g_{k+1}(X_k, X_{k+1}) - g_{k+1}(\hat{X}_k, \hat{X}_{k+1})\|_2^2.$$

It follows from ( $\mathcal{H}_{\text{Liploc}}$ ), Hölder (still with  $p_\nu$  and  $q_\nu$ ) and Minkowski inequalities that

$$\begin{aligned} \|g_{k+1}(X_k, X_{k+1}) - g_{k+1}(\hat{X}_k, \hat{X}_{k+1})\|_2^2 &\leq [g_{k+1}^2]_{\text{Liploc}}^2 \mathbb{E} \left[ (1 + \theta(X_k) + \theta(\hat{X}_k) + \theta(X_{k+1}) + \theta(\hat{X}_{k+1}))^2 |X_{k+1} - \hat{X}_{k+1}|^2 \right] \\ &\quad + [g_{k+1}^1]_{\text{Liploc}}^2 \mathbb{E} \left[ (1 + \theta(X_k) + \theta(\hat{X}_k) + \theta(X_{k+1}) + \theta(\hat{X}_{k+1}))^2 |X_k - \hat{X}_k|^2 \right]. \\ &\leq (M_{k,\nu})^2 \left( [g_{k+1}^2]_{\text{Liploc}}^2 \|X_{k+1} - \hat{X}_{k+1}\|_{2(1+\nu)}^2 + [g_{k+1}^1]_{\text{Liploc}}^2 \|X_k - \hat{X}_k\|_{2(1+\nu)}^2 \right) \end{aligned}$$

where  $M_{k,\nu} := 1 + \|\theta(X_k)\|_{2q_\nu} + \|\theta(\hat{X}_k)\|_{2q_\nu} + \|\theta(X_{k+1})\|_{2q_\nu} + \|\theta(\hat{X}_{k+1})\|_{2q_\nu}$ .

Plugging these bounds in (75), we finally get that, for every  $k = 0, \dots, n-1$ ,

$$\|u_k(X_k) - \hat{u}_k(\hat{X}_k)\|_2^2 \leq \tilde{K} \|u_{k+1}(X_{k+1}) - \hat{u}_{k+1}(\hat{X}_{k+1})\|_2^2 + \alpha_k \|X_k - \hat{X}_k\|_{2(1+\nu)}^2 + \beta_{k+1} \|X_{k+1} - \hat{X}_{k+1}\|_{2(1+\nu)}^2$$



where  $\tilde{K} = 2(K_g)^2$

$$\alpha_k := (M_{k,\nu})^2 ([u_k]_{\text{Liploc}}^2 + 2\|\hat{u}_{k+1}\|_\infty^2 [g_{k+1}^1]_{\text{Liploc}}^2), \quad 0 \leq k \leq n,$$

and

$$\beta_k := 2 (M_{k,\nu} \|\hat{u}_k\|_\infty [g_k^2]_{\text{Liploc}})^2, \quad 1 \leq k \leq n,$$

(we set  $u_{n+1} = 0$  by convention so that  $\alpha_n := ([f]_{\text{Liploc}} M_{n,\nu})^2$ ). It follows by induction that

$$\|u_k(X_k) - \hat{u}_k(\hat{X}_k)\|_2^2 \leq \frac{1}{\tilde{K}^k} \sum_{\ell=k}^n C_{\ell,n}(f, y) \|X_\ell - \hat{X}_\ell\|_{2(1+\nu)}^2, \quad k = 0, \dots, n,$$

where, using the upper-bound for  $[u_\ell]_{\text{Liploc}}$  given by (67) (and the definition of  $\kappa_{g,X}$  that follows),

$$\begin{aligned} C_{\ell,n}(f, y) &:= \tilde{K}^{\ell-1} (\alpha_\ell \tilde{K} + \beta_\ell), \quad \ell = 0, \dots, n \\ &= 2^\ell (M_{\ell,\nu})^2 \left( (K_g)^{2\ell} [u_\ell]_{\text{Liploc}}^2 + (K_g)^{2(n-1)} \|f\|_\infty^2 (2[g_{\ell+1}^1]_{\text{Liploc}}^2 + [g_\ell^2]_{\text{Liploc}}^2) \right) \\ &\leq 2^{\ell+1} (M_{\ell,\nu} (K_g)^n)^2 \left[ \left( \kappa_{g,X}^2 \left( \frac{[P]_{\text{Liploc}}^{n-\ell} - 1}{[P]_{\text{Liploc}} - 1} \right)^2 + \frac{2[g^1]_{\text{Liploc}}^2 + [g^2]_{\text{Liploc}}^2}{2(K_g)^2} \right) \|f\|_\infty^2 \right. \\ &\quad \left. + [P]_{\text{Liploc}}^{2(n-\ell)} [f]_{\text{Liploc}}^2 \right] \end{aligned}$$

(we also used the elementary inequality  $ab \leq \frac{1}{2}(a^2 + b^2)$ ,  $a, b \geq 0$  in the third line). Finally

$$\begin{aligned} |\pi_{y,n} f - \hat{\pi}_{y,n} f|^2 &= |\mathbb{E} u_0(X_0) - \mathbb{E} \hat{u}_0(\hat{X}_0)|^2 \\ &\leq \|u_0(X_0) - \hat{u}_0(\hat{X}_0)\|_2^2 \\ &\leq ((K_g)^n M_{n,\nu})^2 (R_{y,n} \|f\|_\infty^2 + S_{y,n} [f]_{\text{Liploc}}^2) \end{aligned}$$

where

$$R_{y,n} = \sum_{\ell=0}^n \left[ 2^{\ell+1} \left( \kappa_{g,X}^2 \left( \frac{[P]_{\text{Liploc}}^{n-\ell} - 1}{[P]_{\text{Liploc}} - 1} \right)^2 + \frac{2[g^1]_{\text{Liploc}}^2 + [g^2]_{\text{Liploc}}^2}{2(K_g)^2} \right) \|X_\ell - \hat{X}_\ell\|_{2(1+\nu)}^2 \right]$$

and

$$S_{y,n} = \sum_{\ell=0}^n 2^{\ell+1} [P]_{\text{Liploc}}^{2(n-\ell)} \|X_\ell - \hat{X}_\ell\|_{2(1+\nu)}^2.$$

We conclude by Lemma 6.1. □

The previous theorem highlights the usefulness of the distortion mismatch result: it allows to switch from Lipschitz continuous assumptions on the functions  $g_k$  into *local Lipschitz* assumptions.

**Remark 6.4.** Note that if we consider Assumption  $(\mathcal{H}_0)$  instead of Assumption  $(\mathcal{H}_{\text{Liploc}})$  in Theorem 6.3 *we still improve the upper bound established in Theorem 3.1 of [59] since this amounts to setting  $\theta \equiv 0$  and replacing everywhere the “[.]<sub>Liploc</sub>” coefficients by [.]<sub>Lip</sub>*. Then, like for BSDEs, the squared global error appears as the (weighted) cumulated sum of the squared quantization errors.

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## A Proof of Theorem 3.1

**Proof of Theorem 3.1.** STEP 1. Temporarily set for convenience  $\bar{s} = t_{k+1}$  for  $s \in [t_k, t_{k+1})$ . Applying Itô's formula we have

$$\begin{aligned} e^{\alpha T} \tilde{Y}_T^2 &= e^{\alpha t} \tilde{Y}_t^2 + \int_t^T \alpha e^{\alpha s} \tilde{Y}_s^2 ds + 2 \int_t^T e^{\alpha s} \tilde{Y}_s d\tilde{Y}_s + \int_t^T e^{\alpha s} |\tilde{Z}_s|^2 ds \\ &= e^{\alpha t} \tilde{Y}_t^2 + \int_t^T e^{\alpha s} [\alpha \tilde{Y}_s^2 + |\tilde{Z}_s|^2 + 2\tilde{Y}_s f(\underline{s}, \bar{X}_{\underline{s}}, \mathbb{E}_{\underline{s}}(\tilde{Y}_{\bar{s}}), \zeta_{\underline{s}})] ds + 2 \int_t^T e^{\alpha s} \tilde{Z}_s dW_s. \end{aligned}$$

As  $f$  is Lipschitz continuous in  $(t, x, y, z)$ , it is straightforward, setting  $C(f) = [f]_{\text{Lip}} + |f(0, 0, 0, 0)|$ , that

$$\forall t \in [0, T], \forall (x, y, z) \in \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^q, \quad |f(t, x, y, z)| \leq C(f)(1 + |x| + |y| + |z|). \quad (76)$$

Then, it follows that

$$e^{\alpha T} \tilde{Y}_T^2 \leq e^{\alpha t} \tilde{Y}_t^2 + \int_t^T e^{\alpha s} [\alpha \tilde{Y}_s^2 + |\tilde{Z}_s|^2 + 2\tilde{Y}_s C(f)(1 + |\bar{X}_{\underline{s}}| + |\mathbb{E}_{\underline{s}}(\tilde{Y}_{\bar{s}})| + |\zeta_{\underline{s}}|)] ds + 2 \int_t^T e^{\alpha s} \tilde{Z}_s dW_s.$$

Owing to Young's inequality ( $ab \leq \frac{a^2}{2\theta} + \frac{\theta b^2}{2}$ , for every  $\theta > 0$  and  $a, b \geq 0$ ) we get

$$\begin{aligned} e^{\alpha t} \tilde{Y}_t^2 &\leq e^{\alpha T} \tilde{Y}_T^2 - \alpha \int_t^T e^{\alpha s} |\tilde{Y}_s|^2 ds - \int_t^T e^{\alpha s} |\tilde{Z}_s|^2 ds + \theta C(f) \int_t^T e^{\alpha s} \tilde{Y}_s^2 ds \\ &\quad + \frac{C(f)}{\theta} \int_t^T e^{\alpha s} (1 + |\bar{X}_{\underline{s}}|^2 + |\mathbb{E}_{\underline{s}}(\tilde{Y}_{\bar{s}})|^2 + |\zeta_{\underline{s}}|^2) ds - 2 \int_t^T e^{\alpha s} \tilde{Z}_s dW_s \\ &\leq e^{\alpha T} \tilde{Y}_T^2 + (\theta C(f) - \alpha) \int_t^T e^{\alpha s} \tilde{Y}_s^2 ds - \int_t^T e^{\alpha s} |\tilde{Z}_s|^2 ds \\ &\quad + \frac{C(f)}{\theta} \int_t^T e^{\alpha s} (1 + |\bar{X}_{\underline{s}}|^2 + |\mathbb{E}_{\underline{s}}(\tilde{Y}_{\bar{s}})|^2 + |\zeta_{\underline{s}}|^2) ds - 2 \int_t^T e^{\alpha s} \tilde{Z}_s dW_s. \end{aligned}$$

After choosing  $\alpha$  and  $\theta$  such that  $\theta C(f) - \alpha < 0$ , we take the expectation in both sides of the previous inequality and use the fact that  $\mathbb{E}|\mathbb{E}_{\underline{s}}(\tilde{Y}_{\bar{s}})|^2 \leq \mathbb{E}|\tilde{Y}_{\bar{s}}|^2$  (owing to conditional Jensen inequality) to get

$$e^{\alpha t} \mathbb{E}(\tilde{Y}_t^2) + \int_t^T e^{\alpha s} \mathbb{E}|\tilde{Z}_s|^2 ds \leq e^{\alpha T} \mathbb{E}(\tilde{Y}_T^2) + \frac{C(f)}{\theta} \int_t^T e^{\alpha s} (1 + \mathbb{E}|\bar{X}_{\underline{s}}|^2 + \mathbb{E}(\tilde{Y}_{\bar{s}}^2) + \mathbb{E}|\zeta_{\underline{s}}|^2) ds.$$

Owing to the fact that  $\mathbb{E}(\sup_{t \in [0, T]} |\bar{X}_t|^2) \leq C_X(1 + \mathbb{E}|X_0|^2)$  and setting  $t = t_k$ , we have

$$\begin{aligned} e^{\alpha t_k} \mathbb{E}(\tilde{Y}_{t_k}^2) + \int_{t_k}^T e^{\alpha s} \mathbb{E}|\tilde{Z}_s|^2 ds &\leq e^{\alpha T} \mathbb{E}(\tilde{Y}_T^2) + \frac{C(f)}{\theta} \left( \frac{e^{\alpha T} - e^{\alpha t_k}}{\alpha} + C_X(1 + \mathbb{E}|X_0|^2) \right) \\ &\quad + \frac{C(f)}{\theta} \sum_{\ell=k}^{n-1} e^{\alpha t_\ell} \mathbb{E}|\tilde{Y}_{t_{\ell+1}}|^2 + \frac{C(f)}{\theta} \int_{t_k}^T e^{\alpha s} \mathbb{E}|\zeta_{\underline{s}}|^2 ds. \end{aligned}$$

On the other hand, we have

$$\tilde{\zeta}_{t_\ell} = \frac{1}{\Delta_n} \mathbb{E}_\ell \int_{t_\ell}^{t_{\ell+1}} \tilde{Z}_s ds, \quad \text{so that by Jensen's inequality, } |\tilde{\zeta}_{t_\ell}|^2 \leq \frac{1}{\Delta_n} \mathbb{E}_\ell \int_{t_\ell}^{t_{\ell+1}} |\tilde{Z}_s|^2 ds. \quad (77)$$

It follows that

$$\begin{aligned} \int_{t_k}^T e^{\alpha s} \mathbb{E} |\zeta_s|^2 ds &\leq \frac{1}{\Delta_n^2} \mathbb{E} \sum_{\ell=k}^{n-1} \int_{t_\ell}^{t_{\ell+1}} e^{\alpha s} \left( \int_{t_\ell}^{t_{\ell+1}} |\tilde{Z}_u|^2 du \right) ds \\ &\leq \frac{e^{\alpha \Delta_n} - 1}{\alpha \Delta_n} \mathbb{E} \sum_{\ell=k}^{n-1} \int_{t_\ell}^{t_{\ell+1}} e^{\alpha s} |\tilde{Z}_u|^2 du = \frac{e^{\alpha \Delta_n} - 1}{\alpha \Delta_n} \int_{t_k}^T e^{\alpha s} \mathbb{E} |\tilde{Z}_u|^2 du. \end{aligned}$$

Since  $e^{\alpha \Delta_n} - 1 \leq \alpha \Delta_n e^{\alpha \Delta_n}$ , we have

$$\begin{aligned} e^{\alpha t_k} \mathbb{E} |\tilde{Y}_{t_k}|^2 + \int_{t_k}^T e^{\alpha s} \mathbb{E} |\tilde{Z}_s|^2 ds &\leq e^{\alpha T} \mathbb{E} |\tilde{Y}_T|^2 + \frac{C(f)}{\theta \alpha} e^{\alpha T} + \frac{C(f)}{\theta} C_X (1 + \mathbb{E} |X_0|^2) \\ &\quad + \frac{\Delta C(f)}{\theta} \sum_{\ell=k}^{n-1} e^{\alpha t_{\ell+1}} \mathbb{E} |\tilde{Y}_{t_{\ell+1}}|^2 + \frac{C(f)}{\theta} e^{\alpha \Delta_n} \int_{t_k}^T e^{\alpha s} \mathbb{E} |\tilde{Z}_u|^2 ds. \end{aligned}$$

Now, let us choose  $\theta$  so that  $\frac{C(f)}{\theta} e^{\alpha \Delta_n} < 1$ . Owing to the fact that  $\theta C(f) < \alpha$ , this implies that  $C(f) e^{\alpha \Delta_n} < \theta < \frac{\alpha}{C(f)}$ . This constraint holds true if  $e^{\alpha \Delta_n} < \frac{\alpha}{C(f)^2}$ . Taking  $\alpha > C(f)^2 (T \vee 1)$  and owing to the fact that  $e^{\alpha \Delta_n} \rightarrow 1$  as  $n$  goes to infinity we may consequently choose  $\theta \in (C(f)(e^{\alpha \Delta_n} \vee T), \frac{\alpha}{C(f)})$ , for every  $n \geq n_0 \in \mathbb{N}$ . Setting

$$C^{(1,1)} = e^{\alpha T} \mathbb{E} |\tilde{Y}_T|^2 + \frac{C(f)}{\theta \alpha} e^{\alpha T} + \frac{C(f)}{\theta} C_X (1 + \mathbb{E} |X_0|^2), \quad C^{(1,2)} = \frac{C(f)}{\theta} \quad \text{and} \quad C^{(1,3)} = \frac{C(f)}{\theta} e^{\alpha \Delta_n},$$

it follows that, for every  $n \geq n_0$ ,

$$e^{\alpha t_k} \mathbb{E} |\tilde{Y}_{t_k}|^2 + (1 - C^{(1,3)}) \int_{t_k}^T e^{\alpha s} \mathbb{E} |\tilde{Z}_s|^2 ds \leq C^{(1,1)} + \Delta C^{(1,2)} \sum_{\ell=k+1}^n e^{\alpha t_\ell} \mathbb{E} |\tilde{Y}_{t_\ell}|^2. \quad (78)$$

In particular we have  $\mathbb{E} |\tilde{Y}_T|^2 = \mathbb{E} \xi^2 \leq C^{(1,1)}$  and

$$e^{\alpha t_k} \mathbb{E} |\tilde{Y}_{t_k}|^2 \leq C^{(1,1)} + \Delta_n C^{(1,2)} \sum_{\ell=k+1}^n e^{\alpha t_\ell} \mathbb{E} |\tilde{Y}_{t_\ell}|^2, \quad \forall k \in \{0, \dots, n-1\}. \quad (79)$$

Since  $\theta > TC(f)$  then  $TC^{(1,2)} < 1$  and we may show by induction that if  $A \geq C^{(1,1)}/(1 - TC^{(1,2)})$  then

$$\sup_{k=0, \dots, n} e^{\alpha t_k} \mathbb{E} |\tilde{Y}_{t_k}|^2 \leq A \quad \text{so that} \quad \sup_{k=0, \dots, n} \mathbb{E} |\tilde{Y}_{t_k}|^2 \leq A.$$

Now, setting  $k = 0$  in (78) we get

$$\sup_{n \geq 0} \int_0^T e^{\alpha s} \mathbb{E} |\tilde{Z}_s|^2 ds \leq \frac{C^{(1,1)}}{1 - C^{(1,3)}} + \frac{n-k}{n} \frac{C^{(1,2)}}{1 - C^{(1,3)}} A \times T \leq \frac{C^{(1,1)}}{1 - C^{(1,3)}} + \frac{C^{(1,2)}}{1 - C^{(1,3)}} A \times T.$$

Furthermore, since  $|\tilde{\zeta}_{t_k}|^2 \leq \frac{1}{\Delta_n} \mathbb{E}_k \int_{t_k}^{t_{k+1}} |\tilde{Z}_s|^2 ds$  (see (77)), we deduce that

$$\Delta_n \sum_{k=0}^{n-1} \mathbb{E} |\tilde{\zeta}_{t_k}|^2 \leq \int_{t_k}^{t_{k+1}} \mathbb{E} |\tilde{Z}_s|^2 ds \leq C^{(1,4)}$$

where  $C^{(1,4)}$  is a positive real constant not depending on  $n$ .

STEP 2. We show that  $\tilde{Y}$  satisfies

$$\forall t \in [0, T], \mathbb{E}|\tilde{Y}_t - \tilde{Y}_{\underline{t}}|^2 \leq C_{b,\sigma,f,T}|t - \underline{t}|, \quad C_{b,\sigma,f,T} > 0.$$

In fact, we have for every  $t \in [t_k, t_{k+1}]$ ,

$$\tilde{Y}_t = \tilde{Y}_{t_k} - (t - t_k)f(t_k, \bar{X}_{t_k}, \mathbb{E}(\tilde{Y}_{t_{k+1}}|\mathcal{F}_{t_k}), \tilde{\zeta}_{t_k}) + \int_{t_k}^t \tilde{Z}_s dW_s.$$

Then, using Assumption (76) yields

$$\mathbb{E}|\tilde{Y}_t - \tilde{Y}_{t_k}|^2 \leq 8C(f)^2(t - t_k)^2(1 + \mathbb{E}|\bar{X}_{t_k}|^2 + \mathbb{E}|\tilde{Y}_{t_{k+1}}|^2 + \mathbb{E}|\tilde{\zeta}_{t_k}|^2) + 2 \int_{t_k}^t \mathbb{E}|\tilde{Z}_s|^2 ds.$$

Now, thanks to the previous step we know that

$$\sup_{s \in [t_k, t]} \mathbb{E}|\tilde{Z}_s|^2 < +\infty, \quad \sup_{k \in \{0, \dots, n\}} \mathbb{E}|\tilde{Y}_{t_k}|^2 < +\infty \text{ and } \sup_{n \geq 1} \sup_{k \in \{0, \dots, n\}} \mathbb{E}|\tilde{\zeta}_{t_k}|^2 < +\infty.$$

We also know that  $\sup_{n \geq 1} \sup_{k \in \{0, \dots, n\}} \mathbb{E}|\bar{X}_{t_k}|^2 < +\infty$ . As a consequence, there exists a positive real constant  $C_{b,\sigma,f,T}$  such that for every  $t \in [t_k, t_{k+1}]$ ,

$$\forall t \in [t_k, t_{k+1}], \quad \mathbb{E}|\tilde{Y}_t - \tilde{Y}_{t_k}|^2 \leq C_{b,\sigma,f,T}|t - t_k|, \quad k = 0, \dots, n-1.$$

STEP 3. Let  $t \in [0, T]$ . It follows from Itô's formula that

$$\begin{aligned} e^{\alpha t}|Y_t - \tilde{Y}_t|^2 &= 2 \int_t^T e^{\alpha s}(Y_s - \tilde{Y}_s)(f(s, X_s, Y_s, Z_s) - f(s, \bar{X}_{\underline{s}}, \mathbb{E}_{\underline{s}}(\tilde{Y}_{\bar{s}}), \tilde{\zeta}_{\underline{s}})) ds \\ &\quad - \alpha \int_t^T e^{\alpha s}|Y_s - \tilde{Y}_s|^2 ds - \int_t^T e^{\alpha s}|Z_s - \tilde{Z}_s|^2 ds + 2 \int_t^T e^{\alpha s}(Z_s - \tilde{Z}_s) dW_s \\ &\leq 2 \int_t^T e^{\alpha s} [f]_{\text{Lip}} |Y_s - \tilde{Y}_s| (\Delta_n^2 + |X_s - \bar{X}_{\underline{s}}|^2 + |Y_s - \mathbb{E}_{\underline{s}}(\tilde{Y}_{\bar{s}})|^2 + |Z_s - \tilde{\zeta}_{\underline{s}}|^2)^{\frac{1}{2}} ds \\ &\quad - \alpha \int_t^T e^{\alpha s}|Y_s - \tilde{Y}_s|^2 ds - \int_t^T e^{\alpha s}|Z_s - \tilde{Z}_s|^2 ds + 2 \int_t^T e^{\alpha s}(Z_s - \tilde{Z}_s) dW_s. \end{aligned}$$

Using the Young inequality:  $ab \leq \frac{\theta}{2}a^2 + \frac{1}{2\theta}b^2$ ,  $\forall \theta > 0$ , yields

$$\begin{aligned} e^{\alpha t}|Y_t - \tilde{Y}_t|^2 &\leq [f]_{\text{Lip}} \int_t^T e^{\alpha s} \left( \theta |Y_s - \tilde{Y}_s|^2 + \frac{1}{\theta} (\Delta_n^2 + |X_s - \bar{X}_{\underline{s}}|^2 + |Y_s - \mathbb{E}_{\underline{s}}(\tilde{Y}_{\bar{s}})|^2 + |Z_s - \tilde{\zeta}_{\underline{s}}|^2) \right) ds \\ &\quad - \alpha \int_t^T e^{\alpha s}|Y_s - \tilde{Y}_s|^2 ds - \int_t^T e^{\alpha s}|Z_s - \tilde{Z}_s|^2 ds + 2 \int_t^T e^{\alpha s}(Z_s - \tilde{Z}_s) dW_s. \quad (80) \end{aligned}$$

The stochastic integral on the right hand side of the previous inequality is a martingale since both  $Z$  and  $\tilde{Z}$  lie in  $L^2([0, T] \times \Omega, dt \otimes d\mathbb{P})$ . On the other hand, owing to the error bound for the Euler scheme and the fact that  $X$  is an Itô process, we get

$$\mathbb{E}|X_s - \bar{X}_{\underline{s}}|^2 \leq 2(C^{(3,1)}\mathbb{E}|X_s - X_{\underline{s}}|^2 + C^{(3,2)}\mathbb{E}|X_{\underline{s}} - \bar{X}_{\underline{s}}|^2) \leq C^{(3,3)}\Delta_n,$$

for some positive real constants  $C^{(3,1)}$ ,  $C^{(3,2)}$  and  $C^{(3,3)}$ . Then, taking the expectation in (80) and using the fact that

$$\mathbb{E}|Y_s - \mathbb{E}_{\underline{s}}(\tilde{Y}_{\bar{s}})|^2 \leq 2\mathbb{E}|Y_s - \tilde{Y}_s|^2 + 2\mathbb{E}|\tilde{Y}_s - \mathbb{E}_{\underline{s}}(\tilde{Y}_{\bar{s}})|^2$$

yield

$$\begin{aligned} \mathbb{E}\left(e^{\alpha t}|Y_t - \tilde{Y}_t|^2 + \int_t^T e^{\alpha s}|Z_s - \tilde{Z}_s|^2 ds\right) &\leq \left(-\alpha + [f]_{\text{Lip}}\left(\theta + \frac{2}{\theta}\right)\right) \int_t^T e^{\alpha s}\mathbb{E}|Y_s - \tilde{Y}_s|^2 ds \\ &+ \frac{[f]_{\text{Lip}}}{\theta} \left(\frac{e^{\alpha T} - e^{\alpha t}}{\alpha}(\Delta_n^2 + C^{(3,3)}\Delta_n) + 2 \int_t^T e^{\alpha s}\mathbb{E}|\tilde{Y}_s - \mathbb{E}_{\underline{s}}(\tilde{Y}_{\underline{s}})|^2 ds + \int_t^T e^{\alpha s}\mathbb{E}|Z_s - \tilde{\zeta}_{\underline{s}}|^2 ds\right). \end{aligned} \quad (81)$$

We notice that for every  $k \in \{0, \dots, n-1\}$  and for every  $s \in [t_k, t_{k+1})$ ,

$$\tilde{\zeta}_{\underline{s}} = \frac{1}{\Delta_n} \mathbb{E}_k \int_{t_k}^{t_{k+1}} \tilde{Z}_s ds \in \arg \min_{a \in \mathcal{F}_{t_k}} \mathbb{E}_k \int_{t_k}^{t_{k+1}} |\tilde{Z}_s - a|^2 ds$$

and

$$\zeta_{\underline{s}} := \frac{1}{\Delta_n} \mathbb{E}_k \int_{t_k}^{t_{k+1}} Z_s ds \in \arg \min_{a \in \mathcal{F}_{t_k}} \mathbb{E}_k \int_{t_k}^{t_{k+1}} |Z_s - a|^2 ds,$$

where  $a \in \mathcal{F}_{t_k}$  means that  $a$  is an  $\mathbb{R}^q$ -valued  $\mathcal{F}_{t_k}$ -measurable random vector. Then, using the inequality  $\mathbb{E}_k|Z_s - \tilde{\zeta}_{\underline{s}}|^2 \leq 2\mathbb{E}_k|Z_s - \zeta_{\underline{s}}|^2 + 2\mathbb{E}_k|\zeta_{\underline{s}} - \tilde{\zeta}_{\underline{s}}|^2$ , we get

$$\begin{aligned} \int_{t_k}^{t_{k+1}} e^{\alpha s} \mathbb{E}_k |Z_s - \tilde{\zeta}_{\underline{s}}|^2 ds &\leq 2 \int_{t_k}^{t_{k+1}} e^{\alpha s} \mathbb{E}_k |Z_s - \zeta_{\underline{s}}|^2 ds + 2 \int_{t_k}^{t_{k+1}} e^{\alpha s} \mathbb{E}_k |\zeta_{\underline{s}} - \tilde{\zeta}_{\underline{s}}|^2 ds \\ &\leq 2 \int_{t_k}^{t_{k+1}} e^{\alpha s} \mathbb{E}_k |Z_s - Z_{\underline{s}}|^2 ds + \frac{2}{\Delta_n^2} \int_{t_k}^{t_{k+1}} e^{\alpha s} \mathbb{E}_k \left| \mathbb{E}_k \int_{t_k}^{t_{k+1}} (Z_u - \tilde{Z}_u) du \right|^2 ds. \end{aligned} \quad (82)$$

Now, owing to the Cauchy-Schwarz inequality, we have

$$\begin{aligned} \int_{t_k}^{t_{k+1}} e^{\alpha s} \mathbb{E}_k \left| \mathbb{E}_k \int_{t_k}^{t_{k+1}} (Z_u - \tilde{Z}_u) du \right|^2 ds &\leq \Delta_n \int_{t_k}^{t_{k+1}} e^{\alpha s} ds \mathbb{E}_k \int_{t_k}^{t_{k+1}} |Z_u - \tilde{Z}_u|^2 du \\ &= \Delta_n \frac{e^{\alpha \Delta_n} - 1}{\alpha} e^{\alpha t_k} \mathbb{E}_k \int_{t_k}^{t_{k+1}} |Z_u - \tilde{Z}_u|^2 du \\ &\leq \Delta_n \frac{e^{\alpha \Delta_n} - 1}{\alpha} \mathbb{E}_k \int_{t_k}^{t_{k+1}} e^{\alpha s} |Z_u - \tilde{Z}_u|^2 du. \end{aligned}$$

Consequently, taking the expectation in (82) leads to

$$\int_{t_k}^{t_{k+1}} e^{\alpha s} \mathbb{E} |Z_s - \tilde{\zeta}_{\underline{s}}|^2 ds \leq 2 \int_{t_k}^{t_{k+1}} e^{\alpha s} \mathbb{E} |Z_s - Z_{\underline{s}}|^2 ds + 2 \frac{e^{\alpha \Delta_n} - 1}{\alpha \Delta_n} \int_{t_k}^{t_{k+1}} e^{\alpha s} \mathbb{E} |Z_u - \tilde{Z}_u|^2 du$$

Coming back to Inequality (81) and setting  $\alpha = \alpha(\theta) = [f]_{\text{Lip}}\left(\theta + \frac{2}{\theta}\right)$  yields

$$\begin{aligned} \mathbb{E}\left(e^{\alpha t}|Y_t - \tilde{Y}_t|^2 + \int_t^T e^{\alpha s}|Z_s - \tilde{Z}_s|^2 ds\right) &\leq \frac{[f]_{\text{Lip}}}{\theta} \left(\Delta_n C_{b,\sigma,T} + 2 \int_t^T e^{\alpha s} \mathbb{E}|\tilde{Y}_s - \mathbb{E}_{\underline{s}}(\tilde{Y}_{\underline{s}})|^2 ds \right. \\ &\quad \left. + 2 \frac{e^{\alpha \Delta_n} - 1}{\alpha \Delta_n} \int_t^T e^{\alpha s} \mathbb{E}|Z_u - \tilde{Z}_u|^2 du \right. \\ &\quad \left. + 2 \int_t^T e^{\alpha s} \mathbb{E}|Z_s - Z_{\underline{s}}|^2 ds\right). \end{aligned}$$

Owing to Step 2, we have for every  $t \in [0, T]$ ,  $\mathbb{E}|\tilde{Y}_t - \tilde{Y}_{\underline{t}}|^2 \leq C_{b,\sigma,f,T}(t - \underline{t})$  with  $C_{b,\sigma,f,T} > 0$  so that, using the conditional Jensen inequality we get

$$\begin{aligned} \mathbb{E}|\tilde{Y}_s - \mathbb{E}_{\underline{s}}(\tilde{Y}_{\underline{s}})|^2 &\leq 2\mathbb{E}|\tilde{Y}_s - \tilde{Y}_{\underline{s}}|^2 + 2\mathbb{E}|\mathbb{E}_{\underline{s}}(\tilde{Y}_{\underline{s}}) - \tilde{Y}_{\underline{s}}|^2 \\ &\leq 2\mathbb{E}|\tilde{Y}_s - \tilde{Y}_{\underline{s}}|^2 + 2\mathbb{E}|\tilde{Y}_{\underline{s}} - \tilde{Y}_{\underline{s}}|^2 \\ &\leq 4C_{b,\sigma,f,T}\Delta_n. \end{aligned}$$



As a consequence, using that  $\frac{e^{\alpha\Delta_n}-1}{\alpha\Delta_n} \leq e^{\alpha\Delta_n}$ , we have

$$\begin{aligned} \mathbb{E}\left(e^{\alpha t}|Y_t - \tilde{Y}_t|^2 + \int_t^T e^{\alpha s}|Z_s - \tilde{Z}_s|^2 ds\right) &\leq \frac{[f]_{\text{Lip}}}{\theta} \left(\Delta_n C'_{b,\sigma,f,T} + 2e^{\alpha\Delta_n} \int_t^T e^{\alpha s} \mathbb{E}|Z_u - \tilde{Z}_u|^2 du\right) \\ &\quad + 2 \int_t^T e^{\alpha s} \mathbb{E}|Z_s - Z_{\underline{s}}|^2 ds. \end{aligned}$$

Let  $\theta \in [4[f]_{\text{Lip}}, 6[f]_{\text{Lip}}]$ . Then

$$2 \frac{[f]_{\text{Lip}}}{\theta} e^{\alpha\Delta_n} \leq \frac{1}{2} \exp\left([f]_{\text{Lip}}([f]_{\text{Lip}}^2 + \frac{1}{2})\Delta_n\right)$$

so that, for large enough  $n$ , say  $n \geq n_0$ ,  $2 \frac{[f]_{\text{Lip}}}{\theta} e^{\alpha\Delta_n} \leq \frac{3}{4}$  since  $\Delta_n \rightarrow 0$ . It follows that

$$\mathbb{E}\left(e^{\alpha t}|Y_t - \tilde{Y}_t|^2 + \frac{1}{4} \int_t^T e^{\alpha s}|Z_s - \tilde{Z}_s|^2 ds\right) \leq C^{(3,4)} \left(\Delta_n + \int_t^T e^{\alpha s} \mathbb{E}|Z_s - Z_{\underline{s}}|^2 ds + \int_t^T e^{\alpha s} \mathbb{E}|Z_s - \tilde{Z}_s|^2 ds\right).$$

In particular, for every  $k = 0, \dots, n$ , as  $t_k = t_k$ ,

$$\begin{aligned} \mathbb{E}|Y_{t_k} - \tilde{Y}_{t_k}|^2 &\leq C^{(3,4)} \left(\Delta_n + \int_{t_k}^T e^{\alpha s} \mathbb{E}|Z_s - Z_{\underline{s}}|^2 ds\right) \\ &\leq C^{(3,5)} e^{\alpha T} \left(\Delta_n + \int_0^T \mathbb{E}|Z_s - Z_{\underline{s}}|^2 ds\right). \end{aligned}$$

Now, setting  $k = 0$  yields likewise

$$\mathbb{E}\left(\int_0^T e^{\alpha s}|Z_s - \tilde{Z}_s|^2 ds\right) \leq C^{(3,6)} \left(\Delta_n + e^{\alpha T} \int_0^T \mathbb{E}|Z_s - Z_{\underline{s}}|^2 ds\right),$$

which completes the proof since one can always satisfy this inequality for  $n = 1, \dots, n_0$ , by increasing the constant  $C^{(3,6)}$ . □