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A Weak Approximation with Asymptotic Expansion and Multidimensional Malliavin Weights

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Abstract

This paper develops a new efficient scheme for approximations of expectations of the solutions to stochastic differential equations (SDEs). In particular, we present a method for connecting approximate operators based on an asymptotic expansion with multidimensional Malliavin weights to compute a target expectation value precisely. The mathematical validity is given based on Watanabe and Kusuoka theories in Malliavin calculus. Moreover, numerical experiments for option pricing under local and stochastic volatility models confirm the effectiveness of our scheme. Especially, our weak approximation substantially improve the accuracy at deep Out-of-The-Moneys (OTMs). **Keywords**: Asymptotic expansion, Weak approximation, Malliavin calculus, Watanabe theory, Kusuoka Scheme, Option pricing

1 Introduction

Developing an approximation method for expectations of diffusion processes is an interesting topic in various research fields. In fact, it seems so useful that a precise approximation for the expectation would lead to substantial reduction of computational burden so that the subsequent analyses could be very easily implemented. Particularly, in finance it has drawn much attention for more than the past two decades since fast and precise computation is so important in terms of competition and risk management in practice such as in trading and investment.

An example among a large number of the related researches is an asymptotic expansion approach, which is mathematically justified by Watanabe theory (Watanabe (1987)) in Malliavin calculus (e.g. Malliavin (1997)). Especially, the asymptotic expansion have been applied to a broad class of problems in finance: for instance, see Takahashi and Yamada (2012a,b, 2013a,b) and references therein.

Although the asymptotic expansion up to the fifth order is known to be sufficiently accurate for option pricing (e.g. Takahashi et al. (2012)), the main criticism against the method would be that the approximate density function deviates from the true density at its tails that is, some region of the very deep Out-of-The-Money (OTM). However, there

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exist similar problems, at least implicitly in other well-known approximation methods such as Hagan et al. (2002).

On the other hand, the Monte Carlo simulation method is quite popular mainly due to the ease of its implementation. Nevertheless, in order to achieve accuracy sufficient enough in practice, there exists an unavoidable drawback in computational cost under the standard weak approximation schemes of SDEs such as the Euler-Maruyama scheme.

To overcome this problem, Kusuoka (2001, 2003b, 2004) developed a high order weak approximation scheme for SDEs based on Malliavin calculus and Lie algebra, which opened the door for the possibility that the computational speed and the accuracy in the Monte Carlo simulation satisfies stringent requirements in financial business. Independently, Lyons and Victoir (2004) developed a cubature method on the Wiener space. Since then, there have been a large number of researches for weak approximations and its applications to the computational finance inspired by those pioneering works. For instance see Crisan et al. (2013) for the Kusuoka's method and its related works (e.g. Bayer et al. (2013)).

This paper develops a new weak approximation scheme for expectations of functions of the solutions to SDEs. In particular, the scheme connects approximate operators constructed based on the asymptotic expansion. More concretely, a diffusion semigroup is defined as the expectation of an appropriate function of the solution to a certain SDE: for example, $P_t^{\varepsilon} f(x) = E[f(X_t^{x,\varepsilon})]$ with the solution $X_t^{x,\varepsilon}$ of a SDE with perturbation parameter ε and a function f. Then, we approximate P_t^{ε} by an operator $Q_t^{\varepsilon,m}$ which is constructed based on the asymptotic expansion up to a certain order m. Thus, given a partition of [0,T], $\pi = \{(t_0, t_1, \dots, t_n) : 0 = t_0 < t_1 < \dots < t_n = T\}$, we are able to approximate $P_T^{\varepsilon} f(x)$ by connecting the expansion-based approximations sequentially: that is, with $s_k = t_k - t_{k-1}, k = 1, \dots, n$,

$$P_T^{\varepsilon}f(x) \simeq Q_{s_n}^{\varepsilon,m}Q_{s_{n-1}}^{\varepsilon,m}\cdots Q_{s_1}^{\varepsilon,m}f(x).$$

This paper justifies this idea by applying Malliavin calculus, particularly, theories developed by Watanabe (1987), Kusuoka (2003a) and Kusuoka (2001, 2004).

Moreover, we show through numerical examples for option pricing that very few partition such as n = 2 is mostly enough to substantially improve the errors at deep OTMs of expansions with order m = 1, 2. For a related but different approach with similar motivation see Section 5 in Fujii (2013).

The organization of the paper is as follows. The next section introduces the setup and the basic results necessary for the subsequent analysis. Section 3 shows our main result for a new weak approximation of the expectation of diffusion processes. After Section 4 briefly describes an example for the implementation method of our scheme, Section 5 provides numerical experiments for option pricing under local and stochastic volatility models. Section 6 concludes. Appendix gives the proofs of the theorems 1 and 2 as well as the lemma 2 and its proof.

2 Preparation

Let (\mathcal{W}, H, P) be the *d*-dimensional Wiener space and $\mathbf{D}^{k,p}(E), k \geq 1, p \in [1, \infty)$ be the space of *k*-times Malliavin differentiable Wiener functionals $F \in L^p(\mathcal{W}, E)$, where E is a separable Hilbert space. See Watanabe (1987), Ikeda and Watanabe (1989) and Nualart (2006) for more details of the notations. Let $B_t = (B_t^1, \dots, B_t^d)$ be a *d*dimensional Brownian motion. In this paper, we consider the following general perturbed N-dimensional stochastic differential equation with $\varepsilon \in (0, 1]$:

$$X_t^{x,\varepsilon} = x + \int_0^t V_0(\varepsilon, X_s^{x,\varepsilon}) ds + \varepsilon \sum_{j=1}^d \int_0^t V_j(X_s^{x,\varepsilon}) dB_s^j,$$
(2.1)

where $V_0 \in C_b^{\infty}((0,1] \times \mathbf{R}^N; \mathbf{R}^N)$ and $V_j \in C_b^{\infty}(\mathbf{R}^N; \mathbf{R}^N)$, $j = 1, \dots, d$ are bounded. Hereafter, we will use the notation $Vf(x) = \sum_{i=1}^N V^i(x)(\partial f/\partial x_i)(x)$ for $V \in C_b^{\infty}(\mathbf{R}^N; \mathbf{R}^N)$ and f a differentiable function \mathbf{R}^N into \mathbf{R} . $X_t^{x,\varepsilon}$ can be written in the Stratonovich form:

$$X_t^{x,\varepsilon} = x + \int_0^t \tilde{V}_0(\varepsilon, X_s^{x,\varepsilon}) ds + \varepsilon \sum_{j=1}^d \int_0^t \tilde{V}_j(X_s^{x,\varepsilon}) \circ dB_s^j,$$
(2.2)

where

$$\tilde{V}_0^i(\varepsilon, x) = V_0^i(\varepsilon, x) - \frac{\varepsilon^2}{2} \sum_{j=1}^d V_j V_j^i(x), \qquad (2.3)$$

$$\varepsilon \tilde{V}_j^i(x) = \varepsilon V_j^i(x), \quad j = 1, \cdots, d.$$
 (2.4)

Let Y_t^{ε} be a Wiener functional defined by

$$Y_t^{\varepsilon} = \frac{X_t^{x,\varepsilon} - X_t^{x,0}}{\varepsilon}.$$
 (2.5)

Define the Malliavin covariance matrix of Y_t^{ε} :

$$\sigma_{i,j}^{Y_t^{\varepsilon}} = \sum_{k=1}^d \int_0^t D_{s,k} Y_t^{\varepsilon,i} D_{s,k} Y_t^{\varepsilon,j} ds, \quad 1 \le i,j \le N.$$

$$(2.6)$$

We assume the following condition $[\mathbf{H}]$ on the Malliavin covariance matrix in this paper.

[H] For any $t \in (0, T]$,

$$\limsup_{\varepsilon \downarrow 0} \left\| \det(\sigma^{Y_t^{\varepsilon}})^{-1} \right\|_{L^p} < \infty.$$
(2.7)

2.1 The space \mathcal{K}_r

This subsection introduces the space of Wiener functionals \mathcal{K}_r developed by Kusuoka (2003a) and its properties. The element of \mathcal{K}_r is called the *Kusuoka-Stroock function*. See Nee (2010, 2011) and Crisan et al. (2013) for more details of the notations and the proofs.

Definition 1. Given $r \in \mathbf{R}$ and $n \in \mathbf{N}$, we denote by $\mathcal{K}_r(E, n)$ the set of functions $G: (0,1] \times \mathbf{R}^N \to \mathbf{D}^{n,\infty}(E)$ satisfying the following:

1. $G(t, \cdot)$ is n-times continuously differentiable and $[\partial^{\alpha}G/\partial x^{\alpha}]$ is continuous in $(t, x) \in (0, T] \times \mathbf{R}^{N}$ a.s. for any multi-index α of the elements of $\{1, \dots, d\}$ with length $|\alpha| \leq n$.

2. For all $k \le n - |\alpha|, p \in [1, \infty)$,

$$\sup_{t \in (0,1], x \in \mathbf{R}^N} t^{-r/2} \left\| \frac{\partial^{\alpha} G}{\partial x^{\alpha}}(t, x) \right\|_{\mathbf{D}^{k,p}} < \infty.$$
(2.8)

We write \mathcal{K}_r for $\mathcal{K}_r(\mathbf{R},\infty)$.

Next, we show the basic properties of the Kusuoka-Stroock functions. are the following.

Lemma 1. [Properties of Kusuoka-Stroock functions]

- 1. The function $(t,x) \in (0,1] \times \mathbf{R}^N \mapsto X_t^{x,\varepsilon}$ belongs to \mathcal{K}_0 .
- 2. Suppose $G \in \mathcal{K}_r(n)$ where $r \geq 0$. Then, for $i = 1, \cdots, d$,

(a)
$$\int_{0}^{\cdot} G(s,x) dB_{s}^{i} \in \mathcal{K}_{r+1}(n), \text{ and } (b) \int_{0}^{\cdot} G(s,x) ds \in \mathcal{K}_{r+2}(n).$$
 (2.9)
3. If $G_{i} \in \mathcal{K}_{r_{i}}(n_{i}), i = 1, \cdots, N$, then

(a)
$$\prod_{i=1}^{N} G_{i} \in \mathcal{K}_{r_{1}+\dots+r_{N}}(\min_{i} n_{i}), and (b) \sum_{i=1}^{N} G_{i} \in \mathcal{K}_{\min_{i} r_{i}}(\min_{i} n_{i}).$$
 (2.10)

Then, we summarize the Malliavin's integration by parts formula using Kusuoka-Stroock functions. For any multi-index $\alpha^{(k)} := (\alpha_1, \dots, \alpha_k) \in \{1, \dots, N\}^k, k \ge 1$, we denote by $\partial_{\alpha^{(k)}}$ the partial derivative $\frac{\partial^k}{\partial x_{\alpha_1} \cdots \partial x_{\alpha_k}}$.

Proposition 1. Let $G : (0,1] \times \mathbf{R}^N \to \mathbf{D}^\infty = \mathbf{D}^{\infty,\infty}(\mathbf{R})$ be an element of \mathcal{K}_r and let f be a function that belongs to the space $C_b^\infty(\mathbf{R}^N; \mathbf{R})$. Then for any multi-index $\alpha^{(k)} \in \{1, \dots, d\}^k$, $k \ge 1$, there exists $H_{\alpha^{(k)}}(X_t^{\kappa,\varepsilon}, G(t, x)) \in \mathcal{K}_{r-|\alpha^{(k)}|}$ such that

$$E\left[\partial_{\alpha^{(k)}}f(X_t^{x,\varepsilon})G(t,x)\right] = E\left[f(X_t^{x,\varepsilon})H_{\alpha^{(k)}}(X_t^{x,\varepsilon},G(t,x))\right], \ t \in (0,1],$$
(2.11)

with

$$\sup_{\mathbf{\in \mathbf{R}}^{N}} \|H_{\alpha^{(k)}}(X_{t}^{x,\varepsilon}, G(t,x))\|_{L^{p}} \le t^{(r-|\alpha^{(k)}|)/2}C,$$
(2.12)

where $H_{\alpha^{(k)}}(X^{x,\varepsilon}_t,G(t,x))$ is recursively given by

$$H_{(i)}(X_t^{x,\varepsilon}, G(t,x)) = \delta\left(\sum_{j=1}^N G(t,x)\gamma_{ij}^{X_t^{x,\varepsilon}} DX_t^{x,\varepsilon,j}\right), \qquad (2.13)$$

$$H_{\alpha^{(k)}}(X_t^{x,\varepsilon}, G(t,x)) = H_{(\alpha_k)}(X_t^{x,\varepsilon}, H_{\alpha^{(k-1)}}(X_t^{x,\varepsilon}, G(t,x))),$$
(2.14)

and a positive constant C. Here, δ is the Skorohod integral and $(\gamma_{ij}^{X_t^{x,\varepsilon}})_{1 \le i,j \le n}$ is the inverse matrix of the Malliavin covariance of $X_t^{x,\varepsilon}$.

Proof. Apply Corollary 3.7 of Kusuoka and Stroock (1984) and Lemma 8-(3) of Kusuoka (2003a) with Proposition 2.1.4 of Nualart (2006). \Box

Remark 1. Kusuoka (2003a) shows that Proposition 1 holds under the UFG condition. See p. 262 of Kusuoka (2003a) for the definition of the UFG condition. We remark that if the vector fields V_0 and V_i , $i = 1, \dots, d$ satisfy the uniform Hörmander condition, then they satisfy the UFG condition. We also remark that if the vector fields V_0 and V_i , $i = 1, \dots, d$ satisfy the uniform ellipticity condition, then they satisfy the UFG condition.

3 Weak Approximation with Asymptotic Expansion Method

Let $(P_t)_t$ be linear operators on $f \in C_b(\mathbf{R}^N; \mathbf{R})$ defined by

$$P_t f(x) = E[f(X_t^{x,\varepsilon})], \qquad (3.1)$$

where

$$X_t^{x,\varepsilon} = x + \int_0^t V_0(\varepsilon, X_s^{x,\varepsilon}) ds + \varepsilon \sum_{j=1}^d \int_0^t V_j(X_s^{x,\varepsilon}) dB_s^j.$$
(3.2)

We remark that $(P_t)_t$ is a semigroup. Also let $(P_t^0)_t$ be linear operators on $f \in C_b(\mathbf{R}^N; \mathbf{R})$ defined by

$$P_t^0 f(x) = E[f(\bar{X}_t^{x,0})], \qquad (3.3)$$

where

$$\bar{X}_{t}^{x,0} = X_{t}^{x,0} + \varepsilon \frac{\partial}{\partial \varepsilon} X_{t}^{x,\varepsilon}|_{\varepsilon=0}.$$
(3.4)

Note that $\frac{\partial}{\partial \varepsilon} X_t^{x,\varepsilon}|_{\varepsilon=0}$ is a Gaussian random variable.

Remark 2. When $\tilde{V}_0(\varepsilon, x) = \varepsilon \tilde{V}_0(x)$, $\bar{X}_t^{x,0}$ is given by

$$\bar{X}_{t}^{x,0} = x + \varepsilon \sum_{i=0}^{d} V_{i}(x) \int_{0}^{t} dB_{s}^{i},$$
(3.5)

where $B_t^0 = t$.

In the remainder of the paper, we use the following norms and semi-norms:

$$\|f\|_{\infty} = \sup_{x \in \mathbf{R}^{N}} |f(x)|, \quad \|\nabla f\|_{\infty} = \max_{i \in \{1, \cdots, N\}} \left\| \frac{\partial f}{\partial x_{i}} \right\|_{\infty}, \quad f \in C_{b}^{\infty}(\mathbf{R}^{N}; \mathbf{R}), \quad (3.6)$$

$$\|\nabla^{i}f\|_{\infty} = \max_{j_{1},\cdots,j_{i}\in\{1,\cdots,N\}} \left\|\frac{\partial^{i}f}{\partial x_{j_{1}}\cdots\partial x_{j_{i}}}\right\|_{\infty}.$$
(3.7)

Next, as an approximation of P we introduce a linear operator Q^m below. Firstly, for $j \geq 1$, let $P_{\Phi^j}^0$ be a linear operator defined by the following expectation with Malliavin weight

$$P^{0}_{\Phi^{j}}(t)f(x) = E\left[f(\bar{X}^{x,0}_{t})\Phi^{j}_{t}\right],$$
(3.8)

where

$$\Phi_t^j = \sum_{k=1}^j \sum_{\beta_1 + \dots + \beta_k = j+k, \beta_l \ge 2} \sum_{\alpha^{(k)} \in \{1, \dots, N\}^k} \frac{1}{k!}$$
(3.9)

$$H_{\alpha^{(k)}}\left(\frac{\partial}{\partial\varepsilon}X_t^{x,\varepsilon}|_{\varepsilon=0} , \prod_{l=1}^k \frac{1}{\beta_l!} \frac{\partial^{\beta_l}}{\partial\varepsilon^{\beta_l}}|_{\varepsilon=0} X_t^{x,\varepsilon,\alpha_l}\right).$$
(3.10)

Then, $\{Q^m_{(s)}, s \in (0, 1]\}$ is defined as a linear operator:

$$Q_{(s)}^{m}f(x) = P_{s}^{0}f(x) + \sum_{j=1}^{m} \varepsilon^{j} P_{\Phi^{j}}(s)f(x).$$
(3.11)

Remark 3. When $\tilde{V}_0(\varepsilon, x) = \varepsilon \tilde{V}_0(x)$, $X_t^{x,\varepsilon}$ has the following expansion:

$$\begin{aligned} X_t^{x,\varepsilon} &= x + \varepsilon \sum_{j=0}^d \tilde{V}_j(x) \int_0^t \circ dB_s^j \\ &+ \sum_{k=2}^m \varepsilon^k \sum_{\substack{(i_1,\cdots,i_k) \in \{0,1,\cdots,d\}^k, k+\#\{j|i_j=0\} \le m \\ (\tilde{V}_{i_1}\cdots\tilde{V}_{i_k})(x) \int_{0 < t_1 < \cdots < t_k < t} \circ dB_{t_1}^{i_1} \circ \cdots \circ dB_{t_k}^{i_k} \\ &+ \varepsilon^{m+1} R_m(t,x,\varepsilon), \end{aligned}$$

where $R_m(t, x, \varepsilon)$ is the residual. Here, we used the notation $B_t^0 = t$.

Then, we have the following representations for $P_{\Phi^j}^0$, $j \ge 1$ and Q^m .

Proposition 2. It holds

$$P^{0}_{\Phi^{j}}(t)f(x) = E[f(\bar{X}^{x,0}_{t})\mathcal{M}_{(j)}(t,x,\bar{X}^{x,0}_{t})], \qquad (3.12)$$

where $\mathcal{M}_{(j)}(t, x, y) = E[\Phi_t^j | \bar{X}_t^{x,0} = y]$ and

$$Q_{(s)}^{m}f(x) = E[f(\bar{X}_{s}^{x,0})\mathcal{M}^{m}(s,x,\bar{X}_{s}^{x,0})]$$
(3.13)

where $\mathcal{M}^{m}(s, x, y) = 1 + \sum_{j=1}^{m} \varepsilon^{j} \mathcal{M}_{(j)}(s, x, y).$

Proof.

We have

$$P^{0}_{\Phi^{j}}(t)f(x) = \int_{\mathbf{R}^{N}} f(y)E\left[\Phi^{j}_{t}|\bar{X}^{x,0}_{t} = y\right]p(t,x,y)dy$$
$$= E\left[f(\bar{X}^{x,0}_{t})\mathcal{M}_{(j)}(t,x,\bar{X}^{x,0}_{t})\right]$$

and

$$\begin{split} Q^m_{(s)} f(x) &= \int_{\mathbf{R}^N} f(y) \{ 1 + \sum_{j=1}^m \varepsilon^j E[\Phi^j_s | \bar{X}^{x,0}_s = y] \} p(s,x,y) dy \\ &= E[f(\bar{X}^{x,0}_s) \mathcal{M}^m(s,x,\bar{X}^{x,0}_s)], \end{split}$$

where $y \mapsto p(t, x, y)$ is the density of $\bar{X}_t^{x,0}$. \Box

The next theorem shows the asymptotic approximation results for the expectations of the solution to the general perturbed SDEs $X_s^{x,\varepsilon}$.

Theorem 1. We have the following estimates:

1. There exists C > 0 and $n \in \mathbf{N}$ such that

$$\|P_s f - Q_{(s)}^m f\|_{\infty} \le \varepsilon^{m+1} C(\sum_{k=1}^n s^{(m+1+k)/2} \|\nabla^k f\|_{\infty}),$$
(3.14)

for any $s \in (0,1]$ and $f \in C_b^{\infty}(\mathbf{R}^N; \mathbf{R})$.

2. There exists C > 0 such that

$$||P_s f - Q^m_{(s)} f||_{\infty} \le \varepsilon^{m+1} C s^{(m+2)/2}, \tag{3.15}$$

for any $s \in (0,1]$ and Lipschitz continuous function $f : \mathbf{R}^N \to \mathbf{R}$.

3. There exists C > 0 such that

$$\|P_s f - Q_{(s)}^m f\|_{\infty} \le \varepsilon^{m+1} C s^{(m+1)/2}, \tag{3.16}$$

for any $s \in (0,1]$ and bounded Borel function $f : \mathbf{R}^N \to \mathbf{R}$.

Proof.

See Appendix A. \Box

Remark 4. The above results are obtained based on the integration by parts argument for $G(s, x) \in \mathcal{K}_r$ with time $s \in (0, 1]$. However, we are able to show that the same results hold for $s \in (0, T]$, T > 0, using the properties of the elements in the space \mathcal{K}_r^T defined as in Crisan et al. (2013).

Next, for T > 0, $\gamma > 0$, define a partition $\pi = \{(t_0, t_1, \dots, t_n) : 0 = t_0 < t_1 < \dots < t_n = T, t_k = k^{\gamma}T/n^{\gamma}, n \in \mathbf{N}\}$ and $s_k = t_k - t_{k-1}, k = 1, \dots, n$. Using the asymptotic expansion operator Q^m of P, we can guess the following semigroup approximation.

$$E[f(X_T^{x,\varepsilon})] = P_T f(x) = P_{s_n} P_{s_{n-1}} \cdots P_{s_1} f(x) \simeq Q^m_{(s_n)} Q^m_{(s_{n-1})} \cdots Q^m_{(s_1)} f(x).$$

The next theorem shows our main result on the approximation error for this scheme.

Theorem 2. Let T > 0, $\gamma > 0$ and $n \in \mathbf{N}$.

1. For any $f \in C_b^{\infty}(\mathbf{R}^N; \mathbf{R})$, there exists C > 0 such that

$$\|P_T f - Q_{(s_n)}^m Q_{(s_{n-1})}^m \cdots Q_{(s_1)}^m f\|_{\infty} \le \varepsilon^{m+1} \frac{C}{n^{\gamma(m+2)/2}}, \quad 0 < \gamma < m/(m+2),$$
(3.17)

$$\|P_T f - Q^m_{(s_n)} Q^m_{(s_{n-1})} \cdots Q^m_{(s_1)} f\|_{\infty} \le \varepsilon^{m+1} \frac{C}{n^{m/2}} (1 + \log n), \quad \gamma = m/(m+2),$$
(3.18)

$$\|P_T f - Q^m_{(s_n)} Q^m_{(s_{n-1})} \cdots Q^m_{(s_1)} f\|_{\infty} \le \varepsilon^{m+1} \frac{C}{n^{m/2}}, \quad \gamma > m/(m+2).$$
(3.19)

2. For any Lipschitz continuous function $f: \mathbf{R}^N \to \mathbf{R}$, there exists C > 0 such that

$$\|P_T f - Q^m_{(s_n)} Q^m_{(s_{n-1})} \cdots Q^m_{(s_1)} f\|_{\infty} \le \varepsilon^{m+1} \frac{C}{n^{\gamma(m+2)/2}}, \quad 0 < \gamma < m/(m+2),$$
(3.20)

$$\|P_T f - Q_{(s_n)}^m Q_{(s_{n-1})}^m \cdots Q_{(s_1)}^m f\|_{\infty} \le \varepsilon^{m+1} \frac{C}{n^{m/2}} (1 + \log n), \quad \gamma = m/(m+2),$$
(3.21)

$$\|P_T f - Q_{(s_n)}^m Q_{(s_{n-1})}^m \cdots Q_{(s_1)}^m f\|_{\infty} \le \varepsilon^{m+1} \frac{C}{n^{m/2}}, \quad \gamma > m/(m+2).$$
(3.22)

3. For any bounded Borel function $f : \mathbf{R}^N \to \mathbf{R}$, there exists C > 0 such that

$$\|P_T f - Q^m_{(s_n)} Q^m_{(s_{n-1})} \cdots Q^m_{(s_1)} f\|_{\infty} \le \varepsilon^{m+1} \frac{C}{n^{\gamma(m+1)/2}}, \quad 0 < \gamma < (m-1)/(m+1),$$
(3.23)

$$\|P_T f - Q^m_{(s_n)} Q^m_{(s_{n-1})} \cdots Q^m_{(s_1)} f\|_{\infty} \le \varepsilon^{m+1} \frac{C}{n^{(m-1)/2}} (1 + \log n), \quad \gamma = (m-1)/(m+1),$$
(3.24)

$$\|P_T f - Q_{(s_n)}^m Q_{(s_{n-1})}^m \cdots Q_{(s_1)}^m f\|_{\infty} \le \varepsilon^{m+1} \frac{C}{n^{(m-1)/2}}, \quad \gamma > (m-1)/(m+1).$$
(3.25)

Proof.

See Appendix C. \Box

Remark 5. Due to the theorem above, the higher order asymptotic expansion provides the higher order weak approximation. In fact, we can mostly attain enough accuracy even when the expansion order m is low such as m = 1, 2. In Section 5 we confirm this fact through numerical examples.

Remark 6. When $\gamma = 1$, i.e. $s_k = T/n$ for all $k = 1, \dots, n$, we have

1. For any $f \in C_b^{\infty}(\mathbf{R}^N; \mathbf{R})$, there exists C > 0 such that

$$||P_T f - (Q^m_{(T/n)})^n f||_{\infty} \le \varepsilon^{m+1} \frac{C}{n^{m/2}},$$

2. For any Lipschitz continuous function $f: \mathbf{R}^N \to \mathbf{R}$, there exists C > 0 such that

$$||P_T f - (Q^m_{(T/n)})^n f||_{\infty} \le \varepsilon^{m+1} \frac{C}{n^{m/2}},$$

3. For any bounded Borel function $f: \mathbf{R}^N \to \mathbf{R}$, there exists C > 0 such that

$$||P_T f - (Q^m_{(T/n)})^n f||_{\infty} \le \varepsilon^{m+1} \frac{C}{n^{(m-1)/2}}$$

4 Computation with Malliavin Weights

This section illustrates computational scheme for implementation of our method.

4.1**Backward Discrete-time Approximation**

Firstly, for preparation we describe a backward discrete time approximation of our method.

For $s \in (0,1]$ and $x, y \in \mathbf{R}^N$, define $p^m(s, x, y)$ as

$$Q_{(s)}^{m}f(x) = \int_{\mathbf{R}^{N}} f(y)p^{m}(s, x, y)dy.$$
(4.1)

We also recall that the *m*-th order Malliavin weight function \mathcal{M}^m is given as

$$Q_{(s)}^{m}f(x) = E[f(\bar{X}_{s}^{x,0})\mathcal{M}^{m}(s,x,\bar{X}_{s}^{x,0})].$$
(4.2)

Then,

$$p^{m}(s, x, y) = \mathcal{M}^{m}(s, x, y)p(s, x, y), \qquad (4.3)$$

with

$$p(s, x, y) = \frac{1}{(2\pi\varepsilon^2)^{N/2} \det(\Sigma(s))^{1/2}} e^{-\frac{(y-x)\Sigma^{-1}(t)(y-x)^T}{2\varepsilon^2}},$$
(4.4)

with the covariance matrix $\Sigma(s)$ of $\bar{X}_s^{x,0}$. Then, we are able to calculate $(Q^m_{(T/n)})^n f(x)$ as follows:

$$(Q^m_{(T/n)})^n f(x)$$
 (4.5)

$$= \int_{(\mathbf{R}^N)^n} f(y_n) \prod_{i=0}^{n-1} p^m(s_i, y_i, y_{i+1}) dy_n \cdots dy_1$$
(4.6)

$$= \int_{(\mathbf{R}^N)^{n-1}} q_{n-1}(y_{n-1}) \prod_{i=0}^{n-2} p^m(s_i, y_i, y_{i+1}) dy_{n-1} \cdots dy_1$$
(4.7)

$$= \int_{(\mathbf{R}^N)^{n-2}} q_{n-2}(y_{n-2}) \prod_{i=0}^{n-3} p^m(s_i, y_i, y_{i+1}) dy_{n-2} \cdots dy_1$$
(4.8)

$$= \int_{\mathbf{R}^N} q_1(y_1) p^m(s_1, y_0, y_1) dy_1, \tag{4.9}$$

with $y_0 = x$.

4.2**Example of Computational Scheme**

We are able to compute the expectation in the various ways such as numerical integration and Monte Carlo simulation. As an illustrative purpose and an example, this subsection briefly describes a scheme based on Monte Carlo simulation.

When we compute $(Q^m_{(T/n)})^n f(x)$ (i.e. $\gamma = 1$) with simulation, we store the *j*-th $(1 \leq j \leq M)$ outcome of the simulation, $\bar{X}^{x_0,0,\pi,(j)}$ with the time grid π . Then, we calculate an approximate semigroup at each time grid. That is, $q_{n-1}(x)$, $q_{n-2}(x)$ are calculated as follows:

$$q_{n-1}(x) = \int_{\mathbf{R}^N} f(y) p^m(T/n, x, y) dy$$
(4.10)

$$= \int_{\mathbf{R}^N} f(y) \mathcal{M}^m(T/n, x, y) p(T/n, x, y) dy$$
(4.11)

$$\simeq \frac{1}{M} \sum_{j=1}^{M} f(\bar{X}_T^{x_0,0,\pi,(j)}) \mathcal{M}^m(T/n, x, \bar{X}_T^{x_0,0,\pi,(j)})$$
(4.12)

$$q_{n-2}(x) = \int_{\mathbf{R}^N} q_{n-1}(y) p^m(T/n, x, y) dy$$
(4.13)

$$= \int_{\mathbf{R}^N} q_{n-1}(y) \mathcal{M}^m(T/n, x, y) p(T/n, x, y) dy$$
(4.14)

$$\simeq \frac{1}{M} \sum_{j=1}^{M} q_{n-1}(\bar{X}_{t_{n-1}}^{x_0,0,\pi,(j)}) \mathcal{M}^m(T/n, x, \bar{X}_{t_{n-1}}^{x_0,0,\pi,(j)}).$$
(4.15)

Therefore, in general,

$$q_{i-1}(x) = \int_{\mathbf{R}^N} q_i(y) p^m(T/n, x, y) dy$$
 (4.16)

$$= \int_{\mathbf{R}^N} q_i(y) \mathcal{M}^m(T/n, x, y) p(T/n, x, y) dy$$
(4.17)

$$\simeq \frac{1}{M} \sum_{j=1}^{M} q_i(\bar{X}_{t_i}^{x_0,0,\pi,(j)}) \mathcal{M}^m(T/n, x, \bar{X}_{t_i}^{x_0,0,\pi,(j)}).$$
(4.18)

Finally, we obtain an approximation:

$$(Q^{m}_{(T/n)})^{n}f(x) = \int_{\mathbf{R}^{N}} q_{1}(y)p^{m}(T/n, x, y)dy$$
(4.19)

$$= \int_{\mathbf{R}^N} q_1(y) \mathcal{M}^m(T/n, x, y) p(T/n, x, y) dy \qquad (4.20)$$

$$\simeq \frac{1}{M} \sum_{j=1}^{M} q_1(\bar{X}_{t_1}^{x_0,0,\pi,(j)}) \mathcal{M}^m(T/n, x, \bar{X}_{t_1}^{x_0,0,\pi,(j)}).$$
(4.21)

We also remark that if the numerical integration method is applied, the scheme is based on the equations (4.17) and (4.20).

5 Numerical Example

This section demonstrates the effectiveness of our method through the numerical examples for option pricing under local and stochastic volatility models.

5.1 Local volatility model

The first example takes the following local volatility model:

$$dS_t = \sigma(S_t)dB_t, \qquad (5.1)$$
$$S_0 = x.$$

Then, let $(\bar{S}_t^0)_{t\geq 0}$ be the solution to the following SDE:

$$d\bar{S}_0^0 = \sigma(x)dB_t, \qquad (5.2)$$

$$\bar{S}_0^0 = x.$$

In this numerical example, for the payoff function $f(x) = \max\{x - K, 0\}$ or $f(x) = \max\{K - x, 0\}$ where K is a positive constant, we apply the first order asymptotic expansion operator, that is m = 1:

$$Q_{(t)}^{1}f(x) = E[f(\bar{S}_{t}^{x,0})\mathcal{M}^{1}(t,x,\bar{S}_{t}^{x,0})]$$
(5.3)

and the second order asymptotic expansion operator that is, m = 2:

$$Q_{(t)}^2 f(x) = E[f(\bar{S}_t^{x,0})\mathcal{M}^2(t,x,\bar{S}_t^{x,0})].$$
(5.4)

Here, the Malliavin weights $\mathcal{M}^1(t, x, y)$ and $\mathcal{M}^2(t, x, y)$ are given by

$$\mathcal{M}^{1}(t,x,y) = E\left[H_{(1)}\left(\bar{S}_{t}^{x,0}, \frac{1}{2}\frac{\partial^{2}}{\partial\varepsilon^{2}}|_{\varepsilon=0}S_{t}^{x,\varepsilon}\right)|\bar{S}_{t}^{x,0}=y\right],$$

and

$$\mathcal{M}^{2}(t,x,y) = E\left[H_{(1)}\left(\bar{S}_{t}^{x,0}, \frac{1}{6}\frac{\partial^{3}}{\partial\varepsilon^{3}}|_{\varepsilon=0}S_{t}^{x,\varepsilon}\right)|\bar{S}_{t}^{x,0} = y\right] \\ + \frac{1}{2}E\left[H_{(1,1)}\left(\bar{S}_{t}^{x,0}, \left(\frac{1}{2}\frac{\partial^{2}}{\partial\varepsilon^{2}}|_{\varepsilon=0}S_{t}^{x,\varepsilon}\right)^{2}\right)|\bar{S}_{t}^{x,0} = y\right].$$

Also, we specify the local volatility function as $\sigma(x) = \sigma x^{\beta}$ with $\beta = 0.5$. The parameters are set to be $S_0 = 100$ and $\sigma = 4.0$ that corresponds to 40% under the log-normal model at initial value, $S_0 = 100$. The benchmark values are computed by Monte Carlo simulations with 10^7 trials and 1000 time steps for the 1 year maturity case or 2000 time steps for the 10 year maturity case.

Table 1 and Table 2 show the results. We observe that the increase in the number of the time steps improves the approximation. (See Error Rate AE 1 order and Error Rate AE 1 order WeakApprox n = 2, 3 in Table 1.) We also note that our scheme with the second order expansion and two time steps (Error Rate AE 2 order WeakApprox n = 2) improves the base (analytical only) second order expansion (Error Rate AE 2 order), and is able to provide an accurate approximation across all the strikes even for the long maturity case such as the 10 year maturity case in Table 2.

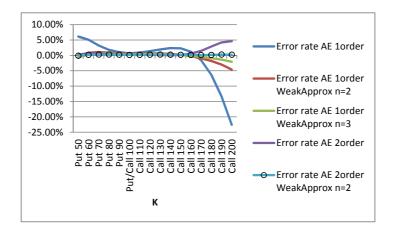


Figure 1: T = 1: Local volatility model, Error rates of the 1st and 2nd order asymptotic expansions and their weak approximations

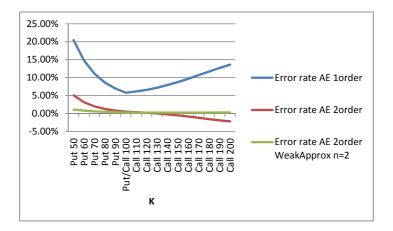


Figure 2: T = 10: Local volatility model, Error rates of the 1st and 2nd order asymptotic expansions and the weak approximations

5.2 Stochastic volatility model

The second example considers the following stochastic volatility model, which is also known as the log-normal SABR model.

$$dS_t = \sigma_t S_t dB_t^1, \ S_0 = z, \tag{5.5}$$

$$d\sigma_t = \nu \sigma_t (\rho dB_t^1 + \sqrt{1 - \rho^2} dB_t^2), \ \sigma_0 = \sigma.$$
 (5.6)

Let $X_{1,t} = \log S_t$ and $x = \log z$. Then, we have

$$dX_{1,t} = -\frac{\sigma_t^2}{2}dt + \sigma_t dB_t^1, \ X_{1,0} = x,$$
(5.7)

$$d\sigma_t = \nu \sigma_t (\rho dB_t^1 + \sqrt{1 - \rho^2} dB_t^2), \ \sigma_0 = \sigma.$$
(5.8)

For some fixed T > 0 and K > 0, the target expectation is given by

$$E[f(X_{1,T},\sigma_T)] = E\left[\hat{f}(X_{1,T})\right] = E\left[\max\left\{e^{X_{1,T}} - K, 0\right\}\right] \text{ or } E\left[\max\left\{K - e^{X_{1,T}}, 0\right\}\right] (5.9)$$

Next, let $(\bar{X}^0_{1,t}, \bar{\sigma}^0_t)_{t\geq 0}$ be the solution to the following SDE:

$$d\bar{X}^{0}_{1,t} = -\frac{\sigma^2}{2}dt + \sigma dB^1_t, \ \bar{X}^{0}_{1,0} = x,$$
(5.10)

$$d\bar{\sigma}_t^0 = \nu \sigma (\rho dB_t^1 + \sqrt{1 - \rho^2} dB_t^2), \ \bar{\sigma}_0 = \sigma.$$
 (5.11)

The parameters are set to be z = 100, $\sigma = 0.3$, $\nu = 0.1$ and $\rho = -0.5$. The benchmark values are calculated by Monte Carlo simulations with 10^7 trials and 1000 time steps for the 1 year maturity case or 2000 times steps for the 2 year maturity case.

In this example, we use the first order two dimensional asymptotic expansion operator with two time steps, that is m = 1 and n = 2. Then, the calculation procedure corresponding to the one in the previous section is the following: Firstly, set $t_0 = 0$, $t_1 = T/2$, $t_2 = T$ and $s = t_k - t_{k-1} = T/2$, (k = 1, 2).

• For
$$(\bar{X}_{1,t_1}^0, \bar{\sigma}_{1,t_1}^0) = (x_1, \sigma_1)$$
 at $t = t_1$

$$q_1(x_1,\sigma_1) = E\left[\hat{f}\left(\bar{X}_{1,s}^{(x_1,\sigma_1),0}\right)\mathcal{M}^1\left(s,(x_1,\sigma_1),\left(\bar{X}_{1,s}^{(x_1,\sigma_1),0},\bar{\sigma}_s^{\sigma_1,0}\right)\right)\right].$$
 (5.12)

• At
$$t = t_0 = 0$$
,

$$q_0(x,\sigma) = E\left[q_1\left(\bar{X}_{1,s}^{(x,\sigma),0}, \bar{\sigma}_s^{\sigma,0}\right) \mathcal{M}^1\left(s, (x,\sigma), \left(\bar{X}_{1,s}^{(x,\sigma),0}, \bar{\sigma}_s^{\sigma,0}\right)\right)\right].$$
 (5.13)

Here, $\mathcal{M}^1(t, (x, \sigma), (x', \sigma'))$ is the two dimensional Malliavin weight given by

$$\mathcal{M}^{1}(t,(x,\sigma),(x',\sigma')) = E\left[H_{(1)}\left(\left(\bar{X}_{1,t}^{(x,\sigma),0},\bar{\sigma}_{t}^{\sigma,0}\right),\frac{1}{2}\frac{\partial^{2}}{\partial\varepsilon^{2}}|_{\varepsilon=0}X_{1,t}^{(x,\sigma),\varepsilon}\right) | \left(\bar{X}_{1,t}^{(x,\sigma),0},\bar{\sigma}_{t}^{\sigma,0}\right) = (x',\sigma')\right] \\ + E\left[H_{(1)}\left(\left(\bar{X}_{1,t}^{(x,\sigma),0},\bar{\sigma}_{t}^{\sigma,0}\right),\frac{1}{2}\frac{\partial^{2}}{\partial\varepsilon^{2}}|_{\varepsilon=0}\sigma_{t}^{\sigma,\varepsilon}\right) | \left(\bar{X}_{1,t}^{(x,\sigma),0},\bar{\sigma}_{t}^{\sigma,0}\right) = (x',\sigma')\right].$$

Actually, at t_1 we need not implement (5.12), but just compute the first order analytical asymptotic expansion for pricing options with the time-to-maturity T/2 and the initial value $(\bar{X}_{1,t_1}^0, \bar{\sigma}_{t_1}^0) = (x_1, \sigma_1)$. That is,

$$\hat{q}_1(x_1, \sigma_1) = E\left[\hat{f}\left(\bar{X}_{1,s}^{(x_1, \sigma_1), 0}\right) \hat{\mathcal{M}}^1\left(s, (x_1, \sigma_1), \bar{X}_{1,s}^{(x_1, \sigma_1), 0}\right)\right],\tag{5.14}$$

where $\hat{\mathcal{M}}^1(s, (x_1, \sigma_1), y) = 1 + \hat{\mathcal{M}}_{(1)}(s, (x_1, \sigma_1), y)$, and $\hat{\mathcal{M}}_{(1)}(s, (x_1, \sigma_1), y)$ stands for the first order one dimensional Malliavin weight:

$$\hat{\mathcal{M}}_{(1)}(s, (x_1, \sigma_1), y) = E\left[H_{(1)}\left(\bar{X}_{1,s}^{(x_1, \sigma_1), 0}, \frac{1}{2}\frac{\partial^2}{\partial\varepsilon^2}|_{\varepsilon=0}X_{1,s}^{(x_1, \sigma_1), \varepsilon}\right)|\bar{X}_{1,s}^{(x_1, \sigma_1), 0} = y\right].$$
(5.15)

Here, $\left(X_t^{(x_1,\sigma_1),\varepsilon}\right)_{t\geq 0}$ is the solution of the perturbed SDE:

$$dX_{1,t}^{\varepsilon} = \varepsilon \left[-\frac{(\sigma_t^{\varepsilon})^2}{2} dt + \sigma_t^{\varepsilon} S_t dB_t^1 \right], \ X_{1,0} = x_1,$$
(5.16)

$$d\sigma_t^{\varepsilon} = \varepsilon \left[\nu \sigma_t^{\varepsilon} (\rho dB_t^1 + \sqrt{1 - \rho^2} dB_t^2) \right], \ \sigma_0^{\varepsilon} = \sigma_1.$$
(5.17)

On the other hand, we apply a conditional expectation formula for multidimensional asymptotic expansions in Takahashi (1999) in order to evaluate the Malliavin weight \mathcal{M}^1 in (5.13).

Table 3 and Table 4 show the results. Again, our scheme with (5.14) and (5.13) (Error rate AE 1st order Weak Approx n = 2) improves the base first order expansion (Error rate AE 1st order) especially for the deep OTM calls and puts.

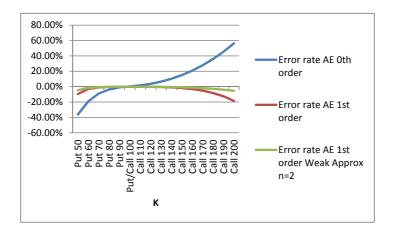


Figure 3: T = 1: Stochastic volatility model, Error rate of the 1st order 2 dimensional asymptotic expansion and the weak approximation

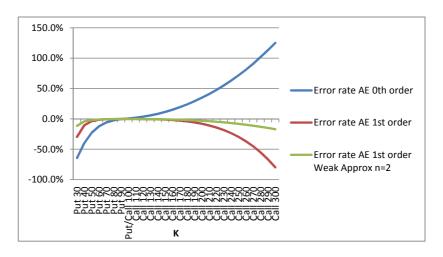


Figure 4: T = 2: Stochastic volatility model, Error rate of the 1st order 2 dimensional asymptotic expansion and the weak approximation

6 Concluding Remarks

In this paper, we have shown a new approximation method for the expectations of the functions of the solutions to SDEs applying an asymptotic expansion with Malliavin calculus. In particular, based on Kusuoka (2001, 2003 a, b, 2004) we have obtained an error estimate for our new weak approximation. Moreover, we have confirmed the validity of

our method through the numerical examples for option pricing under local and stochastic volatility models. The further numerical examination under higher dimensional SDEs is the next our research topic, which will involve a higher order computational scheme for multidimensional expansions developed by Takahashi (1999) and Takahashi and Toda (2013).

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A Proof of Theorem 1

Using the Taylor formula for $E[f(Y_t^{\varepsilon})]$ and the transform $X_t^{x,\varepsilon} = X_t^{x,0} + \varepsilon Y_t^{\varepsilon}$, we have

$$\begin{split} E[f(X_t^{x,\varepsilon})] &= E[f(\bar{X}_t^{x,0})] \\ &+ \sum_{i=1}^m \varepsilon^i \sum_{\alpha^{(k)},\beta^{(k)}}^i E\left[f(\bar{X}_t^{x,0})H_{\alpha_k}\left(\frac{\partial}{\partial\varepsilon}X_t^{x,\varepsilon}|_{\varepsilon=0}, \prod_{l=1}^k \frac{1}{\beta_l!}\frac{\partial^{\beta_l}}{\partial\varepsilon^{\beta_l}}X_t^{x,\varepsilon,\alpha_l}|_{\varepsilon=0}\right)\right] \\ &+ \varepsilon^{m+1} \int_0^1 (1-u)^m \ (m+1) \ \sum_{\alpha^{(k)},\beta^{(k)}}^{m+1} E\left[f(X_t^{x,\varepsilon u})H_{\alpha^{(k)}}\left(Y_t^{\varepsilon u}, \prod_{l=1}^k \frac{1}{\beta_l!}\frac{\partial^{\beta_l}}{\partial\eta^{\beta_l}}X_t^{x,\eta,\alpha_l}|_{\eta=\varepsilon u}\right)\right] du. \end{split}$$

Here,

$$\sum_{\alpha^{(k)},\beta^{(k)}}^{i} = \sum_{k=1}^{i} \sum_{\sum_{j=1}^{k} \beta_j = i+k, \ \beta_j \ge 2} \sum_{\alpha^{(k)} = (\alpha_1, \cdots, \alpha_k) \in \{1, \cdots, N\}^k} \frac{1}{k!}.$$
 (A.1)

In order to estimate the residual term using Proposition 1, in the next lemma we characterize the differentiations of the solution to the general perturbed SDEs $X_t^{x,\varepsilon}$ with respect to ε as elements in the space \mathcal{K}_r .

Lemma 2.

$$\frac{1}{j!}\frac{\partial^j}{\partial\varepsilon^j}X_t^{x,\varepsilon} \in \mathcal{K}_j, \quad j \ge 1,$$

The proof is given in Appendix B.

Then, using the above lemma and Proposition 1, we obtain the following estimates: For $k \leq m+1$, $\sum_{j=1}^{k} \beta_j = m+1+k$, $\alpha^{(k)} = (\alpha_1, \cdots, \alpha_k) \in \{1, \cdots, N\}^k$, 1. $\sup_{x \in \mathbf{R}^N} \left| E \left[f(X_t^{x,\varepsilon}) H_{\alpha^{(k)}} \left(Y_t^{\varepsilon}, \prod_{l=1}^k \frac{1}{\beta_l!} \frac{\partial^{\beta_l}}{\partial \varepsilon^{\beta_l}} X_t^{x,\varepsilon,\alpha_l} \right) \right] \right| \leq Cs^{(m+1+k)/2} \|\nabla^k f\|_{\infty}, (A.2)$ for any $f \in C_b^{\infty}(\mathbf{R}^N)$. 2. $\sup_{x \in \mathbf{R}^N} \left| E \left[f(X_t^{x,\varepsilon}) H_{\alpha^{(k)}} \left(Y_t^{\varepsilon}, \prod_{l=1}^k \frac{1}{\beta_l!} \frac{\partial^{\beta_l}}{\partial \varepsilon^{\beta_l}} X_t^{x,\varepsilon,\alpha_l} \right) \right] \right| \leq Cs^{(m+2)/2} \|\nabla f\|_{\infty}, (A.3)$ for any $f \in C_b^1$.

3.

$$\sup_{x \in \mathbf{R}^{N}} \left| E\left[f(X_{t}^{x,\varepsilon}) H_{\alpha^{(k)}}\left(Y_{t}^{\varepsilon}, \prod_{l=1}^{k} \frac{1}{\beta_{l}!} \frac{\partial^{\beta_{l}}}{\partial \varepsilon^{\beta_{l}}} X_{t}^{x,\varepsilon,\alpha_{l}} \right) \right] \right| \le Cs^{(m+1)/2} \|f\|_{\infty}, \quad (A.4)$$

for an arbitrary bounded continuous function f.

Then, we have the assertion. \Box

B Proof of Lemma 2

We prove the assertion by induction using slightly modified argument in Takahashi and Yamada (2012, 2013). First, the differentiation of $\frac{\partial}{\partial \varepsilon} X_s^{x,\varepsilon}$ with respect to ε is given by

$$\frac{\partial}{\partial \varepsilon} X_s^{x,\varepsilon,l} = \int_0^t \frac{\partial}{\partial \varepsilon} V_0^l(\varepsilon, X_s^{x,\varepsilon}) ds + \sum_{j=1}^d \int_0^t V_j^l(X_s^{x,\varepsilon}) dB_s^j \\
+ \sum_{k=1}^N \int_0^t \partial_k V_0^l(\varepsilon, X_s^{x,\varepsilon}) \frac{\partial}{\partial \varepsilon} X_s^{x,\varepsilon,k} ds \\
+ \varepsilon \sum_{k=1}^N \sum_{j=1}^d \int_0^t \partial_k V_j^l(X_s^{x,\varepsilon}) \frac{\partial}{\partial \varepsilon} X_s^{x,\varepsilon,k} dB_s^j, \quad l = 1, \cdots, N.$$
(B.1)

The above SDE is linear and the order of the Kusuoka-Stroock function $\frac{\partial}{\partial \varepsilon} X_s^{x,\varepsilon}$ is determined by the following term

$$\sum_{j=1}^{d} \int_{0}^{t} J_{t}^{x,\varepsilon} (J_{u}^{x,\varepsilon})^{-1} V_{j}(X_{u}^{x,\varepsilon}) dB_{u}^{j} \in \mathcal{K}_{1}.$$
(B.2)

where $J_t^{x,\varepsilon} = \nabla_x X_t^{x,\varepsilon}$. Since this term gives the minimum order in the terms that consist of (B.1). Here, we use the properties $J_s^{x,\varepsilon}, (J_s^{x,\varepsilon})^{-1} \in \mathcal{K}_0, s \in (0,1]$ and the boundness of $V_j, j = 0, \cdots, d$. We have $\frac{\partial}{\partial \varepsilon} X_s^{t,x,\varepsilon} \in \mathcal{K}_1$ by using the properties 2 and 3 in Lemma 1. For $i \ge 2, \frac{1}{i!} \frac{\partial^i}{\partial \varepsilon^i} X_s^{x,\varepsilon} = \left(\frac{1}{i!} \frac{\partial^i}{\partial \varepsilon^i} X_s^{x,\varepsilon,1}, \cdots, \frac{1}{i!} \frac{\partial^i}{\partial \varepsilon^i} X_s^{x,\varepsilon,N}\right)$ is recursively determined by

the following:

$$\frac{1}{i!} \frac{\partial^{i}}{\partial \varepsilon^{i}} X_{s}^{x,\varepsilon,n} = \frac{1}{i!} \int_{0}^{t} \frac{\partial^{i}}{\partial \varepsilon^{i}} V_{0}^{n}(\varepsilon, X_{u}^{x,\varepsilon}) du \\
+ \sum_{m=1}^{i} \sum_{i^{(k)},\alpha^{(k)}}^{(m)} \frac{1}{(i-1)!} \frac{1}{k!} \int_{0}^{t} \left(\prod_{l=1}^{k} \frac{1}{i_{l}!} \frac{\partial^{i_{l}}}{\partial \varepsilon^{i_{l}}} X_{u}^{x,\varepsilon,\alpha_{l}} \right) \sum_{j=1}^{d} \partial_{\alpha^{(k)}} \frac{\partial^{i-m}}{\partial \varepsilon^{i-m}} V_{0}^{n}(\varepsilon, X_{u}^{x,\varepsilon}) du \\
+ \sum_{i^{(k)},\alpha^{(k)}}^{(i-1)} \int_{0}^{t} \left(\prod_{l=1}^{k} \frac{1}{i_{l}!} \frac{\partial^{i_{l}}}{\partial \varepsilon^{i_{l}}} X_{u}^{x,\varepsilon,\alpha_{l}} \right) \sum_{j=1}^{d} \partial_{\alpha^{(k)}} V_{j}^{n}(X_{u}^{x,\varepsilon}) dB_{u}^{j} \\
+ \varepsilon \sum_{i^{(\beta)},\alpha^{(k)}}^{(i)} \int_{0}^{t} \left(\prod_{l=1}^{k} \frac{1}{i_{l}!} \frac{\partial^{i_{l}}}{\partial \varepsilon^{i_{l}}} X_{u}^{x,\varepsilon,\alpha_{l}} \right) \sum_{j=1}^{d} \partial_{\alpha^{(k)}} V_{j}^{n}(X_{u}^{x,\varepsilon}) dB_{u}^{j}, \quad n = 1, \cdots, N,$$
(B.3)

where

$$\sum_{i^{(k)},\alpha^{(k)}}^{(i)} := \sum_{k=1}^{i} \sum_{i_1 + \dots + i_k = i, i_l \ge 1} \sum_{\alpha^{(k)} \in \{1, \dots, N\}^k} \frac{1}{k!}.$$
 (B.4)

The above SDE is linear and the order of the Kusuoka-Stroock function $\frac{1}{i!} \frac{\partial^i}{\partial \varepsilon^i} X_s^{x,\varepsilon}$ is determined inductively by the term

$$\sum_{i^{(k)},\alpha^{(k)}}^{(i-1)} \int_{0}^{t} J_{t}^{x,\varepsilon} (J_{u}^{x,\varepsilon})^{-1} \left(\prod_{l=1}^{k} \frac{1}{i_{l}!} \frac{\partial^{i_{l}}}{\partial \varepsilon^{i_{l}}} X_{u}^{x,\varepsilon,\alpha_{l}} \right) \sum_{j=1}^{d} \partial_{\alpha^{(k)}} V_{j}(X_{u}^{x,\varepsilon}) dB_{s}^{j} \in \mathcal{K}_{i},$$
(B.5)

Since this term gives the minimum order in the terms that consist of (B.3). Then, $\frac{1}{i!} \frac{\partial^i}{\partial \varepsilon^i} X_s^{x,\varepsilon} \in \mathcal{K}_i \text{ by using the properties 2 and 3 in Lemma 1.} \square$

Proof of Theorem 2 C

We follow the similar argument as in Kusuoka (2001,2003b,2004) and Chapter 3 of Crisan et al.(2013).

Note first that we have the following equality:

$$P_T f(x) - Q_{(s_n)}^m Q_{(s_{n-1})}^m \cdots Q_{(s_1)}^m f(x)$$

$$= P_{T-t_{n-1}} P_{t_{n-1}} f(x) - Q_{(s_n)}^m P_{t_{n-1}} f(x)$$

$$+ Q_{(s_n)}^m P_{t_{n-1}} f(x) - Q_{(s_n)}^m Q_{(s_{n-1})}^m P_{t_{n-2}} f(x)$$

$$+ \cdots$$

$$+ Q_{(s_n)}^m \cdots Q_{(s_2)}^m P_{t_1} f - Q_{(s_n)}^m Q_{(s_{n-1})}^m \cdots Q_{(s_1)}^m f$$

$$= P_{T-t_{n-1}} P_{t_{n-1}} f(x) - Q_{(s_n)}^m P_{t_{n-1}} f(x)$$

$$+ Q_{(s_n)}^m (P_{s_{n-1}} P_{t_{n-2}} f(x) - Q_{(s_{n-1})}^m P_{t_{n-2}} f(x))$$

$$\cdots$$

$$+ Q_{(s_n)}^m \cdots Q_{(s_2)}^m (P_{t_1} f(x) - Q_{(s_1)}^m f(x)).$$

Then, since Q^m is a Markov operator, we have

$$\begin{split} \|P_T f - Q_{(s_n)}^m Q_{(s_{n-1})}^m \cdots Q_{(s_1)}^m f\|_{\infty} \\ \leq & \|P_{s_n} P_{t_{n-1}} f - Q_{(s_n)}^m P_{t_{n-1}} f\|_{\infty} \\ & + \|P_{s_{n-1}} P_{t_{n-2}} f - Q_{(s_{n-1})}^m P_{t_{n-2}} f\|_{\infty} \\ & \cdots \\ & + \|P_{t_1} f - Q_{(s_1)}^m f\|_{\infty} \\ = & \sum_{k=2}^n \|P_{s_k} P_{t_{k-1}} f - Q_{(s_k)}^m P_{t_{k-1}} f\|_{\infty} \\ & + \|P_{t_1} f - Q_{(s_1)}^m f\|_{\infty}. \end{split}$$

First, note that we can directly apply (3.14), (3.15) or (3.16) in Theorem1 to obtain an estimate of $||P_{t_1}f - Q_{(s_1)}^m f||_{\infty}$ for $f \in C_b^{\infty}(\mathbf{R}^N; \mathbf{R})$, a Lipschitz continuous function or a bounded Borel function, respectively. To obtain an estimate of $\sum_{k=2}^n ||P_{s_k}P_{t_{k-1}}f - Q_{(s_k)}^m P_{t_{k-1}}f||_{\infty}$, we apply the results in Theorem 1 to $P_t f$ (in stead of f) as follows.

• By (3.14) in Theorem 1, for $s, t \in (0, 1]$ and $f \in C_b^{\infty}(\mathbf{R}^N; \mathbf{R})$, there exists C and M such that

$$\|P_s P_t f - Q_{(s)}^m P_t f\|_{\infty} \leq \sum_{l=1}^M s^{(m+1+l)/2} C \|\nabla^l P_t f\|_{\infty}$$
(C.1)

$$\leq \sum_{l=1}^{M} s^{(m+1+l)/2} C \|\nabla^{l} f\|_{\infty}.$$
 (C.2)

Hence,

$$\|P_T f - Q_{(s_n)}^m Q_{(s_{n-1})}^m \cdots Q_{(s_1)}^m f\|_{\infty} \le C \sum_{k=2}^n \sum_{l=1}^M s_k^{(m+1+l)/2} \|\nabla^l f\|_{\infty}$$
(C.3)

$$+C\sum_{l=1}^{M} s_1^{(m+1+l)/2} \|\nabla^l f\|_{\infty}.$$
 (C.4)

• By (3.15) in Theorem 1, for $s, t \in (0, 1]$ and $f \in C_b^1(\mathbf{R}^N; \mathbf{R})$, there exists C such that

$$||P_s P_t f - Q^m_{(s)} P_t f||_{\infty} \le s^{(m+2)/2} C ||\nabla P_t f||_{\infty}$$
 (C.5)

$$\leq s^{(m+2)/2} C \|\nabla f\|_{\infty}.$$
 (C.6)

Hence,

$$\|P_T f - Q_{(s_n)}^m Q_{(s_{n-1})}^m \cdots Q_{(s_1)}^m f\|_{\infty} \le C \sum_{k=2}^n s_k^{(m+2)/2} \|\nabla f\|_{\infty}$$
(C.7)

$$+Cs_1^{(m+2)/2} \|\nabla f\|_{\infty}.$$
 (C.8)

• By (3.16) in Theorem 1, for $s, t \in (0, 1]$ and bounded Borel function f on \mathbb{R}^N , there exists C such that

$$\|P_s P_t f - Q_{(s)}^m P_t f\|_{\infty} \leq s^{(m+1)/2} C \|P_t f\|_{\infty}$$
(C.9)

$$\leq s^{(m+1)/2} C \|f\|_{\infty}.$$
 (C.10)

Hence,

$$\|P_T f - Q_{(s_n)}^m Q_{(s_{n-1})}^m \cdots Q_{(s_1)}^m f\|_{\infty} \le C \sum_{k=2}^n s_k^{(m+1)/2} \|f\|_{\infty}$$
(C.11)

$$+Cs_1^{(m+1)/2} ||f||_{\infty}.$$
 (C.12)

Next, we obtain more explicit and compact expressions with regard to n particularly for (C.3), (C.7) and (C.11).

Firstly, from the definition of s_k for $k \in \{2, \dots, n\}$, we have

$$s_k = \frac{\gamma T(k-1)^{\gamma-1}}{n^{\gamma}} \int_{k-1}^k (u/(k-1))^{\gamma-1} du.$$
(C.13)

For $k \in \{2, \dots, n\}$, $(u/(k-1))^{\gamma-1} \le \max\{(k/(k-1))^{\gamma-1}, 1\} \le \max\{2^{\gamma-1}, 1\}$. Then,

$$s_k^{l/2} \leq \left(\frac{\gamma T(k-1)^{\gamma-1}}{n^{\gamma}} \max\{2^{\gamma-1},1\}\right)^{l/2}$$
 (C.14)

$$\leq C(1/n)^{\gamma l/2}(k-1)^{(\gamma-1)l/2}$$
 (C.15)

where $C = C(T, \gamma)$.

We consider the estimates for three different ranges of γ that are larger than, equal to and less than (l-2)/l, respectively. $(\gamma = (l-2)/l$ satisfies $(\gamma - 1)l/2 = -1$.) For $0 < \gamma < (l-2)/l$,

$$C(1/n)^{\gamma l/2} \sum_{k=2}^{n} (k-1)^{(\gamma-1)l/2} \le C(1/n)^{\gamma l/2}.$$
 (C.16)

For $\gamma = (l-2)/l$

$$C(1/n)^{\gamma l/2} \sum_{k=2}^{n} (k-1)^{(\gamma-1)l/2}$$
 (C.17)

$$= C(1/n)^{(l-2)/2} \sum_{k=1}^{n} (k-1)^{-1}$$
 (C.18)

$$\leq C(1/n)^{(l-2)/2}\log n.$$
 (C.19)

For $\gamma > (l-2)/l$

$$C(1/n)^{\gamma l/2} \sum_{k=2}^{n} (k-1)^{(\gamma-1)l/2}$$
 (C.20)

$$= C(1/n)^{(\gamma-1)l/2} (1/n)^{l/2} \sum_{k=2}^{n} (k-1)^{(\gamma-1)l/2}$$
(C.21)

$$= C(1/n)^{(l-2)/2} \sum_{k=2}^{n} \left(\frac{k-1}{n}\right)^{(\gamma-1)l/2} \frac{1}{n}$$
(C.22)

$$\leq C(1/n)^{(l-2)/2}.$$
 (C.23)

Then, by combining an estimate of $||P_{t_1}f - Q_{(s_1)}^m f||_{\infty}$ for $f \in C_b^{\infty}(\mathbf{R}^N; \mathbf{R})$, a Lipschitz continuous function or a bounded Borel function, we have the assertion. \Box