Strong Convergence of Wong-Zakai Approximations of Reflected SDEs in A Multidimensional General Domain

#### Tusheng Zhang

University of Manchester and University of Science and Technology of China

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In this paper, we obtained the strong convergence of Wong-Zakai approximations of reflected SDEs in a general multidimensional domain giving an affirmative answer to the question posed in [ES] by Evans and Stroock.

### Introduction

Let D be a bounded domain in  $R^d$ . Consider the reflected stochastic differential equation (SDE):

$$\begin{cases} dX(t) = \sigma(X(t)) \circ dW(t) + b(X(t))dt + dL(t), \\ X(0) = x_0, \quad X(t) \in \overline{D}, t \ge 0, \\ |L|(t) = \int_0^t I_{\partial D}(X(s))d|L|(s), \end{cases}$$
(1)

where  $W(t), t \ge 0$  is a *m*-dimensional Brownian motion, |L|(t)stands for the total variation of L on the interval [0, t],  $\circ$  indicates a Stratonovich integral. There is a big amount of literature devoted to the study of reflected SDEs. Let us mention a few of them. Reflected SDEs in a convex domain was first studied by H. Tanaka in [T]. Existence and uniqueness of solutions of reflected SDEs in general domains were established by Lions and Sznitman in [LS] and Saisho in [S]. Existence and uniqueness of solutions of reflected SDEs under more general coefficients than the usual Lipschitz conditions were considered in [MR]. The purpose of this paper is to study Wong-Zakai type approximations of above reflected SDEs. Let  $W^n$  be the *n*-dyadic piecewise linear interpolation of W and  $X^n$  the solution of the following reflected random ordinary differential equation:

$$\begin{cases} \dot{X}^{n}(t) = \sigma(X^{n}(t))\dot{W}^{n}(t) + b(X^{n}(t))dt + \dot{L}^{n}(t), \\ X^{n}(0) = x_{0}, \quad X^{n}(t) \in \bar{D}, t \ge 0, \\ |L^{n}|(t) = \int_{0}^{t} I_{\partial D}(X^{n}(s))d|L^{n}|(s). \end{cases}$$
(2)

We are concerned with the strong convergence of  $X^n$  to the solution X. Strong convergence of Wong-Zakai approximations to stochastic differential equations is well known, see e.g. [IW]. However, the convergence of Wong-Zakai approximations to stochastic differential equations with reflection (especially in higher dimensions) is not a trivial matter because of the constraints on the solution and the appearance of the boundary local time.

There are two main papers related to this question. In [P], Petterson established a Wong-Zakai approximations for SDEs with reflection for convex domains. The convexity is too rigid sometimes for applications. In [ES], Evans and Stroock considered Wong-Zakai approximations for reflected SDEs in general domains (as in [LS]) and proved that  $X^n$  converges weakly (in law) to the solution X. In the same paper, the authors also posed the question of whether the strong convergence holds. For some of the interesting applications, we refer the reader to [ES]. The purpose of this paper is to establish the strong convergence ( the  $L^p$ convergence in  $C([0, T], \overline{D})$  of the Wong-Zakai approximations for reflected SDEs in multidimensional general domains, hence giving an affirmative answer to the question in [ES].

## The Main result

Let  $D \subset R^d$  be a bounded domain with boundary  $\partial D$ . For  $x \in \partial D$ , let  $\nu(x) \subset S^{d-1}$  denote a nonempty collection of reflecting directions. Throughout this paper, as in [LS], [ES], we impose the following conditions on the domain.

**D.1**  $\nu(x) \neq \emptyset$  for every  $x \in \partial D$  and there exist a constant  $C_0 \ge 0$  such that

$$(x'-x)\cdot 
u + C_0|x-x'|^2 \ge 0$$
 for all  $x' \in D, x \in \partial D$  and  $\nu \in \nu$ 

**D.2** There exists a function  $\phi \in C^2(\mathbb{R}^d; \mathbb{R})$  and  $\alpha > 0$  such that

 $abla \phi(x) \cdot 
u \geq lpha$  for all  $x \in \partial D$  ,  $u \in 
u(x)$ .

**D.3** There exist  $n \ge 1$ ,  $\lambda > 0$ , K > 0,  $a_1, a_2, ..., a_n \in S^{d-1}$ , and  $x_1, x_2, ..., x_n \in \partial D$  such that  $\partial D \subset \bigcup_{i=1}^n B(x_i, K)$  and  $x \in \partial D \cap B(x_i, 2K) \Longrightarrow \nu \cdot a_i \ge \lambda$  for all  $\nu \in \nu(x)$ .

**Convention**; Throughout this paper, any function G defined on the positive half line  $[0, \infty)$  automatically extends to a function on the whole line by setting  $G(s) = G(s \lor 0)$  when necessary.

## The main result

Let  $W(t) = (W_1(t), W_2(t), ..., W_m(t)), t \ge 0$  be a *m*-dimensional Brownian motion on a completed filtered probability space  $(\Omega, \mathcal{F}, \mathcal{F}_t, P)$ . Suppose  $\sigma = (\sigma_{i,j}) \in C^1(\overline{D}; \mathbb{R}^d \otimes \mathbb{R}^m)$  such that the derivative  $\sigma'$  is Lipschitz continuous and that  $b : \overline{D} \to \mathbb{R}^d$  is Lipschitz continuous.

For  $n \in N$  and  $s \in [\frac{k}{2^n}, \frac{k+1}{2^n})$ , set  $s_n^- = (\frac{k-1}{2^n}) \vee 0$  and  $s_n = \frac{k}{2^n}$ . Let  $W^n$  be the linear interpolation of W defined by

$$W^{n}(t) = W(\frac{k-1}{2^{n}}) + 2^{n}(t - \frac{k}{2^{n}})(W(\frac{k}{2^{n}}) - W(\frac{k-1}{2^{n}}))$$
(3)

for  $t \in [\frac{k}{2^n}, \frac{k+1}{2^n})$ , k = 0, 1, 2, ... Note that the above convention applies here. Let  $\sigma\sigma' : \overline{D} \to R^d$  be defined as

$$(\sigma\sigma'(y))_i = \sum_{j=1}^m \sum_{k=1}^d \frac{\partial\sigma_{i,j}(y)}{\partial y_k} \sigma_{k,j}(y).$$
(4)

With this notation, equation (1) becomes

$$X(t) = x_0 + \int_0^t \sigma(X(s)) dW(s) + \frac{1}{2} \int_0^t \sigma\sigma'(X(s)) ds + \int_0^t b(X(s)) ds + L(t)$$
(5)

#### Definition

We say that (X, L) is a solution to the reflected SDE (5) if (X, L) is a  $\overline{D} \times R^d$ -valued, adapted continuous process such that (i)  $L(t), t \ge 0$  is of bounded variation on any finite sub-interval of  $[0, \infty)$ , (ii) for  $t \ge 0$ ,

$$X(t) = x_0 + \int_0^t \sigma(X(s)) dW(s) + \frac{1}{2} \int_0^t \sigma\sigma'(X(s)) ds + \int_0^t b(X(s)) ds + L(t)$$

almost surely,

### (iii)

$$|L|(t) = \int_0^t I_{\partial D}(X(s))d|L|(s), \qquad L(t) = \int_0^t \nu(X(s))d|L|(s),$$

where |L|(t) stands for the total variation of L on the interval [0, t], the last equality means that  $\frac{dL(t)}{d|L|(t)} \in \nu(X(t))$ .

The solution  $(X^n, L^n)$  to the reflected random ordinary differential equation (2) is defined accordingly.

Under the above assumptions, the existence and uniqueness of  $X^n, X$  are well known now, see, for example, [LS]. Here is the main result.

#### Theorem[The main result]

Let  $X^n, X$  be the solutions to reflected stochastic equations (1) and (2). It holds that for any p > 0 and T > 0,

$$\lim_{n \to \infty} E[\sup_{0 \le t \le T} |X^n(t) - X(t)|^p] = 0.$$
 (6)

The rest of the paper (27 pages) is entirely devoted to the proof of this theorem. Before sketching the proof I like to make a remark.

**Remark**. After the submission of this paper to the Annals of Probability, I was made aware of the existence of the following online preprint by the referee:

[1]. S. Aida and K. Sasaki: Wong-Zakai approximation of solutions for reflecting stochastic differential equations on domains in Euclidean spaces.

The work in these two papers was carried out completely independently. The approaches are different. I hope that the method I present to you could also be used for some other reflected stochastic equations. First of all we recall the following estimates from [ES]. **lemma**[1] Let  $p \ge 2$ , T > 0. Then there exists a constant  $C_1(T, p)$  independent of n such that

$$E[|X^{n}(t) - X^{n}(s)|^{p}] \le C_{1}(T, p)|t - s|^{\frac{p}{2}},$$
(7)

for  $0 \leq s, t \leq T$ .

**lemma**[2] Let  $p \ge 2$ , T > 0. Then there exists a constant  $C_2(T, p)$  such that

$$E[|X(t) - X(s)|^{p}] \le C_{2}(T, p)|t - s|^{\frac{p}{2}},$$
(8)

for  $0 \leq s, t \leq T$ .

Due to (7), (8) above, to prove the main result, it can be shown that one only needs to prove that for any fixed t > 0

$$\lim_{n \to \infty} E[|X^{n}(t) - X(t)|^{2}] = 0.$$
(9)

To prove (9). again because of (7), (8) we may assume that t is a dyadic number, i.e.,  $t = \frac{k_0}{2^{n_0}}$  for some positive integers  $k_0$ ,  $n_0$  and we may also assume  $n \ge n_0$ .

Let  $f(y_1, y_2, y_3) = exp(r(y_1 + y_2))y_3$ . Recall  $\phi$  is the function specified in (D.2). To simplify the exposure, we introduce the following notation:

$$y_1(t) := \phi(X(t)), y_2^n(t) := \phi(X^n(t)), y_3^n(t) := |X^n(t) - X(t)|^2.$$
  
$$f_n(t) := f(y_1(t), y_2^n(t), y_3^n(t)), g_n(t) := exp(ry_1(t) + ry_2^n(t)).$$
  
Since  $X^n, X$  take values in the bounded domain  $\overline{D}$ , we have

$$c_1|X^n(t) - X(t)|^2 \le f_n(t) \le c_2|X^n(t) - X(t)|^2,$$
 (10)

where  $c_1, c_2$  are positive constants independent of n. Thus the proof of (9) reduces to show

$$\lim_{n \to \infty} E[f_n(t)] = 0.$$
 (11)

By Ito's formula, we have

$$\begin{aligned} &f_n(t) \\ = & r \int_0^t f_n(s) < \nabla \phi(X(s)), \sigma(X(s)) dW(s) > \\ &+ r \int_0^t f_n(s) < \nabla \phi(X(s)), b(X(s) > ds \\ &+ & \frac{1}{2}r \int_0^t f_n(s) tr(\phi''(\sigma\sigma^*)(X(s))) ds \\ &+ & \frac{1}{2}r \int_0^t f_n(s) < \nabla \phi(X(s), \sigma\sigma'(X(s)) > ds \\ &+ & r \int_0^t f_n(s) < \nabla \phi(X(s)), \nu(X(s)) > d|L|(s) \\ &+ r \int_0^t f_n(s) < \nabla \phi(X^n(s)), \sigma(X^n(s)) dW^n(s) > \end{aligned}$$

$$+ r \int_{0}^{t} f_{n}(s) < \nabla \phi(X^{n}(s)), b(X^{n}(s)) > ds \\ + r \int_{0}^{t} f_{n}(s) < \nabla \phi(X^{n}(s)), \nu(X^{n}(s)) > d|L^{n}|(s) \\ + 2 \int_{0}^{t} g_{n}(s) < X^{n}(s) - X(s), \sigma(X^{n}(s)) dW^{n}(s) > \\ - 2 \int_{0}^{t} g_{n}(s) < X^{n}(s) - X(s), \sigma(X(s)) dW(s) > \\ + 2 \int_{0}^{t} g_{n}(s) < X^{n}(s) - X(s), \sigma(X(s)) - b(X(s)) > ds$$

$$- \int_{0}^{t} g_{n}(s) < X^{n}(s) - X(s), \sigma \sigma'(X(s)) > ds \\+ 2 \int_{0}^{t} g_{n}(s) < X^{n}(s) - X(s), \nu(X^{n}(s))d|L^{n}|(s) - \nu(X(s))d|L|(s) > \\+ \int_{0}^{t} g_{n}(s)tr(\sigma \sigma^{*}(X(s)))ds \\+ \frac{1}{2}r^{2} \int_{0}^{t} f_{n}(s)|\sigma^{*}\nabla \phi|^{2}(X(s))ds \\- 2r \int_{0}^{t} g_{n}(s) < \sigma^{*}(X(s))(X^{n}(s) - X(s)), \sigma^{*}\nabla \phi(X(s)) > ds.$$
(12)

$$g_n(t)$$

$$= exp(2r\phi(x_0)) + r \int_0^t g_n(s) < \nabla\phi(X(s)), \sigma(X(s))dW(s) >$$

$$+ r \int_0^t g_n(s) < \nabla\phi(X(s)), b(X(s)) > ds$$

$$+ \frac{1}{2}r \int_0^t g_n(s)tr(\phi''(\sigma\sigma^*)(X(s)))ds$$

$$+ \frac{1}{2}r \int_0^t g_n(s) < \nabla\phi(X(s), \sigma\sigma'(X(s)) > ds$$

$$+ r \int_{0}^{t} g_{n}(s) < \nabla \phi(X(s)), \nu(X(s)) > d|L|(s) + r \int_{0}^{t} g_{n}(s) < \nabla \phi(X^{n}(s)), \sigma(X^{n}(s)) dW^{n}(s) > + r \int_{0}^{t} g_{n}(s) < \nabla \phi(X^{n}(s)), b(X^{n}(s)) > ds + r \int_{0}^{t} g_{n}(s) < \nabla \phi(X^{n}(s)), \nu(X^{n}(s)) > d|L^{n}|(s) + \frac{1}{2}r^{2} \int_{0}^{t} g_{n}(s)|\sigma^{*}\nabla \phi|^{2}(X(s)) ds$$
(13)

To bound  $E[f_n(t)]$ , the crucial step is to get proper estimates for the terms

$$rE[\int_0^t f_n(s) < \nabla \phi(X^n(s)), \sigma(X^n(s)) dW^n(s) > ].$$

and

$$rE[\int_0^t g_n(s) < X^n(s) - X(s), \sigma(X^n(s))dW^n(s) >].$$

This will be done in the following two lemmas.

# Sketch of proof

#### **lemma**[3] It holds that

$$\begin{aligned} rE[\int_{0}^{t} f_{n}(s) < \nabla\phi(X^{n}(s)), \sigma(X^{n}(s))dW^{n}(s) >] \\ \leq & C(\frac{1}{2^{n}})^{\frac{1}{2}} + r^{2}E[\int_{0}^{t} f_{n}(s) < \sigma^{*}\nabla\phi(X(s)), \sigma^{*}\nabla\phi(X^{n}(s)) > ds] \\ & + \frac{1}{2}r^{2}E[\int_{0}^{t} f_{n}(s)|\sigma^{*}\nabla\phi|^{2}(X^{n}(s))ds] \\ & + r\int_{0}^{t} < g_{n}(s)\sigma^{*}(X^{n}(s))(X^{n}(s) - X(s)), \sigma^{*}\nabla\phi(X^{n}(s)) > ds \\ & + \frac{1}{2}r\int_{0}^{t} f_{n}(s)\sum_{i=1}^{m}(\sigma^{*}(\nabla(\sigma^{*}\nabla\phi)_{i}))_{i}(X^{n}(s))ds \\ & -2r\int_{0}^{t} < g_{n}(s)\sigma^{*}(X(s))(X^{n}(s) - X(s)), \sigma^{*}\nabla\phi(X^{n}(s)) > (\mathbf{H}s) \end{aligned}$$

## Main steps of the proof of Lemma 3

Set

$$A = r \int_0^t f_n(s) < \nabla \phi(X^n(s)), \sigma(X^n(s)) dW^n(s) > .$$

Write

$$A = r \int_{0}^{t} f_{n}(s_{n}^{-}) < \nabla \phi(X^{n}(s_{n}^{-})), \sigma(X^{n}(s_{n}^{-})) dW^{n}(s) > + r \int_{0}^{t} (f_{n}(s) - f_{n}(s_{n}^{-})) < \nabla \phi(X^{n}(s)), \sigma(X^{n}(s)) dW^{n}(s) > + r \int_{0}^{t} f_{n}(s_{n}^{-}) < \sigma^{*} \nabla \phi(X^{n}(s)) - \sigma^{*} \nabla \phi(X^{n}(s_{n}^{-})), dW^{n}(s) > := A_{1} + A_{2} + A_{3}.$$
(15)

As a stochastic integral, it is easy to see that  $E[A_1] = 0$ .

In view of (12), we further write  $A_2$  as

$$\begin{array}{ll} & A_{2} \\ = & r^{2} \int_{0}^{t} (\int_{s_{n}^{-}}^{s} f_{n}(u) \\ & \times < \nabla \phi(X(u)), \sigma(X(u)) dW(u) >) < \nabla \phi(X^{n}(s)), \sigma(X^{n}(s)) dW^{n}(s) \\ + & r^{2} \int_{0}^{t} (\int_{s_{n}^{-}}^{s} f_{n}(u) < \nabla \phi(X(u)), b(X(u)) du >) \\ & \times < \nabla \phi(X^{n}(s)), \sigma(X^{n}(s)) dW^{n}(s) > \\ + & \frac{1}{2} r^{2} \int_{0}^{t} (\int_{s_{n}^{-}}^{s} f_{n}(u) tr(\phi''(\sigma\sigma^{*})(X(u)) du) \\ & \times < \nabla \phi(X^{n}(s)), \sigma(X^{n}(s)) dW^{n}(s) > \end{array}$$

## Main steps of the proof of Lemma 3

$$+ \frac{1}{2}r^{2}\int_{0}^{t} (\int_{s_{n}^{-}}^{s} f_{n}(u) < \nabla\phi(X(u)), (\sigma\sigma')(X(u)) > du) \\ \times < \nabla\phi(X^{n}(s)), \sigma(X^{n}(s))dW^{n}(s) > \\ + r^{2}\int_{0}^{t} (\int_{s_{n}^{-}}^{s} f_{n}(u) < \nabla\phi(X(u)), \nu(X(u)) > d|L|(u)) \\ \times < \nabla\phi(X^{n}(s)), \sigma(X^{n}(s))dW^{n}(s) > \\ + \cdots \\ := \sum_{i=1}^{17} A_{2i}$$
(16)

We will bound each of the terms. Since  $\nabla\phi,\ b,\ \sigma$  are bounded on  $\bar{D},$  we have

$$E[|A_{22}|] \leq C \int_0^t (s - s_n^-) E[|\dot{W}^n(s)|] ds$$
  
$$\leq C \frac{1}{2^n} \int_0^t (2^n)^{\frac{1}{2}} ds \leq C(\frac{1}{2^n})^{\frac{1}{2}}.$$
(17)

Similarly, it holds that

$$E[|A_{2i}|] \leq C(\frac{1}{2^n})^{\frac{1}{2}}, \quad i=3,4,7,11,12,15,16,17.$$
 (18)

## Main steps of the proof of Lemma 3

To bound  $A_{21}$ , we write it as

$$\begin{array}{ll} A_{21} \\ = & r^2 \int_0^t (\int_{s_n^-}^s [f_n(u) < \nabla \phi(X(u)), \sigma(X(u)dW(u) > -f_n(s_n^-) \times \\ < & \nabla \phi(X(s_n^-)), \sigma(X(s_n^-))dW(u) >]) < \nabla \phi(X^n(s)), \sigma(X^n(s))dW^n(s) \\ + & r^2 \int_0^t (\int_{s_n^-}^s f_n(s_n^-) < \nabla \phi(X(s_n^-)), \sigma(X(s_n^-))dW(u) >) \\ \times & [ < \nabla \phi(X^n(s)), \sigma(X^n(s))dW^n(s) > \\ & - < \nabla \phi(X^n(s_n^-)), \sigma(X^n(s_n^-))dW^n(s) >] \\ + & r^2 \int_0^t f_n(s_n^-) < \nabla \phi(X(s_n^-)), \sigma(X(s_n^-))(W(s) - W(s_n^-)) > \\ & \times < \nabla \phi(X^n(s_n^-)), \sigma(X^n(s_n^-))dW^n(s) > \\ \vdots & A_{21,1} + A_{21,2} + A_{21,3}. \end{array}$$

By Ito isometry and Hölder's inequality,

$$E[A_{21,1}] \leq C \int_{0}^{t} (E[\int_{s_{n}^{-}}^{s} |f_{n}(u)\sigma^{*}\nabla\phi(X(u)) - f_{n}(s_{n}^{-})\sigma^{*}\nabla\phi(X(s_{n}^{-}))|^{2} \\ \times du])^{\frac{1}{2}} (E[|\dot{W}^{n}|^{2}(s)])^{\frac{1}{2}} ds \\ \leq C \int_{0}^{t} (2^{n})^{\frac{1}{2}} (E[\int_{s_{n}^{-}}^{s} |f_{n}(u)\sigma^{*}\nabla\phi(X(u)) - f_{n}(s_{n}^{-}) \\ \times \sigma^{*}\nabla\phi(X(s_{n}^{-}))|^{2} du])^{\frac{1}{2}} ds \\ \leq C \int_{0}^{t} (2^{n})^{\frac{1}{2}} (\frac{1}{2^{n}})^{\frac{1}{2}} (\frac{1}{2^{n}})^{\frac{1}{2}} ds \leq C (\frac{1}{2^{n}})^{\frac{1}{2}}, \qquad (20)$$

where (7), (8) have been used.

For the term  $A_{21,2}$ , we have

$$E[A_{21,2}] \leq C \int_{0}^{t} (E[|W(s) - W(s_{n}^{-})|^{3}])^{\frac{1}{3}} \times (E[|\sigma^{*}\nabla\phi(X^{n}(s)) - \sigma^{*}\nabla\phi(X^{n}(s_{n}^{-}))|^{3}])^{\frac{1}{3}} (E[|\dot{W}^{n}|^{3}(s)])^{\frac{1}{3}} ds \leq C \int_{0}^{t} (2^{n})^{\frac{1}{2}} (\frac{1}{2^{n}})^{\frac{1}{2}} (\frac{1}{2^{n}})^{\frac{1}{2}} ds \leq C (\frac{1}{2^{n}})^{\frac{1}{2}}.$$
(21)

where (7) has been used.

## Main steps of the proof of Lemma 3

#### Now,

$$\begin{aligned} A_{21,3} \\ &= r^2 \sum_k \int_{\frac{k}{2^n}}^{\frac{k+1}{2^n}} f_n(\frac{k-1}{2^n}) < \nabla \phi(X(\frac{k-1}{2^n})), \sigma(X(\frac{k-1}{2^n})(W(s) - W(\frac{k}{2^n})) > < \nabla \phi(X^n(\frac{k-1}{2^n})), \sigma(X^n(\frac{k-1}{2^n}))(W(\frac{k}{2^n}) - W(\frac{k-1}{2^n})) \\ &+ r^2 \sum_k \int_{\frac{k}{2^n}}^{\frac{k+1}{2^n}} f_n(\frac{k-1}{2^n}) < \sigma^* \nabla \phi(X(\frac{k-1}{2^n})), W(\frac{k}{2^n}) - W(\frac{k-1}{2^n}) \\ &> \times < \sigma^* \nabla \phi(X^n(\frac{k-1}{2^n})), W(\frac{k}{2^n}) - W(\frac{k-1}{2^n}) > ds \\ &\coloneqq A_{21,31} + A_{21,32}. \end{aligned}$$

Conditioning on  $\mathcal{F}_{\frac{k}{2^n}}$ , it is easy to see that  $E[A_{21,31}] = 0$ .

### The main steps of proof of Lemma 3

#### Moreover,

$$A_{21,32}$$

$$= r^{2} \sum_{k} f_{n}(\frac{k-1}{2^{n}}) \sum_{i=1}^{m} (\sigma^{*} \nabla \phi)_{i}(X(\frac{k-1}{2^{n}}))(\sigma^{*} \nabla \phi)_{i}(X^{n}(\frac{k-1}{2^{n}}))$$

$$\times (|W_{i}(\frac{k}{2^{n}}) - W_{i}(\frac{k-1}{2^{n}})|^{2} - \frac{1}{2^{n}})$$

$$+ r^{2} \sum_{k} f_{n}(\frac{k-1}{2^{n}}) \sum_{i \neq j} (\sigma^{*} \nabla \phi)_{i}(X(\frac{k-1}{2^{n}}))(\sigma^{*} \nabla \phi)_{j}(X^{n}(\frac{k-1}{2^{n}}))$$

$$\times (W_{i}(\frac{k}{2^{n}}) - W_{i}(\frac{k-1}{2^{n}}))(W_{j}(\frac{k}{2^{n}}) - W_{j}(\frac{k-1}{2^{n}}))$$

$$+ r^{2} \sum_{k} f_{n}(\frac{k-1}{2^{n}}) \sum_{i=1}^{m} (\sigma^{*} \nabla \phi)_{i}(X(\frac{k-1}{2^{n}}))(\sigma^{*} \nabla \phi)_{i}(X^{n}(\frac{k-1}{2^{n}}))(\frac{1}{2^{n}})$$

$$:= A_{21,321} + A_{21,322} + A_{21,323}.$$
(23)

Conditioning on  $\mathcal{F}_{\frac{k-1}{2^n}}$  and using the independence of  $W_i$ ,  $W_j$  for  $i \neq j$ , we find that  $E[A_{21,321}] = 0$  and  $E[A_{21,322}] = 0$ .

## The main steps of proof of Lemma 3

On the other hand,

$$E[A_{21,323}] = r^{2}E[\int_{0}^{t} f_{n}(s) < \sigma^{*}\nabla\phi(X(s)), \sigma^{*}\nabla\phi(X^{n}(s)) > ds] + r^{2}E[\int_{0}^{t} \{f_{n}(s_{n}^{-}) < \sigma^{*}\nabla\phi(X(s_{n}^{-})), \sigma^{*}\nabla\phi(X^{n}(s_{n}^{-})) > -f_{n}(s) < \sigma^{*}\nabla\phi(X(s)), \sigma^{*}\nabla\phi(X^{n}(s)) > \}ds] \le r^{2}E[\int_{0}^{t} f_{n}(s) < \sigma^{*}\nabla\phi(X(s)), \sigma^{*}\nabla\phi(X^{n}(s)) > ds] + C(\frac{1}{2^{n}})^{\frac{1}{2}},$$
(24)

where (7), (8) again have been used. Putting together (19)—(24) we arrive at

$$E[A_{21}] \le CE[\int_0^t f_n(s)ds] + C(\frac{1}{2^n})^{\frac{1}{2}}.$$
 (25)

The term  $A_{25}$  can be bounded as follows.

$$E[A_{25}] \\ \leq CE[\sum_{k} \int_{\frac{k}{2^{n}}}^{\frac{k+1}{2^{n}}} (\int_{\frac{k-1}{2^{n}}}^{s} d|L|(u))2^{n}|W(\frac{k}{2^{n}}) - W(\frac{k-1}{2^{n}})|ds] \\ \leq CE[\sum_{k} (|L|(\frac{k}{2^{n}}) - |L|(\frac{k-1}{2^{n}}))|W(\frac{k}{2^{n}}) - W(\frac{k-1}{2^{n}})|] \\ \leq 2CE[|L|(t) \sup_{|u-v| \leq \frac{1}{2^{n}}} (|W(u) - W(v)|)] \\ \leq 2C(E[|L|^{2}(t)])^{\frac{1}{2}} (\frac{1}{2^{n}})^{\frac{1}{2}} \leq C(\frac{1}{2^{n}})^{\frac{1}{2}}.$$
(26)

Collecting the estimates for all the remaining terms we arrive at

$$E[A_{2}] \leq C(\frac{1}{2^{n}})^{\frac{1}{2}} + r^{2}E[\int_{0}^{t} f_{n}(s) < \sigma^{*}\nabla\phi(X^{n}(s)), \sigma^{*}\nabla\phi(X(s)) > ds] + \frac{1}{2}r^{2}E[\int_{0}^{t} f_{n}(s)|\sigma^{*}\nabla\phi|^{2}(X^{n}(s))ds + r\int_{0}^{t} < g_{n}(s)\sigma^{*}(X^{n}(s))(X^{n}(s) - X(s)), \sigma^{*}\nabla\phi(X^{n}(s)) > ds - 2r\int_{0}^{t} < g_{n}(s)\sigma^{*}(X(s))(X^{n}(s) - X(s)), \sigma^{*}\nabla\phi(X^{n}(s)) > ds.$$

$$(27)$$

### The main steps of the proof of Lemma3

Now we turn to  $A_3$ . By the chain rule, we have

$$\begin{aligned} A_{3} \\ &= r \int_{0}^{t} f_{n}(s_{n}^{-}) \sum_{i=1}^{m} [(\sigma^{*} \nabla \phi)_{i}(X^{n}(s)) - (\sigma^{*} \nabla \phi)_{i}(X^{n}(s_{n}^{-}))] dW_{i}^{n}(s) \\ &= r \int_{0}^{t} f_{n}(s_{n}^{-}) \sum_{i=1}^{m} \int_{s_{n}^{-}}^{s} [\langle \nabla (\sigma^{*} \nabla \phi)_{i}(X^{n}(u)) - \nabla (\sigma^{*} \nabla \phi)_{i}(X^{n}(s_{n}^{-})), \\ &\sigma(X^{n}(u)) dW^{n}(u) \rangle ] dW_{i}^{n}(s) \\ &+ r \int_{0}^{t} f_{n}(s_{n}^{-}) \sum_{i=1}^{m} \int_{s_{n}^{-}}^{s} \langle \nabla (\sigma^{*} \nabla \phi)_{i}(X^{n}(s_{n}^{-})), (\sigma(X^{n}(u)) \\ &- \sigma(X^{n}(s_{n}^{-}))) dW^{n}(u) \rangle dW_{i}^{n}(s) \end{aligned}$$

$$+r \int_{0}^{t} f_{n}(s_{n}^{-}) \sum_{i=1}^{m} \int_{s_{n}^{-}}^{s} < \nabla(\sigma^{*}\nabla\phi)_{i}(X^{n}(s_{n}^{-})), \sigma(X^{n}(s_{n}^{-}))dW^{n}(u) > a + r \int_{0}^{t} f_{n}(s_{n}^{-}) \sum_{i=1}^{m} \int_{s_{n}^{-}}^{s} < \nabla(\sigma^{*}\nabla\phi)_{i}(X^{n}(u)), \nu(X^{n}(u))d|L^{n}|(u) > dW + r \int_{0}^{t} f_{n}(s_{n}^{-}) \sum_{i=1}^{m} \int_{s_{n}^{-}}^{s} < \nabla(\sigma^{*}\nabla\phi)_{i}(X^{n}(u)), b(X^{n}(u))du > dW_{i}^{n}(s) = A_{31} + A_{32} + A_{33} + A_{34} + A_{35}$$

Similar to the estimates for  $A_{214}$ ,  $A_{22}$  and the term  $A_{21,2}$ , it can be shown that

$$E[A_{3i}] \le C(\frac{1}{2^n})^{\frac{1}{2}}, \quad i = 1, 2, 4, 5.$$
 (29)

Now,

$$\begin{aligned} A_{33} &= r \sum_{k} (2^{n})^{2} \int_{\frac{k}{2^{n}}}^{\frac{k+1}{2^{n}}} \int_{\frac{k-1}{2^{n}}}^{\frac{k}{2^{n}}} f_{n}(\frac{k-1}{2^{n}}) \sum_{i=1}^{m} \sum_{j=1}^{m} (\sigma^{*}(\nabla(\sigma^{*}\nabla\phi)_{i}))_{j}(X^{n}(\frac{k-1}{2^{n}}) \\ &\times (W_{i}(\frac{k}{2^{n}}) - W_{i}(\frac{k-1}{2^{n}}))(W_{j}(\frac{k-1}{2^{n}} - W_{j}(\frac{k-2}{2^{n}})) ds du \\ &+ r \sum_{k} (2^{n})^{2} \int_{\frac{k}{2^{n}}}^{\frac{k+1}{2^{n}}} \int_{\frac{k}{2^{n}}}^{s} f_{n}(\frac{k-1}{2^{n}}) \sum_{i=1}^{m} \sum_{j=1}^{m} (\sigma^{*}(\nabla(\sigma^{*}\nabla\phi)_{i}))_{j}(X^{n}(\frac{k-1}{2^{n}}) \\ &\times (W_{i}(\frac{k}{2^{n}}) - W_{i}(\frac{k-1}{2^{n}}))(W_{j}(\frac{k}{2^{n}}) - W_{j}(\frac{k-1}{2^{n}})) ds du \end{aligned}$$

$$= r \sum_{k} f_{n}(\frac{k-1}{2^{n}}) \sum_{i=1}^{m} \sum_{j=1}^{m} (\sigma^{*}(\nabla(\sigma^{*}\nabla\phi)_{i}))_{j}(X^{n}(\frac{k-1}{2^{n}})) \\ \times (W_{i}(\frac{k}{2^{n}}) - W_{i}(\frac{k-1}{2^{n}}))(W_{j}(\frac{k-1}{2^{n}}) - W_{j}(\frac{k-2}{2^{n}})) \\ + \frac{1}{2}r \sum_{k} f_{n}(\frac{k-1}{2^{n}}) \sum_{i=1}^{m} \sum_{j=1}^{m} (\sigma^{*}(\nabla(\sigma^{*}\nabla\phi)_{i}))_{j}(X^{n}(\frac{k-1}{2^{n}})) \\ \times (W_{i}(\frac{k}{2^{n}}) - W_{i}(\frac{k-1}{2^{n}}))(W_{j}(\frac{k}{2^{n}}) - W_{j}(\frac{k-1}{2^{n}})) \\ := A_{331} + A_{332}$$
(30)

Conditioning on  $\mathcal{F}_{\frac{k-1}{2^n}}$ , it is easy to see  $E[A_{331}] = 0$ . For the second term we have

$$\begin{aligned} &A_{332} \\ &= \frac{1}{2}r\sum_{k}f_{n}(\frac{k-1}{2^{n}})\sum_{i\neq j}^{m}(\sigma^{*}(\nabla(\sigma^{*}\nabla\phi)_{i}))_{j}(X^{n}(\frac{k-1}{2^{n}})) \\ &\times(W_{i}(\frac{k}{2^{n}})-W_{i}(\frac{k-1}{2^{n}}))(W_{j}(\frac{k}{2^{n}})-W_{j}(\frac{k-1}{2^{n}})) \\ &+ \frac{1}{2}r\sum_{k}f_{n}(\frac{k-1}{2^{n}})\sum_{i=1}^{m}(\sigma^{*}(\nabla(\sigma^{*}\nabla\phi)_{i}))_{i}(X^{n}(\frac{k-1}{2^{n}})) \\ &\times\{|W_{i}(\frac{k}{2^{n}})-W_{i}(\frac{k-1}{2^{n}})|^{2}-\frac{1}{2^{n}}\} \end{aligned}$$

$$+ \frac{1}{2}r \int_{0}^{t} \{f_{n}(s_{n}^{-}) \sum_{i=1}^{m} (\sigma^{*}(\nabla(\sigma^{*}\nabla\phi)_{i}))_{i}(X^{n}(s_{n}^{-})) - f_{n}(s) \sum_{i=1}^{m} (\sigma^{*}(\nabla(\sigma^{*}\nabla\phi)_{i}))_{i}(X^{n}(s)) \} ds$$

$$+ \frac{1}{2}r \int_{0}^{t} f_{n}(s) \sum_{i=1}^{m} (\sigma^{*}(\nabla(\sigma^{*}\nabla\phi)_{i}))_{i}(X^{n}(s)) ds$$

$$:= A_{3321} + A_{3322} + A_{3323} + A_{3324}$$
(31)

Using the martingale property and the independence of  $W_i$ ,  $W_j$  for  $i \neq j$ , we find that  $E[A_{3321}] = 0$  and  $E[A_{3322}] = 0$ . In view of (7) and (8), we have  $E[A_{3323}] \leq C(\frac{1}{2^n})^{\frac{1}{2}}$ . Thus, we deduce from (30), (31) that

$$E[A_{33}] \leq C(\frac{1}{2^n})^{\frac{1}{2}} + \frac{1}{2}r \int_0^t f_n(s) \sum_{i=1}^m (\sigma^*(\nabla(\sigma^*\nabla\phi)_i))_i(X^n(s)) ds$$
(32)

Finally it follows from (28), (29), (29) that

$$E[A_{3}] \leq C(\frac{1}{2^{n}})^{\frac{1}{2}} + \frac{1}{2}r \int_{0}^{t} f_{n}(s) \sum_{i=1}^{m} (\sigma^{*}(\nabla(\sigma^{*}\nabla\phi)_{i}))_{i}(X^{n}(s)) ds(33)$$

Combining (27) with (33), we complete the proof of Lemma.

### The sketch of the proof

#### lemma[4].We have

$$rE[\int_{0}^{t} g_{n}(s) < X^{n}(s) - X(s), \sigma(X^{n}(s))dW^{n}(s) >]$$

$$\leq rE[\int_{0}^{t} g_{n}(s) < \sigma^{*}\nabla\phi(X^{n}(s)), \sigma^{*}(X^{n}(s))(X^{n}(s) - X(s)) > ds]$$

$$+ 2rE[\int_{0}^{t} g_{n}(s) < \sigma^{*}\nabla\phi(X(s)), \sigma^{*}(X^{n}(s))(X^{n}(s) - X(s)) > ds]$$

$$+ E[\int_{0}^{t} g_{n}(s) \sum_{i=1}^{d} \sum_{j=1}^{m} \sigma_{ij}^{2}(X^{n}(s))ds]$$

$$+ E[\int_{0}^{t} g_{n}(s) \sum_{i=1}^{d} (X_{i}^{n}(s) - X_{i}(s)) \sum_{j=1}^{m} (\sigma^{*}\nabla\sigma_{ij})_{j}(X^{n}(s))ds]$$

$$- 2E[\int_{0}^{t} g_{n}(s) \sum_{i=1}^{d} \sum_{j=1}^{m} \sigma_{ij}(X(s))\sigma_{ij}(X^{n}(s))ds] + C(\frac{1}{2^{n}})^{\frac{1}{2}}.$$
 (34)

#### The sketch of the proof

**Proof of the main result: (Continued)**. Choose  $r < -\frac{2C_0}{\alpha}$ , where  $\alpha$ ,  $C_0$  are the constants appeared in the assumptions (D.1) and (D.2). By the Lipschitz continuity of the coefficients and boundedness of  $\phi$ ,  $\phi''$ ,  $\nabla \phi$ ,  $\sigma \sigma'$  on the domain  $\overline{D}$ , it follows from (12) that

$$\begin{split} & E[f_n(t)] \\ & \leq \quad C_r E[\int_0^t f_n(s) ds] \\ & + \quad E[\int_0^t \{ < rf_n(s) \nabla \phi(X(s)) - 2g_n(s)(X^n(s) - X(s)), \nu(X(s)) > \} d|L| \\ & + \quad r E[\int_0^t f_n(s) < \nabla \phi(X^n(s)), \sigma(X^n(s)) dW^n(s) > ] \\ & + \quad E[\int_0^t \{ < rf_n(s) \nabla \phi(X^n(s)) + 2g_n(s)(X^n(s) - X(s)), \\ & \nu(X^n(s)) > \} d|L^n|(s)] \end{split}$$

## The sketch of the proof

$$+ 2E\left[\int_{0}^{t} g_{n}(s) < X^{n}(s) - X(s), \sigma(X^{n}(s))dW^{n}(s) > \right]$$

$$- E\left[\int_{0}^{t} g_{n}(s) < X^{n}(s) - X(s), \sigma\sigma'(X(s)) > ds\right]$$

$$+ E\left[\int_{0}^{t} g_{n}(s)tr(\sigma\sigma^{*}(X(s)))ds\right]$$

$$- 2rE\left[\int_{0}^{t} g_{n}(s) < \sigma^{*}(X(s))(X^{n}(s) - X(s)), \sigma^{*}\nabla\phi(X(s)) > ds\right]$$
(35)

In view of r < 0 and the assumptions (D.1) and (D.2), we deduce that

$$< rf_{n}(s)\nabla\phi(X(s)) - 2g_{n}(s)(X^{n}(s) - X(s)), \nu(X(s)) >$$

$$= g_{n}(s)[r < \nabla\phi(X(s)), \nu(X(s)) > |x^{n}(s) - X(s)|^{2}$$

$$-2 < X^{n}(s) - X(s), \nu(X(s)) > ]$$

$$\le g_{n}(s)[r\alpha|x^{n}(s) - X(s)|^{2} + 2C_{0}|X^{n}(s) - X(s)|^{2}] \le 0, (36)$$

and similarly

$$< rf_n(s)\nabla\phi(X^n(s)) + 2g_n(s)(X^n(s) - X(s)), \nu(X^n(s)) >$$
  
$$\leq 0.$$
(37)

Thus, using Lemma 3 and Lemma 4, taking into account (36) and (37) we obtain from (35) that

# Sketch of the proof

$$\begin{split} & E[f_n(t)] \\ & \leq \quad C_r E[\int_0^t f_n(s) ds] + C(\frac{1}{2^n})^{\frac{1}{2}} \\ & - \quad E[\int_0^t g_n(s) < X^n(s) - X(s), \sigma \sigma'(X(s)) > ds] \\ & + \quad E[\int_0^t g_n(s) \sum_{i=1}^d \sum_{j=1}^m \sigma_{ij}^2(X(s)) ds] \\ & - \quad 2r E[\int_0^t g_n(s) < \sigma^*(X(s))(X^n(s) - X(s)), \sigma^* \nabla \phi(X(s)) > ds] \\ & + \quad 2r \int_0^t < g_n(s) \sigma^*(X^n(s))(X^n(s) - X(s)), \sigma^* \nabla \phi(X^n(s)) > ds \\ & - \quad 2r \int_0^t < g_n(s) \sigma^*(X(s))(X^n(s) - X(s)), \sigma^* \nabla \phi(X^n(s)) > ds \end{split}$$

# Sketch of the proof

$$+ 2rE[\int_{0}^{t} g_{n}(s) < \sigma^{*}\nabla\phi(X(s)), \sigma^{*}(X^{n}(s))(X^{n}(s) - X(s)) > ds]$$

$$+ E[\int_{0}^{t} g_{n}(s) \sum_{i=1}^{d} \sum_{j=1}^{m} \sigma_{ij}^{2}(X^{n}(s))ds]$$

$$+ E[\int_{0}^{t} g_{n}(s) < X^{n}(s) - X(s), \sigma\sigma'(X^{n}(s)) > ds]$$

$$-2 E[\int_{0}^{t} g_{n}(s) \sum_{i=1}^{d} \sum_{j=1}^{m} \sigma_{ij}(X(s))\sigma_{ij}(X^{n}(s))ds]$$

# Sketch of the proof

$$\leq C_{r}E[\int_{0}^{t}f_{n}(s)ds] + C(\frac{1}{2^{n}})^{\frac{1}{2}} \\ + E[\int_{0}^{t}g_{n}(s)\sum_{i=1}^{d}\sum_{j=1}^{m}(\sigma_{ij}(X(s)) - \sigma_{ij}(X^{n}(s)))^{2}ds] \\ + 2r\int_{0}^{t} < g_{n}(s)(\sigma^{*}(X^{n}(s)) - \sigma^{*}(X(s)))(X^{n}(s) - X(s)), \\ \sigma^{*}\nabla\phi(X^{n}(s)) > ds \\ + 2rE[\int_{0}^{t}g_{n}(s) < \sigma^{*}\nabla\phi(X(s)), \\ (\sigma^{*}(X^{n}(s)) - \sigma^{*}(X(s)))(X^{n}(s) - X(s)) > ds] \\ + E[\int_{0}^{t}g_{n}(s) < X^{n}(s) - X(s), \sigma\sigma'(X^{n}(s)) - \sigma\sigma'(X(s)) > ds] \\ \leq CE[\int_{0}^{t}f_{n}(s)ds] + C(\frac{1}{2^{n}})^{\frac{1}{2}},$$
 (38)

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where the Lipschitz continuity of the coefficients and the fact that  $f_n(s) = g_n(s)|X^n(s) - X(s)|^2$  have been used. Finally by the Gronwall's inequality, we obtain

$$E[f_n(t)] \le C(\frac{1}{2^n})^{\frac{1}{2}} \to 0$$
 (39)

as  $n \to \infty$ , completing the proof of (11), hence the theorem.

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