

The Rate of Convergence for Approximate Solutions of Stochastic Differential Equations

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§ 1. Introduction and results.

Let (Ω, \mathcal{F}, P) be a probability space and $B := \{B(t), t \geq 0\} = \{(B^1(t), B^2(t), \dots, B^r(t)), t \geq 0\}$ an r -dimensional standard Brownian motion on it ($r \geq 1$). We consider a stochastic differential equation (abbreviated by SDE) for a d -dimensional continuous process $X := \{X(t), 0 \leq t \leq 1\}$ ($d \geq 1$):

$$(1.1) \quad dX(t) = \sigma(t, X(t))dB(t) + b(t, X(t))dt,$$

with $X(0) \equiv X_0$, where $\sigma(t, x) = \{\sigma_i^j(t, x), 1 \leq i \leq r, 1 \leq j \leq d\}$ is a Borel measurable function $(t, x) \in [0, 1] \times \mathbf{R}^d \rightarrow \mathbf{R}^d \otimes \mathbf{R}^r$ and $b(t, x) = \{b^j(t, x), 1 \leq j \leq d\}$ is a Borel measurable function $(t, x) \in [0, 1] \times \mathbf{R}^d \rightarrow \mathbf{R}^d$. Suppose that $\sigma(\cdot, \cdot)$ and $b(\cdot, \cdot)$ satisfy the following Lipschitz conditions: For any $x, y \in \mathbf{R}^d$ and $t, s \in [0, 1]$ there exists a positive constant L_1 independent of x, y, s and t such that

$$(1.2) \quad |\sigma(t, x) - \sigma(s, y)|^2 + |b(t, x) - b(s, y)|^2 \leq L_1^2(|x - y|^2 + |t - s|^2),$$

where

$$|a|^2 := \sum_{i=1}^r \sum_{j=1}^d |a_i^j|^2 \quad \text{for } a \in \mathbf{R}^d \otimes \mathbf{R}^r$$

and $|\cdot|$ denotes the Euclidean norm. Then there exists a unique solution of the SDE (1.1) (see, for example, Ikeda-Watanabe [8]). Approximate solutions for (1.1) were constructed by Maruyama [9], and its rate of convergence was studied by Gihman-Skorokhod [2] and Shimizu [17] (see also Greenside-Helfand [4], Janković [5], Janssen [6], Milshtein [10], Platen [11], [12], Rao-Borwanker-Ramkrishna [14], Rümelin [15], Wright [18]). In [2] and [17] on the rate of convergence, approximate solutions are

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constructed from normally distributed random variables (namely, increments of a Brownian motion). In this paper we shall use approximate solutions of (1.1) defined by i.i.d. random variables with a general distribution and investigate the rate of convergence in terms of two probability metrics $l_p(\cdot, \cdot)$ and $\pi(\cdot, \cdot)$ defined below. Our result (Theorem 2) is in a sense a generalization of Borovkov [1] and Gorodetskii [3] (see Remark to Theorem 2). The advantage of defining approximate solutions by i.i.d. random variables, not by normally distributed random variables, is known for instance, in simulation on a digital computer (cf. [6]).

Let $W^d := C([0, 1] \rightarrow \mathbb{R}^d)$ be the space of continuous functions with the uniform norm $\|\cdot\|$, $\mathcal{B}(W^d)$ the topological σ -field of W^d and $\mathcal{P}(W^d)$ the space of all probability measures on $(W^d, \mathcal{B}(W^d))$. For any $0 < p < \infty$ define a metric $l_p(\cdot, \cdot)$ on $\mathcal{P}(W^d)$ by

$$\begin{aligned} l_p(P, Q) &:= \left[\inf_{\mu \in \mathcal{P}_{PQ}} \int_{W^d \times W^d} \|v - w\|^p \mu(dv dw) \right]^{1/\tilde{p}} \\ &= \inf_{\mathcal{L}(Y)=P, \mathcal{L}(Z)=Q} E[\|Y - Z\|^p]^{1/\tilde{p}}, \quad P, Q \in \mathcal{P}(W^d), \end{aligned}$$

where

$$\begin{aligned} \mathcal{P}_{PQ} &:= \{ \mu \in \mathcal{P}(W^d \times W^d) ; \mu(A \times W^d) = P(A), \\ &\quad \mu(W^d \times A) = Q(A) \text{ for all } A \in \mathcal{B}(W^d) \}, \end{aligned}$$

Y and Z are W^d -valued random variables, $\mathcal{L}(\cdot)$ denotes the law of \cdot and $\tilde{p} := \max(1, p)$. It follows from Theorem 1 of [13] that, for $P_n, P \in \mathcal{P}(W^d)$ satisfying

$$\int_{W^d} \|w\|^p P_n(dw) < \infty \quad \text{and} \quad \int_{W^d} \|w\|^p P(dw) < \infty,$$

the convergence $l_p(P_n, P) \rightarrow 0$ as $n \rightarrow \infty$ is equivalent to that

$$P_n \Rightarrow P \quad \text{and} \quad \int_{W^d} \|w\|^p (P_n - P)(dw) \rightarrow 0, \quad \text{as } n \rightarrow \infty,$$

where " \Rightarrow " means the weak convergence in $(W^d, \mathcal{B}(W^d))$. Another metric we consider here is the Lévy-Prokhorov metric $\pi(\cdot, \cdot)$ defined by

$$\pi(P, Q) := \inf\{\varepsilon > 0 ; P(A) \leq \varepsilon + Q(G^\varepsilon(A)) \text{ for all } A \in \mathcal{B}(W^d)\},$$

where $G^\varepsilon(A) := \{w \in W^d ; \|v - w\| < \varepsilon, v \in A\}$. A relationship between $l_p(\cdot, \cdot)$ and $\pi(\cdot, \cdot)$ is that for all $Q, R \in \mathcal{P}(W^d)$,

$$(1.3) \quad \pi(Q, R) \leq l_p(Q, R)^{\tilde{p}/(1+p)}$$

for any positive $p < \infty$, (Rachev [13]).

We next define approximate solutions of the SDE (1.1). Let $\{\xi_k, k \geq 1\} = \{(\xi_k^1, \xi_k^2, \dots, \xi_k^r), k \geq 1\}$ be i.i.d. r -dimensional random variables with zero mean and finite $(2+\delta)$ -th absolute moment for some $\delta > 0$. We suppose that the covariance matrix has non-zero determinant and then it is the identity without loss of generality. Define random variables $\hat{Y}_0, \hat{Y}_1, \dots, \hat{Y}_n$ by

$$\hat{Y}_k := X_0 + \sum_{j=1}^k \frac{\sigma((j-1)/n, \hat{Y}_{j-1}) \xi_j}{n^{1/2}} + \sum_{j=1}^k \frac{b((j-1)/n, \hat{Y}_{j-1})}{n}$$

and $\hat{Y}_0 := X_0$. Let $Y_n := \{Y_n(t); 0 \leq t \leq 1\}$ be a continuous polygonal line defined by

$$Y_n(t) := \hat{Y}_k + (nt - k)(\hat{Y}_{k+1} - \hat{Y}_k),$$

for $k/n \leq t \leq (k+1)/n, k=0, 1, \dots, n-1$. Maruyama (Theorem 2 in [9]) showed that

$$(1.4) \quad P^{Y_n} \Rightarrow P^X, \quad (n \rightarrow \infty),$$

where $P^{Y_n}, P^X \in \mathcal{P}(W^d)$ are the probability measures of Y_n and X , respectively. (1.4) includes classical Donsker's invariance principle as a trivial case where $\sigma(\cdot, \cdot)$ is the identical matrix and $b(\cdot, \cdot)$ is the zero vector. Our main result on the rate of convergence in (1.4) is as follows:

THEOREM 1. *Let $\{\xi_k, k \geq 1\}$ be i.i.d. r -dimensional random variables with zero mean, regular covariance matrix and with $E[|\xi_1|^{2+\delta}] < \infty$ for some $0 < \delta \leq 1$. Assume that $\sigma(\cdot, \cdot)$ and $b(\cdot, \cdot)$ satisfy (1.2) and are bounded, namely,*

$$(1.5) \quad |\sigma(t, x)|^2 + |b(s, y)|^2 \leq L_2^2,$$

where L_2 is a positive constant independent of x, y, s and t . Under these assumptions we have for any $2 \leq p \leq 2+\delta$,

(i) if $d=r=1$, then for any $\varepsilon > p/2$,

$$(1.6) \quad l_p(P^{Y_n}, P^X) = o(n^{-\delta/2(2+\delta)}(\log n)^\varepsilon), \quad (n \rightarrow \infty),$$

(ii) if $r > 1$ and ξ_1 has a bounded or square integrable density, then (1.6) also holds.

From the statement of Theorem 1 for $p=2+\delta$ and (1.3) we have the following result.

THEOREM 2. *Under the same assumptions as in Theorem 1, we have*

(i) if $d=r=1$, then for any $\varepsilon > (2+\delta)^2/2(3+\delta)$,

$$(1.7) \quad \pi(P^{Y_n}, P^X) = o(n^{-\delta/2(3+\delta)}(\log n)^\varepsilon), \quad (n \rightarrow \infty),$$

(ii) if $r > 1$ and ξ_1 has a bounded or square integrable density, then (1.7) also holds.

REMARK TO THEOREM 2. The weak convergence of the sequence of approximate solutions Y_n 's constructed by i.i.d. random variables with a general distribution generalized the well known Donsker's invariance principle, where $\sigma(\cdot, \cdot) \equiv 1$ and $b(\cdot, \cdot) \equiv 0$. In case that $\sigma(\cdot, \cdot) \equiv 1$ and $b(\cdot, \cdot) \equiv 0$, Borovkov [1] and Gorodetskii [3] obtained

$$(1.8) \quad \pi(P^{Y_n}, P^X) = O(n^{-\delta/2(3+\delta)}), \quad (n \rightarrow \infty).$$

In our case, the power of n is the same as their result (1.8), but the convergence is decelerated by the rate $(\log n)^\varepsilon$. However, Theorem 2 is the best possible in the sense that the power of n cannot be improved by a better one, since the estimate (1.8) is known in [16] to be the best possible.

§ 2. Preliminaries.

Define new random variables $\zeta_1, \zeta_2, \dots, \zeta_M$ which are sums of blocks of ξ_k 's as follows;

$$\zeta_k := (\zeta_k^1, \zeta_k^2, \dots, \zeta_k^r) = \sum_{i=(k-1)q+1}^{\{kq\} \wedge n} \frac{\xi_i}{n^{1/2}}, \quad 1 \leq k \leq M,$$

where $q = [n^{2/(2+\delta)}]$, $M = [n/q] + 1 \sim n^{\delta/(2+\delta)}$, $[a]$ being the integral part of a , and $a \wedge b$ means $\min(a, b)$. Let $\{t_k, k=0, 1, \dots, M\}$ be a partition of the interval $[0, 1]$ which is defined by $t_k = k\Delta$ for $0 \leq k \leq M-1$ and $t_M = 1$, where $\Delta := q/n \sim n^{-\delta/(2+\delta)}$. Moreover define increments of the Brownian motion by $\eta_k := (\eta_k^1, \eta_k^2, \dots, \eta_k^r) = B(t_k) - B(t_{k-1})$, $1 \leq k \leq M$. We approximate X and Y_n by the following processes \tilde{X}_n and \tilde{Y}_n : Let $\{\tilde{X}_k, k=0, 1, \dots, M\}$ and $\{\tilde{Y}_k, k=0, 1, \dots, M\}$ be random variables defined by

$$\tilde{X}_k := X_0 + \sum_{j=1}^k \sigma(t_{j-1}, \tilde{X}_{j-1}) \eta_j + \sum_{j=1}^k b(t_{j-1}, \tilde{X}_{j-1})(t_j - t_{j-1}),$$

$$\tilde{Y}_k := X_0 + \sum_{j=1}^k \sigma(t_{j-1}, \tilde{Y}_{j-1}) \zeta_j + \sum_{j=1}^k b(t_{j-1}, \tilde{Y}_{j-1})(t_j - t_{j-1}),$$

for each $1 \leq k \leq M$ and $\tilde{X}_0 = \tilde{Y}_0 = X_0$. Define $D([0, 1] \rightarrow \mathbf{R}^d)$ -valued processes $\tilde{X}_n := \{\tilde{X}_n(t), 0 \leq t \leq 1\}$ and $\tilde{Y}_n := \{\tilde{Y}_n(t), 0 \leq t \leq 1\}$ by $\tilde{X}_n(t) := \tilde{X}_{k-1}$ and $\tilde{Y}_n(t) := \tilde{Y}_{k-1}$ for $t_{k-1} \leq t < t_k$, $1 \leq k \leq M$, and $\tilde{X}_n(1) := \tilde{X}_M$ and $\tilde{Y}_n(1) := \tilde{Y}_M$ for $t=1$, respectively.

One of the main techniques of the proof of Theorem 1 is the following reconstruction of all random variables on a common probability space.

LEMMA 1. *Without changing distributions of $\{\xi_k, 1 \leq k \leq n\}$ and $\{\zeta_k, 1 \leq k \leq M\}$, we can redefine them on a richer probability space with a Brownian motion $\{B(t), t \geq 0\}$ and its increments $\{\eta_k, 1 \leq k \leq M\}$ such that the following properties hold:*

(i) *If $d=r=1$, then for any $0 < \varepsilon < 2 + \delta$ and for each $1 \leq k \leq M$,*

$$(2.1) \quad E[|\zeta_k - \eta_k|^\varepsilon] = O(\Delta^{(\varepsilon - \delta)/2} n^{-\delta/2}), \quad (n \rightarrow \infty).$$

(ii) *If $r > 1$ and ξ_1 has a bounded or square integrable density, then for any $0 < \varepsilon < 2 + \delta$ and each $1 \leq k \leq M$,*

$$(2.2) \quad E[|\zeta_k - \eta_k|^\varepsilon] = O(\Delta^{(\varepsilon - \delta)/2} n^{-\delta/2} (\log n)^{\varepsilon/2}), \quad (n \rightarrow \infty).$$

(iii) *For each $1 \leq k \leq M - 1$,*

$$(2.3) \quad \{\zeta_1, \zeta_2, \dots, \zeta_k, \eta_1, \eta_2, \dots, \eta_k\} \text{ is independent of } \{\zeta_{k+1}, \zeta_{k+2}, \dots, \zeta_M, \eta_{k+1}, \eta_{k+2}, \dots, \eta_M\}.$$

PROOF. Before proving the lemma we give several notation according to [3]. Let $x = (x^1, x^2, \dots, x^r) \in \mathbf{R}^r$. For each $1 \leq k \leq M$ and $1 \leq i \leq r$, let $\mu_k^i(\cdot)$ be the probability measure of $((t_k - t_{k-1})^{-1/2} \zeta_k^1, (t_k - t_{k-1})^{-1/2} \zeta_k^2, \dots, (t_k - t_{k-1})^{-1/2} \zeta_k^i)$ and $F_k^i(\cdot | x^1, \dots, x^i)$ be the right continuous conditional distribution function defined by, for any bounded Borel function ψ ,

$$\begin{aligned} & \int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} \psi(x^1, \dots, x^i) F_k^i(dx^i | x^1, \dots, x^{i-1}) \mu_k^{i-1}(dx^1, \dots, dx^{i-1}) \\ &= \int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} \psi(x^1, \dots, x^i) \mu_k^i(dx^1, \dots, dx^i). \end{aligned}$$

Define the inverse function of $F_k^i(\cdot | x^1, \dots, x^{i-1})$ by

$$(F_k^i)^{-1}(u | x^1, \dots, x^{i-1}) := \sup_{F_k^i(v | x^1, \dots, x^{i-1}) \leq u} v.$$

Let $\Phi(\cdot)$ be the one dimensional standard normal distribution function. Furthermore define transformations $h_k^i, h_k: \mathbf{R}^r \rightarrow \mathbf{R}^1$ by

$$h_k^i(x) := (x^1, \dots, x^{i-1}, (F_k^i)^{-1}(\Phi(x^i) | x^1, \dots, x^{i-1}), x^{i+1}, \dots, x^r),$$

and $h_k := h_k^r \circ h_k^{r-1} \circ \dots \circ h_k^1$. Then we have

$$(2.4) \quad \begin{aligned} & \mathcal{L}\{h_1(t_1^{-1/2} \eta_1), h_2((t_2 - t_1)^{-1/2} \eta_2), \dots, h_M((t_M - t_{M-1})^{-1/2} \eta_M)\} \\ &= \mathcal{L}\{t_1^{-1/2} \zeta_1, (t_2 - t_1)^{-1/2} \zeta_2, \dots, (t_M - t_{M-1})^{-1/2} \zeta_M\}. \end{aligned}$$

Now, applying (2.4), we redefine processes $\{\xi_k\}$, $\{\zeta_k\}$ and $\{B(\cdot)\}$ such that (2.1)–(2.3) are satisfied as follows: Suppose that there is a Brownian motion $\hat{B} := \{\hat{B}(t), t \geq 0\}$ on another probability space $(\hat{\Omega}, \hat{\mathcal{F}}, \hat{P})$. Define

$$(2.5) \quad \{\hat{\xi}_1, \hat{\xi}_2, \dots, \hat{\xi}_M\} := \{t_1^{1/2}h_1(t_1^{-1/2}\hat{\eta}_1), (t_2 - t_1)^{1/2}h_2((t_2 - t_1)^{-1/2}\hat{\eta}_2), \\ \dots, (t_M - t_{M-1})^{1/2}h_M((t_M - t_{M-1})^{-1/2}\hat{\eta}_M)\},$$

where $\hat{\eta}_1, \dots, \hat{\eta}_M$ are increments of \hat{B} and $\mathcal{L}\{\hat{\eta}_k, 1 \leq k \leq M\} = \mathcal{L}\{\eta_k, 1 \leq k \leq M\}$. Then, from (2.4), $\mathcal{L}\{\hat{\xi}_k, 1 \leq k \leq M\} = \mathcal{L}\{\zeta_k, 1 \leq k \leq M\}$. We next construct $\{\xi_k\}$ by the following method. Define probability measures U and V by, for any $A_1 \in \mathcal{B}(\mathbf{R}^r \otimes \mathbf{R}^n)$, $A_2 \in \mathcal{B}(\mathbf{R}^r \otimes \mathbf{R}^M)$ and $A_3 \in \mathcal{B}(W^r)$,

$$U(A_1 \times A_2) := P\{(\xi_1, \dots, \xi_n) \in A_1, (\zeta_1, \dots, \zeta_M) \in A_2\},$$

$$V(A_2 \times A_3) := P\{(\hat{\xi}_1, \dots, \hat{\xi}_M) \in A_2, \hat{B} \in A_3\}.$$

Put

$$U_{A_1}(A_2) := U(A_1 \times A_2), \quad V_{A_3}(A_2) := V(A_2 \times A_3),$$

$$H(A_2) := U(\mathbf{R}^r \otimes \mathbf{R}^M \times A_2) = V(A_2 \times W^r).$$

Since $U_{A_1}(\cdot)$ is absolute continuous with respect to $H(\cdot)$, there exists a $\mathcal{B}(\mathbf{R}^r \otimes \mathbf{R}^M)$ -measurable function $p_{A_1}(\cdot)$ such that

$$U_{A_1}(A_2) = \int_{A_2} p_{A_1}(y) H(dy).$$

Furthermore there also exists a $\mathcal{B}(\mathbf{R}^r \otimes \mathbf{R}^M)$ -measurable function $q_{A_3}(\cdot)$ such that

$$V_{A_3}(A_2) = \int_{A_2} q_{A_3}(y) H(dy).$$

Define a probability measure Q on $(\mathbf{R}^r \otimes \mathbf{R}^n) \times (\mathbf{R}^r \otimes \mathbf{R}^M) \times W^r$ by

$$Q(A_1 \times A_2 \times A_3) := \int_{A_2} p_{A_1}(y) q_{A_3}(y) H(dy).$$

Finally define a new probability space $(\Omega', \mathcal{F}', P')$ by $\Omega' := (\mathbf{R}^r \otimes \mathbf{R}^n) \times (\mathbf{R}^r \otimes \mathbf{R}^M) \times W^r$, where \mathcal{F}' is the completion of the topological σ -field $\mathcal{B}(\Omega')$ by Q and $P' := Q$. Keeping the relation (2.5) in mind, we can redefine $\{\xi_k\}$, $\{\zeta_k\}$ and $\{B(\cdot)\}$ without changing their distributions on the common probability space $(\Omega', \mathcal{F}', P')$ by putting for each $\omega = (\omega_1, \omega_2, \omega_3) \in \Omega'$,

$$(\xi_1, \dots, \xi_n)(\omega) := \omega_1, \quad (\zeta_1, \dots, \zeta_M)(\omega) := \omega_2 \quad \text{and} \quad B(\cdot, \omega) := \omega_3.$$

Now, from (2.5), the relation (2.3) in Lemma 1 can be easily shown. Moreover (2.1) and (2.2) are proved by Borovkov (Lemma 1 in [1]) and Gorodetskii (Lemma 2 in [3]), respectively. \square

Finally we need the following three lemmas. In what follows, as a positive constant independent of n , we use a K which may be different in the different equations and $L := \max(L_1, L_2)$.

LEMMA 2 (Fuk [7]). *Let $\{\nu_k, 1 \leq k \leq n\}$ be a square integrable martingale difference sequence with respect to a reference family of σ -fields $\{\mathcal{A}_k, 0 \leq k \leq n\}$ such that $E(\nu_k | \mathcal{A}_{k-1}) = 0$ a.s. for each k . Suppose there exist sequences of positive numbers $\{g_k, 1 \leq k \leq n\}$ and $\{h_k, 1 \leq k \leq n\}$ such that*

$$E(\nu_k^2 | \mathcal{A}_{k-1}) \leq g_k \quad \text{and} \quad E(|\nu_k|^{2+\delta} | \mathcal{A}_{k-1}) \leq h_k \quad \text{a.s.}$$

for some $\delta > 0$ and each k . Then for any positive v

$$P\left\{\max_{1 \leq k \leq n} \left| \sum_{i=1}^k \nu_i \right| \geq u\right\} \leq \sum_{k=1}^n P\{|\nu_k| \geq v\} + 2 \exp\left\{-\beta uv^{-1} \log\left(\frac{\beta uv^{1+\delta}}{H}\right) + 1\right\} + 2 \exp\left(\frac{-\alpha^2 u^2}{2e^\alpha G}\right),$$

where $\alpha = 2/(4+\delta)$, $\beta = 1 - \alpha$, $G = g_1 + \dots + g_n$ and $H = h_1 + \dots + h_n$.

LEMMA 3. For any $2 \leq p \leq 2 + \delta$,

$$E\left[\max_{1 \leq k \leq M} \max_{1 \leq t \leq q} \left| \sum_{j=(k-1)q+1}^{((k-1)q+t) \wedge n} \frac{\sigma((j-1)/n, \hat{Y}_{j-1}) \xi_j}{n^{1/2}} \right|^p\right] = O(\Delta^{p/2} (\log n)^{p/2}), \quad (n \rightarrow \infty).$$

PROOF. Put

$$A := \max_{1 \leq k \leq M} \max_{1 \leq t \leq q} \left| \sum_{j=(k-1)q+1}^{((k-1)q+t) \wedge n} \frac{\sigma((j-1)/n, \hat{Y}_{j-1}) \xi_j}{n^{1/2}} \right|^p.$$

By integration by parts, we have, for any $\lambda > 0$,

$$\begin{aligned} (2.6) \quad E[A] &= \int_{\{A \leq \lambda \Delta^{p/2} (\log n)^{p/2}\}} AdP + \int_{\{A > \lambda \Delta^{p/2} (\log n)^{p/2}\}} AdP \\ &\leq \lambda \Delta^{p/2} (\log n)^{p/2} + \int_{\{A > \lambda \Delta^{p/2} (\log n)^{p/2}\}} AdP \\ &\leq 2\lambda \Delta^{p/2} (\log n)^{p/2} + \int_{\lambda \Delta^{p/2} (\log n)^{p/2}}^{\infty} P\{A > x\} dx. \end{aligned}$$

Putting $\Delta^{p/2} y = x$, we have

$$\begin{aligned}
(2.7) \quad & \int_{\lambda \Delta^{p/2} (\log n)^{p/2}}^{\infty} P\{A > x\} dx = \Delta^{p/2} \int_{\lambda (\log n)^{p/2}}^{\infty} P\{A^{1/p} > \Delta^{1/2} y^{1/p}\} dy \\
& \leq \Delta^{p/2} \int_{\lambda (\log n)^{p/2}}^{\infty} \sum_{k=1}^M P\left\{ \max_{1 \leq t \leq q} \left[\sum_{m=1}^d \left(\sum_{l=1}^r \sum_{j=(k-1)q+1}^{(k-1)q+t \wedge n} \frac{\sigma_m^l((j-1)/n, \hat{Y}_{j-1}) \xi_j^l}{n^{1/(2+\delta)}} \right)^2 \right]^{1/2} > y^{1/p} \right\} dy \\
& \leq \sum_{m=1}^d \sum_{l=1}^r \Delta^{p/2} \int_{\lambda (\log n)^{p/2}}^{\infty} \sum_{k=1}^M P\left\{ \max_{1 \leq t \leq q} \left| \sum_{j=(k-1)q+1}^{(k-1)q+t \wedge n} \frac{\sigma_m^l((j-1)/n, \hat{Y}_{j-1}) \xi_j^l}{n^{1/(2+\delta)}} \right| > \frac{y^{1/p}}{rd} \right\} dy.
\end{aligned}$$

Let $\mathcal{A}_k := \sigma\{\xi_1, \dots, \xi_k\}$ and $\nu_k^{lm} := \sigma_m^l((j-1)/n, \hat{Y}_{j-1}) \xi_j^l / n^{1/(2+\delta)}$ for each k, l and m . Let us agree to write $\nu_k, \sigma(\cdot, \cdot)$ and ξ_k for $\nu_k^{lm}, \sigma_m^l(\cdot, \cdot)$ and ξ_k^l . Since, from (1.5),

$$E(\nu_j^2 | \mathcal{A}_{j-1}) = \frac{\sigma((j-1)/n, \hat{Y}_{j-1})^2 E[\xi_j^2]}{n^{2/(2+\delta)}} \leq Kn^{-2/(2+\delta)} \quad \text{a.s.},$$

$$E(|\nu_j|^{2+\delta} | \mathcal{A}_{j-1}) = \frac{|\sigma((j-1)/n, \hat{Y}_{j-1})|^{2+\delta} E[|\xi_j|^{2+\delta}]}{n} \leq Kn^{-1} \quad \text{a.s.},$$

we can take $G = Kqn^{-2/(2+\delta)} = K$ and $H = qKn^{-1} = Kn^{-2/(2+\delta)}$. Furthermore we put $u = y^{1/p}/rd$ and $v = cy^{1/p}$ for some $c > 0$ and apply Lemma 2 as follows;

$$\begin{aligned}
(2.8) \quad & P\left\{ \max_{1 \leq t \leq q} \left| \sum_{j=(k-1)q+1}^{(k-1)q+t \wedge n} \frac{\sigma((j-1)/n, \hat{Y}_{j-1}) \xi_j}{n^{1/(2+\delta)}} \right| > \frac{y^{1/p}}{rd} \right\} \\
& \leq \sum_{j=(k-1)q+1}^{(k-1)q \wedge n} P\left\{ \left| \frac{\sigma((j-1)/n, \hat{Y}_{j-1}) \xi_j}{n^{1/(2+\delta)}} \right| > cy^{1/p} \right\} \\
& \quad + \exp\left[-\frac{\beta}{crd} \log\left(\frac{\beta y^{(2+\delta)/p} c^{1+\delta} n^{\delta/(2+\delta)}}{Krd} \right) + 1 \right] \\
& \quad + 2 \exp\left(\frac{-\alpha^2 y^{2/p}}{2e^\alpha K r^2 d^2} \right) \\
& \leq \sum_{j=(k-1)q+1}^{(k-1)q \wedge n} P\left\{ |\xi_j| > \frac{n^{1/(2+\delta)} y^{1/p}}{L} \right\} \\
& \quad + Ky^{-\beta(2+\delta)/crpd} n^{-\beta\delta/crd(2+\delta)} + 2 \exp\left(\frac{-\alpha^2 y^{2/p}}{2e^\alpha L r^2 d^2} \right).
\end{aligned}$$

We can easily see that

$$(2.9) \quad M \Delta^{p/2} \int_{\lambda (\log n)^{p/2}}^{\infty} \exp\left(\frac{-\alpha^2 y^{2/p}}{2e^\alpha L r^2 d^2} \right) dy \leq K \Delta^{p/2} (\log n)^{p/2}$$

for sufficiently large $\lambda > 0$, and

$$\begin{aligned}
(2.10) \quad & M \Delta^{p/2} \int_{\lambda (\log n)^{p/2}}^{\infty} y^{-\beta(2+\delta)/crpd} n^{-\beta\delta/crd(2+\delta)} dy \\
& \leq K \Delta^{p/2} (\log n)^{p/2}
\end{aligned}$$

for sufficiently small $c > 0$. Furthermore,

$$\begin{aligned}
 (2.11) \quad & \Delta^{p/2} \int_{\lambda(\log n)^{p/2}}^{\infty} \sum_{k=1}^M \sum_{j=(k-1)q+1}^{\{kq\} \wedge n} P\{|\xi_j| > n^{1/(2+\delta)} y^{1/p}/L\} dy \\
 & \leq n \Delta^{p/2} \int_1^{\infty} P\{|\xi_1|^{2+\delta} > Kny\} dy \\
 & \leq (\Delta^{p/2}/K) \int_{Kn}^{\infty} P\{|\xi_1|^{2+\delta} > x\} dx \\
 & \leq (\Delta^{p/2}/K) E[|\xi_1|^{2+\delta}].
 \end{aligned}$$

Hence we finish the proof from (2.6)-(2.11). \square

LEMMA 4. For any positive T ,

$$(2.12) \quad E[\max_{0 \leq s \leq T} \max_{s \leq t \leq s+T\Delta} |B(t) - B(s)|^p] = O(\Delta^{p/2} (\log n)^{p/2}), \quad (n \rightarrow \infty).$$

PROOF. Let $u_k := Tt_k$ for each k . For any s with $u_{l-1} \leq s \leq u_l$,

$$\begin{aligned}
 (2.13) \quad & \max_{s \leq t \leq s+T\Delta} |B(t) - B(s)| = \max\{ \max_{s \leq t \leq u_l} |(B(u_{l-1}) - B(t)) - (B(u_{l-1}) - B(s))|, \\
 & \quad \max_{u_l \leq t \leq s+T\Delta} |(B(u_{l-1}) - B(u_l)) + (B(u_l) - B(t)) - (B(u_{l-1}) - B(s))| \} \\
 & \leq \max\{ 2 \max_{u_{l-1} \leq t \leq u_l} |B(t) - B(u_{l-1})|, \\
 & \quad 2 \max_{u_{l-1} \leq t \leq u_l} |B(t) - B(u_{l-1})| + \max_{u_l \leq t \leq u_{l+1}} |B(t) - B(u_l)| \} \\
 & = 2 \max_{u_{l-1} \leq t \leq u_l} |B(t) - B(u_{l-1})| + \max_{u_l \leq t \leq u_{l+1}} |B(t) - B(u_l)|.
 \end{aligned}$$

Let $J := \max_{1 \leq l \leq M} \max_{u_{l-1} \leq t \leq u_l} |B(t) - B(u_{l-1})|$ and $I\{\cdot\}$ be the indicator function of \cdot . Then the right hand side of (2.13) is bounded by

$$\begin{aligned}
 (2.14) \quad & 3E[J^p] = 3 \int_{\{J > 2\Delta^{1/2}(\log n)^{1/2}\}} J^p dP + 3 \int_{\{J \leq 2\Delta^{1/2}(\log n)^{1/2}\}} J^p dP \\
 & \leq 3 \int J^p \cdot I \left[\bigcup_{l=1}^M \{ \max_{u_{l-1} \leq t \leq u_l} |B(t) - B(u_{l-1})| > 2\Delta^{1/2}(\log n)^{1/2}, \right. \\
 & \quad \left. \max_{u_{l-1} \leq t \leq u_l} |B(t) - B(u_{l-1})| \geq \max_{k \neq l} \max_{u_{k-1} \leq t \leq u_k} |B(t) - B(u_{k-1})| \right] dP \\
 & \quad + 6\Delta^{p/2}(\log n)^{p/2} \\
 & \leq 3 \sum_{l=1}^M \int I \{ \max_{u_{l-1} \leq t \leq u_l} |B(t) - B(u_{l-1})| > 2\Delta^{1/2}(\log n)^{1/2} \} \\
 & \quad \times \max_{u_{l-1} \leq t \leq u_l} |B(t) - B(u_{l-1})|^p dP + 6\Delta^{p/2}(\log n)^{p/2}.
 \end{aligned}$$

Now we can easily see that

$$\begin{aligned}
(2.15) \quad & \int I\{ \max_{u_{l-1} \leq t \leq u_l} |B(t) - B(u_{l-1})| > 2\Delta^{1/2}(\log n)^{1/2} \} \times \max_{u_{l-1} \leq t \leq u_l} |B(t) - B(u_{l-1})|^p dP \\
& \leq 2 \int I\{ \max_{u_{l-1} \leq t \leq u_l} (B(t) - B(u_{l-1})) > 2\Delta^{1/2}(\log n)^{1/2} \} \\
& \quad \times \max_{u_{l-1} \leq t \leq u_l} \{(B(t) - B(u_{l-1})) \vee 0\}^p dP \\
& \leq K\Delta^{p/2} \int_{2(\log n)^{1/2}}^{\infty} x^p \Phi(dx) \leq K\Delta^{p/2} n^{-1}.
\end{aligned}$$

Hence (2.12) follows from (2.13)-(2.15). \square

§ 3. Proof of Theorem 1.

Note $\|X - Y_n\| \leq \|X - \bar{X}_n\| + \|\bar{X}_n - \bar{Y}_n\| + \|\bar{Y}_n - Y_n\|$. To estimate the left hand side, we consider three terms on the right hand side, each of which will be estimated in the following three lemmas.

LEMMA 5. For any $2 \leq p \leq 2 + \delta$,

$$E[\|X - \bar{X}_n\|^p] = O(\Delta^{p/2}(\log n)^{p/2}), \quad (n \rightarrow \infty).$$

PROOF. For simplicity, we prove only the case $r=1$. The case $r > 1$ can be treated similarly. For $t_k \leq t < t_{k+1}$, $k=0, 1, \dots, M-1$, let $\sigma_n(t) := \sigma(t_{k-1}, \bar{X}_{k-1})$ and $b_n(t) := b(t_{k-1}, \bar{X}_{k-1})$. Obviously, for $t_k \leq t < t_{k+1}$, we have

$$\begin{aligned}
(3.1) \quad X(t) - \bar{X}_n(t) &= \int_0^t (\sigma(s, X(s)) - \sigma_n(s)) dB(s) + \int_{t_k}^t \sigma_n(s) dB(s) \\
& \quad + \int_0^t (b(s, X(s)) - b_n(s)) ds + \int_{t_k}^t b_n(s) ds \\
&= \int_0^t (\sigma(s, X(s)) - \sigma(s, \bar{X}_n(s))) dB(s) \\
& \quad + \int_0^t (\sigma(s, \bar{X}_n(s)) - \sigma_n(s)) dB(s) + \int_{t_k}^t \sigma_n(s) dB(s) \\
& \quad + \int_0^t (b(s, X(s)) - b(s, \bar{X}_n(s))) ds \\
& \quad + \int_0^t (b(s, \bar{X}_n(s)) - b_n(s)) ds + \int_{t_k}^t b_n(s) ds.
\end{aligned}$$

We first estimate the third term of the right hand side of (3.1).

$$\begin{aligned}
(3.2) \quad & E \left[\max_{1 \leq l \leq k+1} \max_{t_{l-1} \leq s < t_l} \left| \int_{t_{l-1}}^s \sigma_n(u) dB(u) \right|^p \right] \\
& = E \left[\max_{1 \leq l \leq k+1} \max_{t_{l-1} \leq s < t_l} |B(A(s)) - B(A(t_{l-1}))|^p \right]
\end{aligned}$$

where $A(t) := \int_0^t \sigma_n(s)^2 ds$ is the quadratic variation process of the martingale $N(t) := \int_0^t \sigma_n(s) dB(s)$. By assumption (1.5) we have

$$A(t) \leq L^2 t \quad \text{and} \quad A(t+\Delta) - A(t) \leq L^2 \Delta \quad \text{a.s.}$$

Thus the right hand side of (3.2) is bounded by

$$\begin{aligned} (3.3) \quad & E \left[\max_{0 \leq s \leq t_k} \max_{s \leq t \leq s+\Delta} |B(A(t)) - B(A(s))|^p \right] \\ &= E \left[\max_{0 \leq s \leq t_k} \max_{A(s) \leq t \leq A(s+\Delta)} |B(t) - B(A(s))|^p \right] \\ &\leq E \left[\max_{0 \leq s \leq L^2 t_k} \max_{s \leq t \leq s+L^2 \Delta} |B(t) - B(s)|^p \right]. \end{aligned}$$

Hence, combining (3.2), (3.3) with (2.12) of Lemma 4, we have

$$(3.4) \quad E \left[\max_{1 \leq l \leq k+1} \max_{t_{l-1} \leq s < t_l} \left| \int_{t_{l-1}}^s \sigma_n(u) dB(u) \right|^p \right] \leq K \Delta^{p/2} (\log n)^{p/2}.$$

Now from a moment inequality for martingales (see for example Theorem 3.1 in Ikeda-Watanabe [8], Chapter III), Jensen's inequality and condition (1.2), we have

$$\begin{aligned} (3.5) \quad & E \left[\max_{0 \leq s \leq t} \left| \int_0^s \{\sigma(u, X(u)) - \sigma(u, \bar{X}_n(u))\} dB(u) \right|^p \right] \\ &\leq KE \left[\int_0^t |\sigma(u, X(u)) - \sigma(u, \bar{X}_n(u))|^p du \right]^{p/2} \\ &\leq K \int_0^t E [|\sigma(u, X(u)) - \sigma(u, \bar{X}_n(u))|^p] du \\ &\leq KL^p \int_0^t E [|X(u) - \bar{X}_n(u)|^p] du \\ &\leq KL^p \int_0^t E \left[\max_{0 \leq u \leq s} |X(u) - \bar{X}_n(u)|^p \right] ds. \end{aligned}$$

For $t_k \leq t < t_{k+1}$ we have from (1.2) and (1.5),

$$\begin{aligned} E [|\sigma(t, \bar{X}_n(t)) - \sigma_n(t)|^p] &\leq L^p E [(|t - t_{k-1}|^p + |\tilde{X}_k - \tilde{X}_{k-1}|^p)] \\ &\leq K \Delta^p + KE [|\sigma(t_{k-1}, \tilde{X}_{k-1}) \eta_k|^p] + KE [|b(t_{k-1}, \tilde{X}_{k-1})(t - t_{k-1})|^p] \\ &\leq K \Delta^p + K \Delta^{p/2}. \end{aligned}$$

Hence, in the same way as in (3.5), we have

$$\begin{aligned} (3.6) \quad & E \left[\max_{0 \leq s \leq t} \left| \int_0^s \{\sigma(u, \bar{X}_n(u)) - \sigma_n(u)\} dB(u) \right|^p \right] \\ &\leq K \int_0^t E [|\sigma(u, \bar{X}_n(u)) - \sigma_n(u)|^p] du \leq K \Delta^{p/2}. \end{aligned}$$

Furthermore from Jensen's inequality,

$$(3.7) \quad E \left[\max_{0 \leq s \leq t} \left| \int_0^s \{b(u, X(u)) - b(u, \bar{X}_n(u))\} du \right|^p \right] \\ \leq KL^p \int_0^t E \left[\max_{0 \leq u \leq s} |X(u) - \bar{X}(u)|^p \right] ds ,$$

$$(3.8) \quad E \left[\max_{0 \leq s \leq t} \left| \int_0^s \{b(u, \bar{X}_n(u)) - b_n(u)\} du \right|^p \right] \\ \leq K \int_0^s E [|b(u, \bar{X}_n(u)) - b_n(u)|^p] du \leq K\Delta^{p/2} .$$

Moreover, from (1.5),

$$(3.9) \quad E \left[\max_{1 \leq l \leq k+1} \max_{t_{l-1} \leq s < t_l} \left| \int_{t_{l-1}}^s b_n(u) du \right|^p \right] \\ \leq E \left[\max_{1 \leq l \leq k+1} \max_{t_{l-1} \leq s < t_l} \left\{ \int_{t_{l-1}}^s L du \right\}^p \right] \leq L^p \Delta^p .$$

Combining (3.1) and (3.4)–(3.9) and using Gronwall's inequality, we complete the proof of the lemma. \square

LEMMA 6. For any $2 \leq p \leq 2 + \delta$,

$$E[||Y_n - \bar{Y}_n||^p] = O(\Delta^{p/2} (\log n)^{p/2}), \quad (n \rightarrow \infty) .$$

PROOF. We prove only the case $r=1$ again. For $t_k \leq t < t_{k+1}$,

$$\begin{aligned} \max_{t_k \leq s \leq t} |Y_n(s) - \bar{Y}_n(s)| &= \max_{kq < i \leq [nt]+1} |\hat{Y}_i - \tilde{Y}_k| \\ &\leq \left| \sum_{j=1}^{kq} \frac{\sigma((j-1)/n, \hat{Y}_{j-1}) \xi_j}{n^{1/2}} - \sum_{i=1}^k \sigma(t_{i-1}, \tilde{Y}_{i-1}) \zeta_i \right| \\ &\quad + \max_{kq < i \leq [nt]+1} \left| \sum_{j=kq+1}^i \frac{\sigma((j-1)/n, \hat{Y}_{j-1}) \xi_j}{n^{1/2}} \right| \\ &\quad + \left| \sum_{j=1}^{kq} \frac{b((j-1)/n, \hat{Y}_{j-1})}{n} - \sum_{i=1}^k \frac{b(t_{i-1}, \tilde{Y}_{i-1}) q}{n} \right| \\ &\quad + \max_{kq < i \leq [nt]+1} \left| \sum_{j=kq+1}^i \frac{b((j-1)/n, \hat{Y}_{j-1})}{n} \right| \\ &\leq \left| \sum_{i=1}^k \sum_{j=(i-1)q+1}^{iq} \frac{\{\sigma((j-1)/n, \hat{Y}_{j-1}) - \sigma(t_{i-1}, \tilde{Y}_{i-1})\} \xi_j}{n^{1/2}} \right| \\ &\quad + \max_{kq < i \leq [nt]+1} \left| \sum_{j=kq+1}^i \frac{\sigma((j-1)/n, \hat{Y}_{j-1}) \xi_j}{n^{1/2}} \right| \\ &\quad + \left| \sum_{i=1}^k \sum_{j=(i-1)q+1}^{iq} \frac{\{b((j-1)/n, \hat{Y}_{j-1}) - b(t_{i-1}, \tilde{Y}_{i-1})\}}{n} \right| \\ &\quad + \sum_{j=kq+1}^{[nt]+1} \frac{|b((j-1)/n, \hat{Y}_{j-1})|}{n} . \end{aligned}$$

Thus, by Doob's inequality,

$$\begin{aligned}
 (3.10) \quad & E[\max_{0 \leq s \leq t} |\bar{Y}_n(s) - Y_n(s)|^p] \\
 & \leq KE \left[\left| \sum_{l=1}^k \sum_{j=(l-1)q+1}^{lq} \frac{\{\sigma((j-1)/n, \hat{Y}_{j-1}) - \sigma(t_{l-1}, \tilde{Y}_{l-1})\} \xi_j}{n^{1/2}} \right|^p \right] \\
 & \quad + KE \left[\max_{1 \leq l \leq k} \max_{1 \leq i \leq q} \left| \sum_{j=(l-1)q+1}^{((l-1)q+i) \wedge n} \frac{\sigma((j-1)/n, \hat{Y}_{j-1}) \xi_j}{n^{1/2}} \right|^p \right] \\
 & \quad + KE \left[\left| \sum_{l=1}^k \sum_{j=(l-1)q+1}^{lq} \frac{b((j-1)/n, \hat{Y}_{j-1}) - b(t_{l-1}, \tilde{Y}_{l-1})}{n} \right|^p \right] \\
 & \quad + KE \left[\max_{1 \leq l \leq k} \max_{1 \leq i \leq q} \left\{ \sum_{j=(l-1)q+1}^{((l-1)q+i) \wedge n} \frac{|b((j-1)/n, \hat{Y}_{j-1})|}{n} \right\}^p \right] \\
 & =: D_1 + D_2 + D_3 + D_4,
 \end{aligned}$$

say. Since $\{\sigma((j-1)/n, \hat{Y}_{j-1}) - \sigma(t_{l-1}, \tilde{Y}_{l-1})\} \xi_j$, $(l-1)q+1 \leq j \leq lq$ and $\{\sigma((j-1)/n, \hat{Y}_{j-1}) \xi_j\}$, $1 \leq j \leq n$ are martingale differences, we have from Theorem 3.1 in [5], (1.2) and (1.5) that

$$\begin{aligned}
 (3.11) \quad & D_1 \leq Kn^{-p/2} E \left[\left\{ \sum_{l=1}^k \sum_{j=(l-1)q+1}^{lq} E[\{\sigma((j-1)/n, \hat{Y}_{j-1}) - \sigma(t_{l-1}, \tilde{Y}_{l-1})\}^2 \xi_j^2 | \mathcal{G}_{j-1}] \right\}^{p/2} \right] \\
 & \leq KE \left[\left\{ \sum_{l=1}^k \sum_{j=(l-1)q+1}^{lq} \frac{|\hat{Y}_{j-1} - \tilde{Y}_{l-1}|^2 + \Delta^2}{n} \right\}^{p/2} \right] \\
 & \leq K \int_0^t E[\max_{0 \leq u \leq s} |Y_n(u) - \bar{Y}_n(u)|^p] ds + K\Delta^p,
 \end{aligned}$$

where \mathcal{G}_j is the σ -field generated by ξ_1, \dots, ξ_j for each j . Now, using Lemma 3, we have

$$(3.12) \quad D_2 \leq K\Delta^{p/2} (\log n)^{p/2}.$$

Furthermore, from Jensen's inequality and (1.5), we have

$$\begin{aligned}
 (3.13) \quad & D_3 \leq KE \left[\left\{ \sum_{l=1}^k \sum_{j=(l-1)q+1}^{lq} \frac{|\hat{Y}_{j-1} - \tilde{Y}_{l-1}| + \Delta}{n} \right\}^p \right] \\
 & \leq K \sum_{l=1}^k \sum_{j=(l-1)q+1}^{lq} \frac{E[|\hat{Y}_{j-1} - \tilde{Y}_{l-1}|^p]}{n} + K \sum_{l=1}^k \sum_{j=(l-1)q+1}^{lq} \frac{\Delta^p}{n} \\
 & \leq K \int_0^t E[\max_{0 \leq u \leq s} |Y_n(u) - \bar{Y}_n(u)|^p] du + K\Delta^p,
 \end{aligned}$$

$$(3.14) \quad D_4 \leq K \left(\frac{Lq}{n} \right)^p \leq K\Delta^p.$$

Combining (3.10)-(3.14) and using Gronwall's inequality, we conclude the lemma. \square

LEMMA 7. We can redefine the processes \bar{X}_n and \bar{Y}_n on a richer probability space such that the following relations hold:

(i) If $d=r=1$, then for any $2 \leq p \leq 2+\delta$,

$$E[\|\bar{X}_n - \bar{Y}_n\|^p] = O(\Delta^{p/2}), \quad (n \rightarrow \infty).$$

(ii) If $r > 1$ and ξ_1 has a bounded or square integrable density, then for any $2 \leq p \leq 2+\delta$,

$$E[\|\bar{X}_n - \bar{Y}_n\|^p] = O(\Delta^{1/2}(\log n)^{p/2}), \quad (n \rightarrow \infty).$$

PROOF. Let $d=r=1$. For $t_k \leq t < t_{k+1}$,

$$\begin{aligned} (3.15) \quad \max_{0 \leq s \leq t} |\bar{X}_n(s) - \bar{Y}_n(s)| &= \max_{1 \leq i \leq k} |\tilde{X}_i - \tilde{Y}_i| \\ &\leq KE \left[\max_{1 \leq i \leq k} \left| \sum_{j=1}^i \sigma(t_{j-1}, \tilde{X}_{j-1}) \eta_j - \sum_{j=1}^i \sigma(t_{j-1}, \tilde{Y}_{j-1}) \zeta_j \right|^p \right] \\ &\quad + KE \left[\max_{1 \leq i \leq k} \left| \sum_{j=1}^i b(t_{j-1}, \tilde{X}_{j-1})(t_j - t_{j-1}) - \sum_{j=1}^i b(t_{j-1}, \tilde{Y}_{j-1})(t_j - t_{j-1}) \right|^p \right] \\ &\leq KE \left[\max_{1 \leq i \leq k} \left| \sum_{j=1}^i \{ \sigma(t_{j-1}, \tilde{X}_{j-1}) - \sigma(t_{j-1}, \tilde{Y}_{j-1}) \} \eta_j \right|^p \right] \\ &\quad + KE \left[\max_{1 \leq i \leq k} \left| \sum_{j=1}^i \sigma(t_{j-1}, \hat{Y}_{j-1}) (\eta_j - \zeta_j) \right|^p \right] \\ &\quad + KE \left[\max_{1 \leq i \leq k} \left| \sum_{j=1}^i \{ b(t_{j-1}, \tilde{X}_{j-1}) - b(t_{j-1}, \tilde{Y}_{j-1}) \} (t_j - t_{j-1}) \right|^p \right] \\ &=: I_1 + I_2 + I_3, \end{aligned}$$

say. We first deal with I_1 . Let $\sigma'_n(s) := \sigma(t_{j-1}, \tilde{X}_{j-1}) - \sigma(t_{j-1}, \tilde{Y}_{j-1})$ for $t_j \leq s < t_{j+1}$, $j=0, 1, \dots, M-1$. Since $\{\sigma'_n(s), s < t_k\}$ is $\sigma\{\eta_1, \eta_2, \dots, \eta_{k-1}\}$ -measurable because of relation (2.4) of Lemma 1, I_1 is represented by

$$I_1 = KE \left[\max_{1 \leq i \leq k} \left| \int_0^{t_i} \sigma'_n(s) dB(s) \right|^p \right].$$

Thus, from Theorem 3.1 in [5] and condition (1.2),

$$\begin{aligned} (3.16) \quad I_1 &\leq KE \left[\left| \int_0^{t_k} \sigma'_n(s) dB(s) \right|^p \right] \leq K \int_0^{t_k} E[|\sigma'_n(s)|^p] ds \\ &\leq K \int_0^t E \left[\max_{0 \leq u \leq s} |\bar{X}_n(u) - \bar{Y}_n(u)|^p \right] du. \end{aligned}$$

We next estimate I_2 . By (2.3),

$$E[\sigma(t_{j-1}, \tilde{Y}_{j-1})(\eta_j - \zeta_j) | \mathcal{H}_{j-1}] = 0 \quad \text{a.s.}$$

for each j , where \mathcal{H}_j is the σ -field generated by $\eta_1, \dots, \eta_j, \zeta_1, \dots, \zeta_j$ for

each $1 \leq j \leq M$. Thus, from Theorem 3.1 in [8] and (1.5), (2.1), we have

$$\begin{aligned}
 (3.17) \quad I_2 &\leq KE \left[\sum_{j=1}^k E(|\sigma(t_{j-1}, \tilde{Y}_{j-1})(\eta_j - \zeta_j)|^2 | \mathcal{H}_{j-1}) \right]^{p/2} \\
 &\leq KE \left[\sum_{j=1}^k |\sigma(t_{j-1}, \tilde{Y}_{j-1})|^2 E[|\eta_j - \zeta_j|^2] \right]^{p/2} \\
 &\leq KL^p \left\{ \sum_{j=1}^k E[|\eta_j - \zeta_j|^2] \right\}^{p/2} \\
 &\leq K(k\Delta^{(2-\delta)/2} n^{-\delta/2})^{p/2} \leq Kt\Delta^{p/2}.
 \end{aligned}$$

When $r > 1$, we can similarly prove that

$$I_2 \leq KL^p \left\{ \sum_{j=1}^k E[|\eta_j - \zeta_j|^2] \right\}^{p/2},$$

and by using (2.2) instead of (2.1), we have

$$(3.18) \quad I_2 \leq K(k\Delta^{(2-\delta)/2} n^{-\delta/2} \log n)^{p/2} \leq Kt\Delta^{p/2} (\log n)^{p/2}.$$

As for I_3 , letting $b'_n(s) := b(t_{j-1}, \tilde{X}_{j-1}) - b(t_{j-1}, \tilde{Y}_{j-1})$ for $t_j \leq s < t_{j+1}$, $j = 0, 1, \dots, M-1$, we have from (1.2) that

$$\begin{aligned}
 (3.19) \quad I_3 &= KE \left[\max_{0 \leq j \leq k} \left| \int_0^{t_j} b'_n(s) ds \right|^p \right] \leq K \int_0^{t_k} E[|b'_n(s)|^p] ds \\
 &\leq K \int_0^t E[\max_{0 \leq u \leq s} |\tilde{X}_n(u) - \tilde{Y}_n(u)|^p] du.
 \end{aligned}$$

Combining (3.15)-(3.19) we have

$$\begin{aligned}
 E[\max_{0 \leq s \leq t} |\tilde{X}_n(s) - \tilde{Y}_n(s)|^p] &\leq K \int_0^t E[\max_{0 \leq u \leq s} |\tilde{X}_n(u) - \tilde{Y}_n(u)|^p] du \\
 &\quad + \begin{cases} Kt\Delta^{p/2} & \text{if } d=r=1, \\ Kt\Delta^{p/2} (\log n)^{p/2} & \text{if } r>1, \end{cases}
 \end{aligned}$$

for any $0 \leq t \leq 1$. Consequently the lemma is proved by Gronwall's inequality. □

PROOF OF THEOREM 1. Without changing distributions we can reconstruct W^d -valued processes X and Y_n on the common probability space $(\Omega', \mathcal{F}', P')$ by Lemmas 1 and 4-6 such that the conclusion of Theorem 1 holds, namely, for any $\varepsilon > p/2$,

$$l_x(P^X, P^{Y_n}) \leq E[\|X - Y_n\|^p]^{1/p} \leq K\Delta^{p/2} (\log n)^{p/2} = o(\Delta^{p/2} (\log n)^\varepsilon)$$

as $n \rightarrow \infty$. Therefore we finish the proof of Theorem 1. □

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