

# ON THE $\epsilon$ -ENTROPY OF DIFFUSION PROCESSES

KIMIO KAZI

(Received Jan. 25, 1969; revised April 17, 1969)

## Summary

In the present paper we give an evaluation of  $\epsilon$ -entropy of a one dimensional diffusion process  $\xi(t)$ ,  $0 \leq t \leq T$  whose generator is

$$(1) \quad \mathfrak{G} = \frac{1}{2} a(x)^2 \frac{d^2}{dx^2} \quad (x \in R),$$

where the diffusion coefficient  $a(x)^2$  satisfies

$$(2) \quad |a(x) - a(y)| \leq L|x - y|,$$

$$(3) \quad 0 < k \leq a(x)^2 \leq K$$

for every  $x$  and  $y$  ( $L$ ,  $k$  and  $K$  are positive constants). We assume  $\xi(0) = 0$  for simplicity of calculation. Then we can prove the following:

**THEOREM.** *Under the conditions (2) and (3),  $\epsilon$ -entropy  $H_\epsilon(\{\xi(t)\})$  of  $\xi(t)$ ,  $0 \leq t \leq T$  is asymptotically evaluated for small  $\epsilon > 0$ ,*

$$\frac{k}{eK} \cdot \frac{1}{\pi^2} \left\{ \int_0^T \sqrt{Ea(\xi(u))^2} du \right\}^2 \frac{1}{\epsilon^2} \lesssim H_\epsilon(\{\xi(t)\}) \lesssim \frac{2}{\pi^2} \left\{ \int_0^T \sqrt{Ea(\xi(u))^2} du \right\}^2 \frac{1}{\epsilon^2}. *$$

Previously Kolmogorov stated in [3] without proof "For a diffusion process whose generator is given by (1)  $H_\epsilon(\{\xi(t)\})$  is calculated by the formula:

$$H_\epsilon(\{\xi(t)\}) = \frac{4}{\pi} \left\{ \int_0^T Ea(\xi(u))^2 du \right\} \frac{1}{\epsilon^2} + o\left(\frac{1}{\epsilon^2}\right) \quad (\epsilon \rightarrow 0)$$

under certain natural conditions". However, in consideration of Pinsker's results for Gaussian processes [5] and our present theorem this formula appears inaccurate. For the proof of the theorem we use the well-known formula of  $\epsilon$ -entropy for finite dimensional random variables (lemma 3).

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\*  $f(\epsilon) \lesssim g(\epsilon)$  means  $\overline{\lim}_{\epsilon \rightarrow 0} \frac{f(\epsilon)}{g(\epsilon)} \leq 1$ .

1. In this section we prepare several lemmas for a general stochastic process  $\xi(t)$  and indicate the general line of the proof of the theorem. The  $\varepsilon$ -entropy of a real-valued stochastic process  $\xi = \{\xi(t)\}_{0 \leq t \leq T}$ ,  $E \int_0^T \xi(u)^2 du < \infty$ , is by definition

$$H_\varepsilon(\xi) = \inf_{\eta = \{\eta(t)\}} \left\{ I(\xi, \eta); E \int_0^T |\xi(u) - \eta(u)|^2 du \leq \varepsilon^2 \right\},$$

where  $I(\xi, \eta)$  is Kolmogorov's amount of information [3] and the infimum is taken over all measurable processes  $\eta = \{\eta(t)\}_{0 \leq t \leq T}$ . If  $\xi = (\xi_1, \xi_2, \dots)$  with  $E \sum_{j=1}^{\infty} \xi_j^2 < \infty$  is a  $l^2$ -valued random variable,  $H_\varepsilon(\xi)$  is defined by

$$H_\varepsilon(\xi) = \inf_{\eta = (\eta_1, \dots)} \left\{ I(\xi, \eta); E \sum_{j=1}^{\infty} |\xi_j - \eta_j|^2 \leq \varepsilon^2 \right\}.$$

In the case of a finite dimensional random variable  $\xi = (\xi_1, \dots, \xi_n)$  with  $E \sum_{j=1}^n \xi_j^2 < \infty$ , the infimum of  $I(\xi, \eta)$  shall be taken over all  $\eta = (\eta_1, \dots, \eta_n)$  with  $E \sum_{j=1}^n |\xi_j - \eta_j|^2 \leq \varepsilon^2$ . We can reduce the calculation of the  $\varepsilon$ -entropy of a stochastic process to that of infinite dimensional random variable by the following lemma 1, which is due to Y. Baba.

LEMMA 1. If  $\xi(t)$  ( $0 \leq t \leq T$ ),  $E\xi(t) = 0$ ,  $E \int_0^T \xi(u)^2 du < \infty$ , is a mean continuous process with covariance function  $r(t, s) = E\{\xi(t)\xi(s)\}$ , then

$$H_\varepsilon(\{\xi(t)\}) = H_\varepsilon((\xi_1, \xi_2, \dots)),$$

where  $\xi_j = \int_0^T \xi(u)\varphi_j(u)du$  and  $\varphi_j(t)$  is the  $j$ th eigenfunction of the integral equation:

$$(4) \quad \int_0^T r(t, s)\varphi(s)ds = \sigma\varphi(t).$$

PROOF. As is well known, the integral operator  $R$  with kernel  $r(t, s)$  defines a symmetric, positive definite, completely continuous operator in  $L^2[0, T]$ . If we arrange the eigen values of  $R$  as  $\sigma_1 \geq \sigma_2 \geq \dots \rightarrow 0$ , we know immediately from general theory

$$(5) \quad E\xi_j = 0, \quad E\xi_i\xi_j = \sigma_j\delta_{ij},$$

$$E \sum_{j=1}^{\infty} \xi_j^2 = \sum_{j=1}^{\infty} \sigma_j = E \int_0^T \xi(u)^2 du < \infty.$$

Now take an arbitrary measurable process  $\eta(t)$  ( $0 \leq t \leq T$ ) such that

$$E \int_0^T |\xi(u) - \eta(u)|^2 du \leq \varepsilon^2,$$

and define

$$\eta_j = \int_0^T \eta(u) \varphi_j(u) du .$$

Obviously, it holds that

$$(6) \quad E \sum_{j=1}^{\infty} |\xi_j - \eta_j|^2 = E \int_0^T |\xi(u) - \eta(u)|^2 du \leq \epsilon^2 .$$

Since the linear operation from  $L^2[0, T]$  to  $l^2$ :

$$\zeta(\cdot) \rightarrow (\zeta_1, \zeta_2, \dots), \quad \zeta_j = \int_0^T \zeta(u) \varphi_j(u) du$$

is one to one, onto and bimeasurable mapping\*, we have

$$(7) \quad I(\{\xi(t)\}, \{\eta(t)\}) = I((\xi_1, \xi_2, \dots), (\eta_1, \eta_2, \dots))$$

in view of a fundamental property of amount of information: a one to one, onto and bimeasurable mapping preserves amount of information [3]. From (6) and (7) the result of the lemma follows at once.

As to a  $l^2$ -valued random variable we have the following:

LEMMA 2. Let a random variable  $(\xi_1, \xi_2, \dots)$  satisfy (5) and  $\sum_{j=1}^{\infty} \sigma_j < \infty$ . If  $\epsilon^2 \leq \sum_{j=1}^{\infty} \sigma_j$ , following inequalities hold;

$$H_{\epsilon}((\xi_1, \xi_2, \dots)) \geq H_{\epsilon}((\xi_1, \dots, \xi_n)) \quad \text{for every } n,$$

$$H_{\epsilon}((\xi_1, \xi_2, \dots)) \leq H_{\theta}((\xi_1, \dots, \xi_m)),$$

where  $m$  is an arbitrary integer such that  $\epsilon^2 - \sum_{j=m+1}^{\infty} \sigma_j = \theta^2 > 0$ .

PROOF. The first inequality is trivial according to the definition of  $\epsilon$ -entropy and a property of amount of information [3]. As to the second, we see easily from the definition

$$\begin{aligned} & H_{\epsilon}((\xi_1, \xi_2, \dots)) \\ & \leq \inf_{(\eta_1, \dots, \eta_m)} \left\{ I((\xi_1, \xi_2, \dots), (\eta_1, \dots, \eta_m, 0, 0, \dots)); \right. \\ & \qquad \qquad \qquad \left. E \sum_{j=1}^m |\xi_j - \eta_j|^2 \leq \epsilon^2 - \sum_{j=m+1}^{\infty} \sigma_j \right\} \\ & \leq \inf_{(\eta_1, \dots, \eta_m)} \left\{ I((\xi_1, \xi_2, \dots), (\eta_1, \dots, \eta_m)); E \sum_{j=1}^m |\xi_j - \eta_j|^2 \leq \theta^2 \right\} \\ & \quad \text{and random variables } (\xi_1, \xi_2, \dots), (\xi_1, \dots, \xi_m), (\eta_1, \dots, \eta_m) \end{aligned}$$

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\* It is easily proved that we may consider  $\zeta(t)$  ( $0 \leq t \leq T$ ) with  $E \int_0^T \zeta(t)^2 dt < \infty$  to be a  $L^2[0, T]$  valued random variable.

$$\begin{aligned} & \text{form a Markov chain} \}^{(*)} \\ & = \inf_{(\eta_1, \dots, \eta_m)} \left\{ I((\xi_1, \dots, \xi_m), (\eta_1, \dots, \eta_m)); E \sum_{j=1}^m |\xi_j - \eta_j|^2 \leq \theta^2 \right\} \\ & = H_\theta((\xi_1, \dots, \xi_m)). \end{aligned}$$

Here we note that the range of the infimum of (#) is not empty. In fact we may give an example of the conditional density function of  $(\eta_1, \dots, \eta_m)$  with respect to  $(\xi_1, \xi_2, \dots)$ :

$$\begin{aligned} p(y_1, \dots, y_m | x_1, x_2, \dots) &= \frac{1}{(2\pi\theta^2\alpha m^{-1})^{m/2}} \exp \left\{ -\frac{m}{2\alpha\theta^2} \sum_{j=1}^m (y_j - \alpha x_j)^2 \right\}, \\ \alpha &= 1 - \frac{\theta^2}{\sum_{j=1}^m \sigma_j} > 0. \end{aligned}$$

LEMMA 3. If  $n$  dimensional random variable  $(\xi_1, \xi_2, \dots, \xi_n)$  with  $\beta = E \sum_{j=1}^n \xi_j^2 < \infty$  has a bounded continuous density function  $p(x_1, x_2, \dots, x_n)$ , then

$$H_\varepsilon((\xi_1, \dots, \xi_n)) \geq \frac{n}{2} \log \frac{1}{\varepsilon^2} + \frac{n}{2} \log n - n \log \sqrt{2\pi\varepsilon} + h((\xi_1, \dots, \xi_n)),$$

$$\begin{aligned} H_\varepsilon((\xi_1, \dots, \xi_n)) &\leq \frac{n}{2} \log \frac{1}{\varepsilon^2} + \frac{n}{2} \log n - n \log \sqrt{2\pi\varepsilon \left(1 - \frac{\varepsilon^2}{\beta}\right)} \\ &\quad + h((\xi_1, \dots, \xi_n)) + o(1) \end{aligned}$$

as  $\varepsilon \downarrow 0$ , where  $h((\xi_1, \dots, \xi_n)) = - \int_{R^n} p(x_1, \dots, x_n) \log p(x_1, \dots, x_n) dx_1 \cdots dx_n$  is the differential entropy of  $(\xi_1, \dots, \xi_n)$ .

For the proof of lemma 3, [2] and [4] should be referred. We omit the proof and note only that the latter inequality is a little stronger than the inequality in [4] which is proved under more general conditions about probability density function. We might rather derive these inequalities following ideas of [2].

Lemmas 1, 2 and 3 enable us to evaluate  $H_\varepsilon(\{\xi(t)\})$  of a stochastic process from above and below with the help of the formulas of  $\varepsilon$ -entropy for finite dimensional random variables, i.e. the inequalities in lemma 3.

2. Throughout the rest of the paper let  $\xi(t)$  ( $0 \leq t \leq T$ ) be a diffusion process introduced in Summary. We may consider such  $\xi(t)$  to be constructed by the stochastic integral equation:

$$\xi(t) = \int_0^t a(\xi(u)) dB(u) \quad (B(u) \text{ is a Brownian motion}).$$

Its covariance function

$$r(t, s) = \int_0^{t \wedge s} E a(\xi(u))^2 du \quad (t \wedge s = \min \{t, s\})$$

is obviously continuous in  $t$  and  $s$ . We trace the argument of section 1. For this case, for the eigenvalues of the integral equation (4) we have

LEMMA 4.

$$\sigma_j = C j^{-2} + o(j^{-2}), \quad C = \frac{1}{\pi^2} \left\{ \int_0^T \sqrt{E a(\xi(u))^2} du \right\}^2.$$

PROOF. In this case (4) is equivalent to the boundary value problem of a second order differential equation:

$$\begin{cases} -\frac{d}{dt} \left\{ \frac{1}{E a(\xi(u))^2} \frac{d\varphi}{dt} \right\} = \frac{1}{\sigma} \varphi \\ \varphi(0) = \varphi'(T) = 0. \end{cases}$$

The statement of the lemma follows from the result of ([1], p. 361).

Define random variables

$$\xi_j = \int_0^T \xi(u) \varphi_j(u) du \quad (j = 1, 2, \dots),$$

where  $\{\varphi_j(t)\}$  are continuous eigen functions corresponding to the integral equation (4). In order to investigate the characteristic function of  $(\xi_1, \xi_2, \dots, \xi_n)$ :

$$\phi(\lambda_1, \lambda_2, \dots, \lambda_n) = E \left\{ \exp \left( i \sum_{j=1}^n \lambda_j \xi_j \right) \right\},$$

we introduce a process

$$\zeta(t) = \exp \left\{ i \sum_{j=1}^n \lambda_j \int_t^T \xi(u) \varphi_j(u) du \right\} \quad (0 \leq t \leq T).$$

If we put  $v(t, x) = E_{t,x}[\zeta(t)]$ , denoting by  $E_{t,x}$  the expectation with respect to the conditional probability  $P_{t,x}(\cdot) = P(\cdot | \xi(t) = x)$ , there holds a relation

$$\phi(\lambda_1, \lambda_2, \dots, \lambda_n) = v(0, 0).$$

On the other hand, since for  $u \geq t$

$$\xi(u) = \xi(t) + \int_t^u a(\xi(s)) dB(s)$$

holds with probability one, we have almost surely

$$(8) \quad \begin{aligned} \zeta(t) &= \exp \left\{ i \xi(t) \sum_{j=1}^n \lambda_j f_j(t) \right\} \cdot \tilde{\zeta}(t), \\ \tilde{\zeta}(t) &= \exp \left\{ i \sum_{j=1}^n \lambda_j \int_0^t a(\xi(s)) f_j(s) dB(s) \right\}, \\ f_j(s) &= \int_s^T \varphi_j(u) du. \end{aligned}$$

We have used a fact that we can change the order of ordinary integral and stochastic integral in this case.

Taking expectations  $E_{t,x}$  of both sides of (8), we obtain

$$v(t, x) = \exp \left\{ ix \sum_{j=1}^n \lambda_j f_j(t) \right\} E_{t,x}[\tilde{\zeta}(t)].$$

LEMMA 5.  $\tilde{v}(t, x) = E_{t,x}[\tilde{\zeta}(t)]$  is written as follows:

$$(9) \quad \tilde{v}(t, x) = E_{t,x} \left[ \exp \left\{ \int_0^T A(s, \xi(s)) ds \right\} \right],$$

where

$$A(t, x) = -\frac{1}{2} a(x)^2 \sum_{j=1}^n \lambda_j^2 f_j^2(t).$$

PROOF. We apply Ito's formula of stochastic integral to  $\tilde{\zeta}(t)$  to get

$$\tilde{\zeta}(t) = \tilde{\zeta}(T) + \int_t^T A(s, \xi(s)) \tilde{\zeta}(s) ds.$$

Taking expectations of both sides and using Markov property, we know  $\tilde{v}(t, x)$  satisfies the following equation:

$$(10) \quad \tilde{v}(t, x) = 1 + E_{t,x} \int_t^T A(s, \xi(s)) \tilde{v}(s, \xi(s)) ds.$$

Because of boundedness of  $|A(t, x)|$  it is easily shown by usual iteration method that (10) has a unique solution (9).

On the basis of lemma 5 we obtain the following estimate about the characteristic function of  $(\xi_1, \dots, \xi_n)$ :

LEMMA 6.

$$|\phi(\lambda_1, \lambda_2, \dots, \lambda_n)| \leq \exp \left\{ -\frac{1}{2} \cdot \frac{k}{K} \sum_{j=1}^n \sigma_j \lambda_j^2 \right\}.$$

PROOF. As  $\phi(\lambda_1, \lambda_2, \dots, \lambda_n) = v(0, 0) = \tilde{v}(0, 0)$ , we see from lemma 5,

$$(11) \quad \begin{aligned} |\phi(\lambda_1, \lambda_2, \dots, \lambda_n)| &\leq E_{0,0} \left| \exp \left\{ \int_0^T A(s, \xi(s)) ds \right\} \right| \\ &= E \exp \left\{ -\frac{1}{2} \int_0^T a(\xi(s))^2 \sum_{j=1}^n \lambda_j^2 f_j^2(s) ds \right\} \end{aligned}$$

$$\leq \exp \left\{ -\frac{k}{2} \sum_{j=1}^n \lambda_j^2 \int_0^T f_j(s)^2 ds \right\}.$$

On the other hand multiply by  $\varphi_j(t)$  the both sides of the following integral equation, which is actually equation (4),

$$\sigma_j \varphi_j(t) = \int_0^t r(s) \varphi_j(s) ds + r(t) \int_t^T \varphi_j(s) ds,$$

where  $r(s) = \int_0^s Ea(\xi(u))^2 du$ , and integrate from 0 to  $T$  to get the relation

$$\begin{aligned} \sigma_j &= 2 \int_0^T r(t) \varphi_j(t) \left\{ \int_t^T \varphi_j(s) ds \right\} dt \\ &= - \int_0^T r(t) \frac{d}{dt} \left\{ \int_t^T \varphi_j(s) ds \right\}^2 dt \\ &= \int_0^T r'(t) \left\{ \int_t^T \varphi_j(s) ds \right\}^2 dt = \int_0^T Ea(\xi(t))^2 f_j(t)^2 dt. \end{aligned}$$

Hence

$$\int_0^T f_j(t)^2 dt \geq \frac{\sigma_j}{K}.$$

This inequality together with (11) proves lemma 6.

We need a lemma estimating the differential entropy from above and below :

LEMMA 7.  $n$  dimensional random variable  $(\xi_1, \xi_2, \dots, \xi_n)$  has a continuous bounded probability density function  $p(x_1, x_2, \dots, x_n)$  and its differential entropy  $h((\xi_1, \xi_2, \dots, \xi_n))$  is bounded from above and below as follows :

$$h((\xi_1, \xi_2, \dots, \xi_n)) \leq \log \prod_{j=1}^n (2\pi e \sigma_j)^{1/2},$$

$$h((\xi_1, \xi_2, \dots, \xi_n)) \geq -\log \prod_{j=1}^n \left( \frac{K}{2\pi k \sigma_j} \right)^{1/2}.$$

PROOF. As the characteristic function  $\phi(\lambda_1, \lambda_2, \dots, \lambda_n)$  is a  $L^1$ -function of  $(\lambda_1, \lambda_2, \dots, \lambda_n)$  from lemma 6, there exists a density function  $p(x_1, x_2, \dots, x_n)$  which is represented by its inverse Fourier transformation :

$$p(x_1, x_2, \dots, x_n) = \frac{1}{(2\pi)^n} \int_{R^n} \exp \left( -i \sum_{j=1}^n \lambda_j x_j \right) \phi(\lambda_1, \lambda_2, \dots, \lambda_n) d\lambda_1 \dots d\lambda_n.$$

Obviously  $p(x_1, x_2, \dots, x_n)$  is continuous and bounded :

$$M = \sup p(x_1, x_2, \dots, x_n)$$

$$\begin{aligned} &\leq \frac{1}{(2\pi)^n} \int |\phi(\lambda_1, \lambda_2, \dots, \lambda_n)| d\lambda_1 d\lambda_2 \dots d\lambda_n \\ &= \prod_{j=1}^n \left( \frac{K}{2\pi k\sigma_j} \right)^{1/2}. \end{aligned}$$

The first inequality of the lemma follows at once from the fact that differential entropy takes its maximum value in case of Gaussian random variable when  $E\xi_j=0$ , and covariances  $E\xi_i\xi_j=\sigma_j\delta_{ij}$  ( $i, j=1, 2, \dots, n$ ). The second inequality follows from a trivial inequality  $h((\xi_1, \xi_2, \dots, \xi_n)) \geq -\log M'$  for every  $M' \geq M$ .

3. Now we proceed to the proof of the asymptotic inequalities of the theorem. As is verified in 2, lemma 1, 2 and 3 are applicable to the diffusion process  $\xi(t)$  ( $0 \leq t \leq T$ ). We combine inequalities shown in lemmas to get the desired evaluations.

(i) Evaluation from above;

Take a sufficiently small  $\varepsilon^2 \leq \sum_{j=1}^{\infty} \sigma_j$ . For each  $m$  such that  $\varepsilon^2 - \sum_{j=m+1}^{\infty} \sigma_j = \theta^2 > 0$  we have from lemmas 1, 2, 3, 7 and 4

$$\begin{aligned} H_\varepsilon(\{\xi(t)\}) &\leq H_\theta((\xi_1, \dots, \xi_m)) \\ &\leq \frac{m}{2} \log \frac{1}{\theta^2} + \frac{m}{2} \log m - m \log \sqrt{2\pi e \left(1 - \varepsilon^2 / \sum_{j=1}^m \sigma_j\right)} \\ &\quad + h((\xi_1, \dots, \xi_m)) + o(1) \\ &\leq \frac{1}{2} \log \prod_{j=1}^m \frac{\sigma_j}{\theta^2/m} - m \log \sqrt{1 - \varepsilon^2 / \sum_{j=1}^m \sigma_j} + o(1). \end{aligned}$$

If we choose  $m$  and  $\theta$  so that  $\frac{\theta^2}{m} \sim \sigma_m^*$ , the relations  $\theta^2 = \varepsilon^2 - \sum_{j=m+1}^{\infty} \sigma_j$  and  $\sigma_j = Cj^{-2} + o(j^{-2})$  (lemma 4) and  $\sum_{j=m+1}^{\infty} \frac{1}{j^2} \sim \frac{1}{m^2}$  determine  $m = \left[ \frac{2C}{\varepsilon^2} \right]^{**}$ .

Finally we have by using Stirling's formula  $m! = \sqrt{2\pi} e^{-m} m^{m+1/2}$ ,

$$H_\varepsilon(\{\xi(t)\}) \leq m + o(m) = 2C \frac{1}{\varepsilon^2} + o\left(\frac{1}{\varepsilon^2}\right).$$

(ii) Evaluation from below;

Take a sufficiently small  $\varepsilon > 0$ . For every  $n$  we have from lemmas 1, 2, 3, 7 and 4

$$H_\varepsilon(\{\xi(t)\}) \geq H_\varepsilon((\xi_1, \dots, \xi_n))$$

\*)  $f_m \sim g_m$  means  $\lim f_m/g_m = 1$ .

\*\*)  $[x]$  is the integer part of  $x$ .



$$\begin{aligned} &\geq \frac{n}{2} \log \frac{1}{\epsilon^2} + \frac{n}{2} \log n - n \log \sqrt{2\pi e} + h((\xi_1, \dots, \xi_n)) \\ &\geq \frac{n}{2} \log \frac{1}{\epsilon^2} + \frac{n}{2} \log n - n \log \sqrt{2\pi e} - \log \prod_{j=1}^n \left( \frac{K}{2\pi k \sigma_j} \right)^{1/2} \end{aligned}$$

and by using Stirling's formula

$$= \frac{n}{2} \log \frac{kC}{\epsilon^2 eK} - \frac{n}{2} \log n + n + o(n).$$

If we choose  $n = \left\lceil \frac{kC}{eK} \frac{1}{\epsilon^2} \right\rceil$ , the first and second terms of the last line cancel each other to be  $o(n)$  and we have

$$H_\epsilon(\{\xi(t)\}) \geq n + o(n) = \frac{kC}{eK} \frac{1}{\epsilon^2} + o\left(\frac{1}{\epsilon^2}\right).$$

Thus completes the proof.

*Remark 1.* We can extend our theorem also for a temporally inhomogeneous diffusion process with slight modification of the above discussion. Let  $\xi(t)$  ( $0 \leq t \leq T$ ) be a diffusion process constructed by the stochastic integral equation:

$$\xi(t) = \int_0^t b(u, \xi(u)) du + \int_0^t a(u, \xi(u)) dB(u) \quad (0 \leq t \leq T)$$

where we assume

$$\begin{aligned} |a(t, x) - a(t, y)| + |b(t, x) - b(t, y)| &\leq L|x - y|, \\ b(t, x)^2 &\leq L(1 + x^2), \\ 0 < k \leq a(t, x)^2 &\leq K. \end{aligned}$$

Then we have

$$\frac{k}{eK} \frac{1}{\pi^2} \left\{ \int_0^T \sqrt{E a(u, \xi(u))^2} du \right\}^2 \frac{1}{\epsilon^2} \lesssim H_\epsilon(\{\xi(t)\}) \lesssim \frac{2}{\pi^2} \left\{ \int_0^T \sqrt{E a(u, \xi(u))^2} du \right\}^2 \frac{1}{\epsilon^2}.$$

*Remark 2.* Our evaluation (i) in the proof of the theorem is quite analogous to that of infinite dimensional Gaussian random variable [5].

THE INSTITUTE OF STATISTICAL MATHEMATICS\*)

\*) Now at Tokyo Education University

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