# ON AN APPROXIMATION ORDER OF THE OPTIMAL STOPPING PROBLEM FOR n-DIMENSIONAL DIFFUSION PROCESSES

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**Abstract.** An approximation order of the optimal stopping problem for multidimensional diffusion processes by the corresponding semidiscretization is considered.

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## 1. Preliminaries

Let  $(\Omega, \mathcal{F}, P)$  be a probability space, and  $W_t = (W_t^1, \dots, W_t^n)$  be *n*-dimensional standard Brownian motion defined on this space. Denote by  $F^W = (\mathcal{F}_t^W)_{t>0}$  the natural filtration of  $W_t$  completed with respect to P.

On the time interval  $T = [0, \infty)$  let us consider the stochastic differential equation

$$dX_s = b(X_s)ds + \sigma(X_s)dW_s, \quad X_0 = x \in \mathbb{R}^n, \tag{1}$$

where

**A.**  $b(x) = (b^1(x), \dots, b^n(x))$  and  $\sigma(x) = (\sigma_j^i(x))$ ,  $i, j = 1, \dots, n$ , are locally Lipschitz functions from  $\mathbb{R}^n$  into  $\mathbb{R}^n$  and the space of  $n \times n$  real matrices, respectively, which satisfy the linear growth condition

$$||b(x)|| \le k(1 + ||x||), \quad ||\sigma(x)|| \le k(1 + ||x||)$$

with a constant k; here  $\|\cdot\|$  stands for the Euclidean norm (Frobenius norm for  $\sigma(x)$ ).

As is well known (see [2], Ch. VIII, § 2, Theorem 4), under condition **A** the stochastic differential equation (1) has a unique strong solution  $X_t = (X_t^1, \ldots, X_t^n)$  which is a Markov diffusion process.

Let D be a bounded domain in the space  $\mathbb{R}^n$ , and  $\overline{D}$  and  $\partial D$  be its closure and smooth boundary (say, of  $C^2$ ), respectively. Assume that g = g(x) is a Lipschitz function defined on  $\overline{D}$  with the Lipschitz constant L, and c = c(x) is a continuous function defined on  $\overline{D}$ .

Let us introduce the first moment at which the process  $X_t$ ,  $t \in T$ , exits from the domain D:

$$\sigma(D) = \inf (t \ge 0 : X_t \notin D),$$

for which  $\sup_{x\in\overline{D}} E_x \sigma(D) < \infty$  and let us consider the optimal stopping problem in the domain  $\overline{D}$ :

$$S(x) = \sup_{\tau \in \mathfrak{M}} E_x \left[ g(X_{\tau \wedge \sigma(D)}) e^{-r(\tau \wedge \sigma(D))} + \int_0^{\tau \wedge \sigma(D)} c(X_t) e^{-rt} dt \right], \tag{2}$$

where  $P_x$  is the probability measure corresponding to the initial condition  $X_0 = x$ ,  $E_x$  is the sign of taking expectation w.r.t.  $P_x$ ,  $\mathfrak{M}$  is the class of all stopping moments w.r.t. the filtration  $F^W = (\mathcal{F}_t^W)_{t \geq 0}$ , and r > 0 is some constant.

Let  $X_t^{\sigma(D)} = X_{t \wedge \sigma(D)}$  be the stopped process which is a solution of the following stochastic differential equation:

$$dX_s^{\sigma(D)} = \widetilde{b}(X_s^{\sigma(D)}) ds + \widetilde{\sigma}(X_s^{\sigma(D)}) dW_s,$$

where  $\widetilde{b}(x) = b(x)\chi_D(x)$ ,  $\widetilde{\sigma}(x) = \sigma(x)\chi_D(x)$  and  $\chi_D(x)$  is the characteristic function of D.

The optimal stopping problem (2) can be equivalently rewritten in terms of stopped diffusion processes as

$$S(x) = \sup_{\tau \in \mathfrak{M}} E_x \left[ g(X_{\tau}^{\sigma(D)}) e^{-\int_0^{\tau} \widetilde{r}(X_s^{\sigma(D)}) ds} + \int_0^{\tau} \widetilde{c}(X_t^{\sigma(D)}) e^{-\int_0^t \widetilde{r}(X_s^{\sigma(D)}) ds} dt \right], \quad (3)$$

where  $\widetilde{r}(x) = r \cdot \chi_D(x)$ ,  $\widetilde{c}(x) = c(x) \cdot \chi_D(x)$ .

Assume that h, 0 < h < 1, is the parameter that tends to zero. Denote by  $\mathfrak{M}_h$  the class of stopping moments  $\tau_h$ , where  $\tau_h$  takes the values  $0, h, \ldots, nh, \ldots$ , and the set  $\{\tau_h \leq nh\} \in \mathcal{F}_{nh}^W$ .

The discrete analog of the problem (3) is written as follows (see [1]):

$$S_h(x) = \sup_{\tau_h \in \mathfrak{M}_h} E_x \left[ g(X_{\tau_h}^{\sigma(D)}) e^{-\int_0^{\tau_h} \widetilde{r}(X_s^{\sigma(D)}) ds} + \int_0^{\tau_h} \widetilde{c}(X_t^{\sigma(D)}) e^{-\int_0^t \widetilde{r}(X_s^{\sigma(D)}) ds} dt \right]. \tag{4}$$

Denote by  $\tau^*$  the optimal stopping time of problem (3) (see [3], Ch. 3, Theorem 3). Besides, introduce the so-called pseudo-optimal stopping moment  $\tau'_h$  defined as follows:

$$\tau'_h = \inf (nh : nh \ge \tau^*),$$

which is an admissible stoping time from  $\mathfrak{M}_h$ . In [1], requiring only continuity of g(x), Bensoussan and Robins showed that  $S_h(x)$  converges to S(x) as  $h \to 0$ .

# 2. Formulation and Proof of the Basic Result

**Theorem.** Let  $(X_t, P_x)$ ,  $t \in T$ , be an n-dimensional diffusion process given by the stochastic differential equation (1) with the coefficients b(x) and  $\sigma(x)$  satisfying condition  $\mathbf{A}$ , and g(x) be the Lipschitz function defined on  $\overline{D}$ . Then for the functions S(x) and  $S_h(x)$  defined by (3) and (4), respectively, the following estimate is valid:

$$\sup_{x \in \overline{D}} |S(x) - S_h(x)| \le p \cdot h^{1/2},$$

where  $p = C_1 + rH + L\sqrt{2nC_2^2 + 2n^2C_3^2}$ , r is introduced in relation (2) and H,  $C_1$ ,  $C_2$ ,  $C_3$  are the constants such that for  $x \in \overline{D}$ 

$$|g(x)| \le H$$
,  $|c(x)| \le C_1$ ,  $|b^i(x)| \le C_2$ ,  $|\sigma_i^i(x)| \le C_3$ ,  $i, j = 1, \dots, n$ .

*Proof.* It is obvious from (4) that

$$S_h(x) \ge E_x \left[ g(X_{\tau_h'}^{\sigma(D)}) e^{-\int_0^{\tau_h'} \widetilde{r}(X_s^{\sigma(D)}) \, ds} + \int_0^{\tau_h'} \widetilde{c}(X_t^{\sigma(D)}) e^{-\int_0^t \widetilde{r}(X_s^{\sigma(D)}) \, ds} \, dt \right],$$

and therefore

$$0 \leq S(x) - S_{h}(x) \leq E_{x} \left[ g(X_{\tau^{*}}^{\sigma(D)}) e^{-\int_{0}^{\tau^{*}} \widetilde{r}(X_{s}^{\sigma(D)}) ds} + \int_{0}^{\tau^{*}} \widetilde{c}(X_{t}^{\sigma(D)}) e^{-\int_{0}^{t} \widetilde{r}(X_{s}^{\sigma(D)}) ds} dt \right]$$
$$- E_{x} \left[ g(X_{\tau'_{h}}^{\sigma(D)}) e^{-\int_{0}^{\tau'_{h}} \widetilde{r}(X_{s}^{\sigma(D)}) ds} + \int_{0}^{\tau'_{h}} \widetilde{c}(X_{t}^{\sigma(D)}) e^{-\int_{0}^{t} \widetilde{r}(X_{s}^{\sigma(D)}) ds} dt \right].$$
 (5)

Clearly,

$$g(X_{\tau^*}^{\sigma(D)})e^{-\int_{0}^{\tau^*} \widetilde{r}(X_{s}^{\sigma(D)}) ds} - g(X_{\tau_{h}'}^{\sigma(D)})e^{-\int_{0}^{\tau_{h}'} \widetilde{r}(X_{s}^{\sigma(D)}) ds}$$

$$= \left(g(X_{\tau^*}^{\sigma(D)}) - g(X_{\tau_{h}'}^{\sigma(D)})\right)e^{-\int_{0}^{\tau_{h}'} \widetilde{r}(X_{s}^{\sigma(D)}) ds}$$

$$+ g(X_{\tau^*}^{\sigma(D)})e^{-\int_{0}^{\tau^*} \widetilde{r}(X_{s}^{\sigma(D)}) ds} \left(1 - e^{-\int_{\tau^*}^{\tau_{h}'} \widetilde{r}(X_{s}^{\sigma(D)}) ds}\right). \tag{6}$$

If we use the elementary inequality  $1 - e^{-z} < z$ , z > 0, then (6) leads to the following inequality

$$g(X_{\tau^*}^{\sigma(D)})e^{-\int_{0}^{\tau^*} \widetilde{r}(X_{s}^{\sigma(D)}) ds} - g(X_{\tau'_{h}}^{\sigma(D)})e^{-\int_{0}^{\tau'_{h}} \widetilde{r}(X_{s}^{\sigma(D)}) ds}$$

$$\leq \left| g(X_{\tau^*}^{\sigma(D)}) - g(X_{\tau'_{h}}^{\sigma(D)}) \right| + \left| g(X_{\tau^*}^{\sigma(D)}) \right| \int_{\tau^*}^{\tau'_{h}} \widetilde{r}(X_{s}^{\sigma(D)}) ds. \tag{7}$$

Taking into account (7) in (5), we obtain

$$0 \le S(x) - S_h(x) \le E_x \left[ \left| g(X_{\tau^*}^{\sigma(D)}) - g(X_{\tau_h'}^{\sigma(D)}) \right| + \left| g(X_{\tau^*}^{\sigma(D)}) \right| \int_{\tau^*}^{\tau_h'} \widetilde{r}(X_s^{\sigma(D)}) \, ds + \int_{\tau^*}^{\tau_h'} \left| \widetilde{c}(X_t^{\sigma(D)}) \right| e^{-\int_0^t \widetilde{r}(X_s^{\sigma(D)}) \, ds} \, dt \right].$$

We have

$$\int_{\tau^*}^{\tau_h'} |\widetilde{c}(X_t^{\sigma(D)})| e^{-\int_0^t \widetilde{r}(X_s^{\sigma(D)}) ds} dt \le C_1(\tau_h' - \tau^*) \le C_1 h,$$

$$|g(X_{\tau^*}^{\sigma(D)})| \int_{\tau^*}^{\tau_h'} \widetilde{r}(X_s^{\sigma(D)}) ds \le r H(\tau_h' - \tau^*) \le r H h.$$

It remains to estimate the value  $E_x \left| g(X_{\tau^*}^{\sigma(D)}) - g(X_{\tau'_h}^{\sigma(D)}) \right|$ . Since g(x) is the Lipschitz function defined on  $\overline{D}$ , we have

$$\begin{split} E_{x} \Big| g(X_{\tau^{*}}^{\sigma(D)}) - g(X_{\tau_{h}}^{\sigma(D)}) \Big| &\leq L E_{x} \Big\| X_{\tau^{*}}^{\sigma(D)} - X_{\tau_{h}}^{\sigma(D)} \Big\| \leq L \Big( E_{x} \Big\| X_{\tau^{*}}^{\sigma(D)} - X_{\tau_{h}}^{\sigma(D)} \Big\|^{2} \Big)^{1/2}, \\ E_{x} \Big\| X_{\tau^{*}}^{\sigma(D)} - X_{\tau_{h}}^{\sigma(D)} \Big\|^{2} &= E_{x} \Big\| \int_{\tau^{*}}^{\tau_{h'}} \widetilde{b}(X_{t}^{\sigma(D)}) \, dt + \int_{\tau^{*}}^{\tau_{h'}} \widetilde{\sigma}(X_{t}^{\sigma(D)}) \, dW_{t} \Big\|^{2} \\ &\leq 2 E_{x} \sum_{i=1}^{n} \left[ \int_{\tau^{*}}^{\tau_{h'}} \widetilde{b}^{i}(X_{t}^{\sigma(D)}) \, dt \right]^{2} + 2 E_{x} \sum_{i=1}^{n} \left[ \int_{\tau^{*}}^{\tau_{h'}} \sum_{j=1}^{n} \left( \widetilde{\sigma}_{j}^{i}(X_{t}^{\sigma(D)}) \right)^{2} \, dt \right] \\ &\leq E_{x} \left[ 2 n C_{2}^{2} (\tau_{h}^{\prime} - \tau^{*})^{2} + 2 n^{2} C_{3}^{2} (\tau_{h}^{\prime} - \tau^{*}) \right]. \end{split}$$

Finally,

$$\sup_{x \in \overline{D}} |S(x) - S_h(x)| \le C_1 h + rHh + \sqrt{h(2nC_2^2 + 2n^2C_3^2)} \cdot L \le p \cdot h^{1/2}. \quad \Box$$

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