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## Article

# Density Formula in Malliavin Calculus by Using Stein's Method and Diffusions

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**Abstract:** Let  $G$  be a random variable of functionals of an isonormal Gaussian process  $X$  defined on some probability space. An explicit formula for the density of  $G$  is obtained by Nourdin and Viens (2009) [Density formula and concentration inequalities with Malliavin calculus, *Elec. J. of Probab.*, 14(78). 2287-2309]. In this paper, unlike previous studies, we will use Stein's method for invariant measures of diffusions to obtain the density formula of  $G$ . Using this, we will show that the diffusion coefficient of a Itô diffusion with an invariant measure having a density can be expressed as in terms of operators in Malliavin calculus.

**Keywords:** Malliavin calculus; Stein's method; density function; standard normal random variable; Itô diffusion

## 1. Introduction

Let  $X = \{X(h), h \in \mathfrak{H}\}$ , where  $\mathfrak{H}$  is a real separable Hilbert space, be an isonormal Gaussian process defined on a probability space  $(\Omega, \mathfrak{F}, \mathbb{P})$ , and let  $G$  be a random variable of functionals of an isonormal Gaussian process  $X$ .

The following formula on the density of a random variable  $G$  is a well-known fact of the Malliavin calculus: if  $\frac{DG}{\|DG\|_{\mathfrak{H}}}$  belongs to the domain of divergence operator  $\delta$ , then the law of  $G$  has a continuous and bounded density  $p_G$  given by

$$p_G(x) = \mathbb{E} \left[ \mathbf{1}_{\{G > x\}} \delta \left( \frac{DG}{\|DG\|_{\mathfrak{H}}} \right) \right] \text{ for all } x \in \mathbb{R}.$$

Several examples are detailed in Section 2.1.1 of Nualart's book [1] (or [2]). Nourdin and Viens (2009) prove a new general formula for  $p_G$  which does not refer to divergence operator  $\delta$ . For a random variable  $G \in \mathbb{D}^{1,2}$  with  $\mathbb{E}[G] = 0$ , where  $\mathbb{D}^{1,2}$  is the domain of the Malliavin derivative operator  $D$  with respect to  $X$  such that the Malliavin derivative  $DG$  of  $G$  is a random element belonging in  $\mathfrak{H}$  with  $\mathbb{E}[\|DG\|_{\mathfrak{H}}^2] < \infty$ , we define the function  $g_G$  by

$$g_G(x) = \mathbb{E}[\langle DG, -DL^{-1}G \rangle_{\mathfrak{H}} | G = x]. \quad (1)$$

The operator  $L$  appearing in (1) is the so-called generator of the Ornstein-Uhlenbeck semigroup and  $L^{-1}$  is its pseudo-inverse. For details, see the section 2. It is well known that  $g_G$  is non-negative on the support of the law of  $G$  (see Proposition 3.9 in [3]).

Under some general conditions on a random variable  $G$ , Nourdin and Viens (2009) obtain the new formula of the density  $p_G$  for the law of  $G$  provided it exists. A precise statement is given in the following theorem:

**Theorem 1.** [Nourdin and Viens] *The law of  $G$  admits a density (with respect to Lebesgue measure), say  $p_G$ , if and only if the random variable  $g_G(G)$  is strictly positive almost surely. In this case, the support of  $p_G$ , denoted by  $\text{supp}(p_G)$ , is a closed interval of  $\mathbb{R}$  containing zero and, for almost all  $x \in \text{supp}(p_G)$ ,*

$$p_G(x) = \frac{\mathbb{E}[|G|]}{2g_G(x)} \exp \left( - \int_0^x \frac{y}{g_G(y)} dy \right). \quad (2)$$

Assume that the density  $p$  satisfies the following conditions: it is continuous, bounded, with  $\int_l^u x^2 p(x) dx < \infty$ . Let us set an interval  $I = (l, u)$  ( $-\infty \leq l < u \leq \infty$ ). Then

$$\begin{cases} p(x) > 0 & \text{if } x \in I \\ p(x) = 0 & \text{if } x \in I^c \end{cases}.$$

We define a continuous function  $b$  on  $I$  such that there exists  $e \in (l, u)$  satisfying

$$\begin{cases} b(x) > 0 & \text{if } x \in (l, e) \\ b(x) < 0 & \text{if } x \in (e, u) \end{cases}.$$

$bp$  is bounded on  $I$  and

$$\int_l^u b(x)p(x)dx = 0.$$

Define

$$a(x) = \frac{2}{p(x)} \int_l^x b(y)p(y)dy. \quad (3)$$

Then the diffusion with the invariant density  $p$  has the Stochastic Differential Equation (SDE) with the form

$$dX_t = b(X_t)dt + \sqrt{a(X_t)}dW_t, \quad (4)$$

where  $W$  is a standard Brownian motion.

In this paper, we derive the new density formula of a random variable  $G$ , that satisfies appropriate conditions related to Malliavin calculus, from the following equation: for every  $z \in \mathbb{R}$ ,

$$\begin{aligned} \mathbb{P}(G \leq z) - \mathbb{P}(F \leq z) &= \mathbb{E} \left[ \tilde{h}'_z(G) \left( \frac{1}{2}a(G) + \langle -DL^{-1}b(G), DG \rangle_{\mathfrak{H}} \right) \right] \\ &\quad + \mathbb{E}[b(G)]\mathbb{E}[\tilde{h}_z(G)], \end{aligned} \quad (5)$$

where  $F$  is a random variable with the invariant density  $p$  and  $\tilde{h}_z$  is a solution to the *Stein's equation* (for detailed explanation of *Stein's method*, see [4–6]). Also we will show that the diffusion coefficient  $a$  of SDE (4) can be written in an explicit form like (1) if the random variable  $G$  in (5) with its value on  $I$  has a density  $p$  and satisfies  $b(G) \in L^2(\Omega)$ .

The rest of this paper is organized as follows. Section 2 reviews some basic notations, and the contents of Malliavin calculus. In section 3, we will briefly discuss the construction of a diffusion process with an invariant density  $p$  and then describe our main results. Finally, as an application of our main results, in Section 4, we give some examples.

## 2. Preliminaries

In this section, we present some basic facts about Malliavin operators defined on spaces of random elements that are functionals of possibly infinite-dimensional Gaussian fields. For a more detailed explanation, see [1,7]. Suppose that  $\mathfrak{H}$  is a real separable Hilbert space with a scalar product denoted by  $\langle \cdot, \cdot \rangle_{\mathfrak{H}}$ . Let  $X = \{X(h), h \in \mathfrak{H}\}$  be an isonormal Gaussian process, that is a centered Gaussian family of random variables such that  $\mathbb{E}[X(h)X(g)] = \langle h, g \rangle_{\mathfrak{H}}$ . For every  $n \geq 1$ , let  $\mathbb{H}_n$  be the  $n$ th Wiener

chaos of  $X$ , that is the closed linear subspace of  $L^2(\Omega)$  generated by  $\{H_n(X(h)) : h \in \mathfrak{H}, \|h\|_{\mathfrak{H}} = 1\}$ , where  $H_n$  is the  $n$ th Hermite polynomial. We define a linear isometric mapping  $I_n : \mathfrak{H}^{\odot n} \rightarrow \mathbb{H}_n$  by  $I_n(h^{\odot n}) = n!H_n(X(h))$ , where  $\mathfrak{H}^{\odot n}$  is the symmetric tensor product. It is well known that any square integrable random variable  $F \in L^2(\Omega, \mathfrak{F}, \mathbb{P})$  ( $\mathfrak{F}$  denotes the  $\sigma$ -field generated by  $X$ ) can be expanded into a series of multiple stochastic integrals:

$$F = \sum_{q=0}^{\infty} I_q(f_q),$$

where  $f_0 = \mathbb{E}[F]$ , the series converges in  $L^2$ , and the functions  $f_q \in \mathfrak{H}^{\odot q}$  are uniquely determined by  $F$ . Let  $\mathfrak{S}$  be the class of smooth and cylindrical random variables  $F$  of the form

$$F = f(X(\varphi_1), \dots, X(\varphi_n)), \quad (6)$$

where  $n \geq 1$ ,  $f \in C_b^\infty(\mathbb{R}^n)$  and  $\varphi_i \in \mathfrak{H}$ ,  $i = 1, \dots, n$ . The Malliavin derivative of  $F$  with respect to  $X$  is the element of  $L^2(\Omega, \mathfrak{H})$  defined by

$$DF = \sum_{i=1}^n \frac{\partial f}{\partial x_i}(X(\varphi_1), \dots, X(\varphi_n)) \varphi_i. \quad (7)$$

We denote by  $\mathbb{D}^{l,p}$  the closure of its associated smooth random variable class with respect to the norm

$$\|F\|_{l,p}^p = \mathbb{E}(|F|^p) + \sum_{k=1}^l \mathbb{E}(\|D^k F\|_{\mathfrak{H}^{\otimes k}}^p).$$

We denote by  $\delta$  the adjoint of the operator  $D$ , also called the *divergence operator*. The domain of  $\delta$ , denoted by  $\text{Dom}(\delta)$ , is an element  $u \in L^2(\Omega; \mathfrak{H})$  such that

$$|\mathbb{E}(\langle D^l F, u \rangle_{\mathfrak{H}^{\otimes l}})| \leq C(\mathbb{E}|F|^2)^{1/2} \quad \text{for all } F \in \mathbb{D}^{l,2}.$$

If  $u \in \text{Dom}(\delta)$ , then  $\delta(u)$  is the element of  $L^2(\Omega)$  defined by the duality relationship

$$\mathbb{E}[F\delta(u)] = \mathbb{E}[\langle DF, u \rangle_{\mathfrak{H}}] \quad \text{for every } F \in \mathbb{D}^{1,2}.$$

Recall that  $F \in L^2(\Omega)$  can be expanded as  $F = \mathbb{E}[F] + \sum_{q=1}^{\infty} P_q F$ , where  $p_q$  is the projection operator  $L^2(\Omega)$  to the  $q$ th Wiener chaos  $\mathbb{H}_n$ . The operator  $L$  is defined through the projection operator  $P_q$ ,  $q = 0, 1, 2, \dots$ , as  $L = \sum_{q=0}^{\infty} -qP_q$ , and is called the *infinitesimal generator of the Ornstein-Uhlenbeck semigroup*. The relationship between the operator  $D$ ,  $\delta$ , and  $L$  is given as follows:  $\delta DF = -LF$ , that is, for  $F \in L^2(\Omega)$  the statement  $F \in \text{Dom}(L)$  is equivalent to  $F \in \text{Dom}(\delta D)$  (i.e,  $F \in \mathbb{D}^{1,2}$  and  $DF \in \text{Dom}(\delta)$ ), and in this case  $\delta DF = -LF$ . For any  $F \in L^2(\Omega)$ , we define the operator  $L^{-1}$ , which is the *pseudo-inverse* of  $L$ , as  $L^{-1}F = \sum_{q=1}^{\infty} \frac{1}{q} P_q F$ . Note that  $L^{-1}$  is an operator with values in  $\mathbb{D}^{2,2}$  and  $LL^{-1}F = F - \mathbb{E}[F]$  for all  $F \in L^2(\Omega)$ .

### 3. Diffusion Process with Invariant Measures and Main Results

In this section, we will give the construction of a diffusion process with an invariant measure, and present our main results in this paper.

#### 3.1. Diffusion Process with Invariant Measures

In this section, we will briefly describe the construction of a diffusion process with an invariant measure  $\mu$  having a density  $p$  with respect to the Lebesgue measure (for more details, see [8,9]).

Let  $F$  be a random variable with a probability measure  $\mu$  on  $I = (l, u)$  ( $-\infty \leq l < u \leq \infty$ ) with a density  $p$  which is continuous, bounded, strictly positive on  $I$  and  $\mathbb{E}[F^2] < \infty$ . Let  $b$  be a continuous function on  $I$  such that there exists  $e \in (l, u)$  that satisfies  $b(x) > 0$  for  $e \in (l, u)$  and  $b(x) < 0$  for  $e \in (l, u)$ . Moreover, the function  $bp$  is bounded on  $I$  and

$$\mathbb{E}[b(F)] = 0. \quad (8)$$

For  $x \in I$ , define

$$a(x) = \frac{2}{p(x)} \int_l^x b(y)p(y)dy. \quad (9)$$

Then the diffusion coefficient  $a$  in (9) is strictly positive for all  $x \in (l, u)$ , and also satisfies  $\mathbb{E}[a(F)] < \infty$ . The equation (9) implies that, for some  $c \in I$ ,

$$p(x)a(x) = p(c)a(c) \exp \left( \int_c^x \frac{2b(y)}{a(y)} dy \right). \quad (10)$$

Then the following SDE

$$dX_t = b(X_t)dt + \sqrt{a(X_t)}dB_t, \quad (11)$$

has a unique ergodic Markovian weak solution with the invariant density  $p$ .

Let  $\mathcal{C}_0(I) = \{f : I \rightarrow \mathbb{R} \mid f \text{ is continuous on } I \text{ vanishing at the boundary of } I\}$ . For  $f \in \mathcal{C}_0(I)$ , define

$$h_f(x) = \int_0^x \tilde{h}_f(y)dy,$$

where

$$\tilde{h}_f(x) = \frac{2 \int_l^x (f(y) - \mathbb{E}[f(F)])p(y)dy}{a(x)p_F(x)}.$$

Then  $h_f$  satisfies the following *Stein's equation*:

$$\begin{aligned} f(x) - \mathbb{E}[f(F)] &= b(x)h'_f(x) + \frac{1}{2}a(x)h''_f(x) \\ &= b(x)\tilde{h}_f(x) + \frac{1}{2}a(x)\tilde{h}'_f(x), \end{aligned} \quad (12)$$

where  $F$  is a random variable with a probability measure  $\mu$  as its law.

### 3.2. Main Results

Before describing our main result in this paper, we begin with the following simple result, given in Theorem 2.9.1 in [7].

**Lemma 1.** Suppose that  $F, G \in \mathbb{D}^{1,2}$  and let  $g : \mathbb{R} \rightarrow \mathbb{R}$  be a continuously differentiable with bounded derivative (or when  $g$  is only almost everywhere differentiable, one needs  $G$  to have an absolutely continuous). Then

$$\mathbb{E}[Fg(G)] = \mathbb{E}[F]\mathbb{E}[g(G)] + \mathbb{E}[g'(G)\langle DF, -DL^{-1}G \rangle_{\mathfrak{H}}]. \quad (13)$$

Let us set

$$g_{b(G)}(x) = \mathbb{E}[\langle -DL^{-1}(b(G) - \mathbb{E}[b(G)]), DG \rangle_{\mathfrak{H}} | G = x]. \quad (14)$$

Similar to the proof of Proposition 3.9 in [3], we will show that  $g_{b(G)}(x)$  is non-negative almost everywhere with respect to the law of  $G$ .

**Proposition 1.** Let  $G \in \mathbb{D}^{1,2}$ . Then we have that  $g_{b(G)}(x) \geq 0$  for almost everywhere with respect to the law of  $G$ , say  $H_G(x) = \mathbb{P}(G \leq x)$ .

**Proof:** Let  $q$  be a smooth non-negative real function. Define

$$Q(x) = \begin{cases} \int_{\beta}^x q(y)dy & \text{if } x \geq \beta \\ -\int_x^{\beta} q(y)dy & \text{if } x < \beta, \end{cases}$$

where  $\beta \in \mathbb{R}$  is a constant that satisfies  $b(x) - \mathbb{E}[b(G)] > 0$  for  $\beta \in (l, u)$  and  $b(x) - \mathbb{E}[b(G)] < 0$  for  $\beta \in (l, u)$ . Since  $Q(x) \geq 0$  for  $x \geq \beta$  and  $Q(x) < 0$  for  $x < \beta$ , we have  $\mathbb{E}[(b(G) - \mathbb{E}[b(G)])Q(G)] \geq 0$ . An application of Lemma 13 yields that

$$\begin{aligned} \mathbb{E}[(b(G) - \mathbb{E}[b(G)])Q(G)] &= \mathbb{E}[\langle -DL^{-1}(b(G) - \mathbb{E}[b(G)]), DG \rangle_{\mathcal{H}}] \\ &= \int_{-\infty}^{\infty} g_{b(G)}(x)q(x)dH_G(x) \geq 0. \end{aligned} \quad (15)$$

By an approximation of the function  $q$ , we can show that for all Borel measurable set  $B \in \mathfrak{B}(\mathbb{R})$ , we have

$$\int_B g_{b(G)}(x)q(x)dH_G(x) \geq 0.$$

This obviously implies that  $g_{b(G)}(x) \geq 0$  for almost everywhere with respect to the law of  $G$ .  $\square$

**Lemma 2.** *If the random variable  $g_{b(G)}(G)$  is strictly positive almost surely, then the law of  $G$  has a density with respect to Lebesgue measure, say  $p_G$ .*

**Proof:** By a similar argument to the proof of Theorem 3.1 in [10], we have that, for any Borel set  $B \in \mathfrak{B}(\mathbb{R})$  and any  $n \geq 1$ ,

$$\begin{aligned} &\mathbb{E} \left[ (b(G)\mathbb{E}[b(G)]) \int_{-\infty}^G \mathbf{1}_{B \cap [-n, n]}(x)dx \right] \\ &= \mathbb{E} \left[ (b(G)\mathbb{E}[b(G)]) \mathbf{1}_{B \cap [-n, n]}(G) g_{b(G)}(G) \right]. \end{aligned} \quad (16)$$

The same argument as for the case of  $b(G) = G$  in the proof of Theorem 3.1 in [10] shows that the law of  $G$  has a density.  $\square$

An explicit formula for the density is the following statement:

**Theorem 2.** *Let  $F$  be a random variable having the law  $\mu$ , and let  $G$  be a random variable in  $\mathbb{D}^{1,2}$  with  $b(G) \in \mathbb{L}^2(\Omega)$ . Assume that the random variable  $g_{b(G)}(G)$  is strictly positive almost surely and*

$$\|b\tilde{h}_f\|_{\infty} \leq C\|f\|_{\infty} = \sup_{x \in I} |f(x)| < \infty. \quad (17)$$

*In this case, the support of  $p_G$ , denoted by  $\text{supp}(p_G)$ , is a closed interval of  $\mathbb{R}$  and, for almost all  $x \in \text{supp}(p_G)$ ,*

$$p_G(x) = \frac{p_G(\beta)g_{b(G)}(\beta)}{g_{b(G)}(x)} \exp \left( - \int_{\beta}^x \frac{b(y) - \mathbb{E}[b(G)]}{g_{b(G)}(y)} dy \right) \quad (18)$$

*for some  $\beta \in \text{supp}(p_G)$ .*

**Proof:** Obviously, using (10) shows that the function  $\tilde{h}_f$  can be written as

$$\begin{aligned} \tilde{h}_f(x) &= \frac{2}{p_F(\beta)a(\beta)} \exp \left( - \int_{\beta}^x \frac{2b(y)}{a(y)} dy \right) \\ &\quad \times \int_I^x (f(y) - \mathbb{E}[f(F)])p_F(y)dy. \end{aligned} \quad (19)$$



Let us set  $H_F(x) = \mathbb{P}(F \leq x)$ . If  $f(x) = \mathbf{1}_{(-\infty, z]}(x)$  for  $z \in \mathbb{R}$ , we write  $h_f = h_z$  and  $\tilde{h}_f = \tilde{h}_z$ . Then the function  $\tilde{h}_z$  can be written as

$$\begin{aligned} \tilde{h}_z(x) &= \frac{2}{p_F(\beta)a(\beta)} \exp\left(-\int_{\beta}^x \frac{2b(y)}{a(y)} dy\right) \\ &\times \begin{cases} H_F(z)[1 - H_F(x)] & \text{if } x \geq z \\ H_F(x)[1 - H_F(z)] & \text{if } x < z. \end{cases} \end{aligned} \quad (20)$$

From (20), it follows that for  $x \geq z$ ,

$$\begin{aligned} \tilde{h}'_z(x) &= \frac{2}{p_F(\beta)a(\beta)} \exp\left(-\int_{\beta}^x \frac{2b(y)}{a(y)} dy\right) \\ &\times \left\{ \left(-\frac{2b(x)}{a(x)}\right) H_F(z)[1 - H_F(x)] - p_F(x)H_F(z) \right\}. \end{aligned} \quad (21)$$

For  $x < z$ ,

$$\begin{aligned} \tilde{h}'_z(x) &= \frac{2}{p_F(\beta)a(\beta)} \exp\left(-\int_{\beta}^x \frac{2b(y)}{a(y)} dy\right) \\ &\times \left\{ \left(-\frac{2b(x)}{a(x)}\right) H_F(x)[1 - H_F(z)] + p_F(x)[1 - H_F(z)] \right\}. \end{aligned} \quad (22)$$

If  $f(x) = \mathbf{1}_{(-\infty, z]}(x)$  for  $x \in I$ , we take  $f_n \in \mathcal{C}_0(I)$  such that  $\{f_n\}$  is an increasing sequence and  $f_n(x) \rightarrow f(x)$  for all  $x \in I$ . Obviously, by the dominated convergence theorem, we have that, as  $n \rightarrow \infty$ ,

$$\tilde{h}_{f_n}(x) \rightarrow \tilde{h}_z(x) \text{ and } \tilde{h}'_{f_n}(x) \rightarrow \tilde{h}'_z(x) \text{ for all } x \in I. \quad (23)$$

The bound of (17) yields that, for all  $n \geq 1$ ,

$$\|b\tilde{h}_{f_n}\|_{\infty} \leq C\|f_n\|_{\infty} \leq 1. \quad (24)$$

Combining (10) with the bound in (17), we also get, for all  $n \geq 1$ ,

$$\|a\tilde{h}'_{f_n}\|_{\infty} \leq C\|f_n\|_{\infty} \leq 1. \quad (25)$$

From (12), it follows that, for  $f_n \in \mathcal{C}_0(I)$ ,

$$\mathbb{E}[f_n(G)] - \mathbb{E}[f_n(F)] = \mathbb{E}[b(G)\tilde{h}_{f_n}(G)] + \mathbb{E}\left[\frac{1}{2}a(G)\tilde{h}'_{f_n}(G)\right]. \quad (26)$$

Due to the bounds of (24) and (25), the dominated convergence theorem can be applied to (26), which gives the following limit value:

$$\begin{aligned} \mathbb{P}(G \leq z) - \mathbb{P}(F \leq z) &= \mathbb{E}\left[(b(G) - \mathbb{E}[b(G)])\tilde{h}_z(G)\right] \\ &\quad + \mathbb{E}[b(G)]\mathbb{E}[\tilde{h}_z(G)] + \mathbb{E}\left[\frac{1}{2}a(G)\tilde{h}'_z(G)\right]. \end{aligned} \quad (27)$$

Applying (13) in Lemma 1 to the first expectation in (27), we obtain that

$$\begin{aligned}\mathbb{P}(G \leq z) - \mathbb{P}(F \leq z) &= \mathbb{E} \left[ \langle -DL^{-1}(b(G) - \mathbb{E}[b(G)]), DG \rangle_{\mathfrak{H}} \tilde{h}'_z(G) \right] \\ &\quad + \mathbb{E} \left[ \frac{1}{2} a(G) \tilde{h}'_z(G) \right] + \mathbb{E}[b(G)] \mathbb{E}[\tilde{h}_z(G)] \\ &= \mathbb{E} \left[ \tilde{h}'_z(G) \mathbb{E}[\langle -DL^{-1}(b(G) - \mathbb{E}[b(G)]), DG \rangle_{\mathfrak{H}} | G] \right] \\ &\quad + \mathbb{E} \left[ \frac{1}{2} a(G) \tilde{h}'_z(G) \right] + \mathbb{E}[b(G)] \mathbb{E}[\tilde{h}_z(G)].\end{aligned}\quad (28)$$

Differentiating the both sides in (28) yields that

$$\begin{aligned}p_G(z) - p_F(z) &= \frac{\partial}{\partial z} \int_{-\infty}^{\infty} \tilde{h}'_z(x) \left\{ g_{b(G)}(x) + \frac{1}{2} a(x) \right\} p_G(x) dx \\ &\quad + \mathbb{E}[b(G)] \frac{\partial}{\partial z} \int_{-\infty}^{\infty} \tilde{h}_z(x) p_G(x) dx.\end{aligned}\quad (29)$$

Next, we concentrate on the computations of two integrals in (29). Using (21) and (22) gives that

$$\frac{\partial}{\partial z} \int_{-\infty}^{\infty} \tilde{h}'_z(x) \left\{ g_{b(G)}(x) + \frac{1}{2} a(x) \right\} p_G(x) dx := J_1(z) + J_2(z),$$

where

$$\begin{aligned}J_1(z) &= \frac{\partial}{\partial z} \int_{-\infty}^z \tilde{h}'_z(x) \left\{ g_{b(G)}(x) + \frac{1}{2} a(x) \right\} p_G(x) dx \\ J_2(z) &= \frac{\partial}{\partial z} \int_z^{\infty} \tilde{h}'_z(x) \left\{ g_{b(G)}(x) + \frac{1}{2} a(x) \right\} p_G(x) dx\end{aligned}$$

Obviously, we write  $J_1(z) = J_{11}(z) + J_{12}(z)$ ,

$$\begin{aligned}J_{11}(z) &= \tilde{h}'_z(z) \left\{ g_{b(G)}(z) + \frac{1}{2} a(z) \right\} p_G(z), \\ J_{12}(z) &= \int_{-\infty}^z \frac{\partial}{\partial z} \tilde{h}'_z(x) \left\{ g_{b(G)}(x) + \frac{1}{2} a(x) \right\} p_G(x) dx.\end{aligned}$$

For  $J_{12}$ , we first differentiate  $\tilde{h}'_z(x)$  with respect to  $z$ . For  $x < z$ ,

$$\begin{aligned}\frac{\partial}{\partial z} \tilde{h}'_z(x) &= \frac{2}{p_F(c)a(c)} \exp \left( - \int_c^x \frac{2b(y)}{a(y)} dy \right) \\ &\quad \times \left\{ \left( \frac{2b(x)}{a(x)} \right) H_F(x) p_F(z) - p_F(x) p_F(z) \right\}.\end{aligned}\quad (30)$$



By (22) and (30), we get

$$J_{11}(z) = \frac{2}{p_F(c)a(c)} \exp\left(-\int_c^z \frac{2b(y)}{a(y)} dy\right) \times \left\{ \left(-\frac{2b(z)}{a(z)}\right) H_F(z)[1-H_F(z)] + p_F(z)[1-H_F(z)] \right\} \times \left\{ g_{b(G)}(z) + \frac{1}{2}a(z) \right\} p_G(z), \quad (31)$$

$$J_{12}(z) = \frac{2}{p_F(c)a(c)} \int_{-\infty}^z \exp\left(-\int_c^x \frac{2b(y)}{a(y)} dy\right) \times \left\{ \left(\frac{2b(x)}{a(x)}\right) H_F(x)p_F(z) - p_F(x)p_F(z) \right\} \times \left\{ g_{b(G)}(x) + \frac{1}{2}a(x) \right\} p_G(x) dx. \quad (32)$$

For  $x \geq z$ ,

$$\frac{\partial}{\partial z} \tilde{h}'_z(x) = \frac{2}{p_F(\beta)a(\beta)} \exp\left(-\int_\beta^x \frac{2b(y)}{a(y)} dy\right) \times \left\{ \left(-\frac{2b(x)}{a(x)}\right) p_F(z)[1-H_F(x)] - p_F(x)p_F(z) \right\}. \quad (33)$$

On the other hand, we write  $J_2(z) = J_{21}(z) + J_{22}(z)$ , where

$$J_{21}(z) = -\tilde{h}'_z(z) \left\{ g_{b(G)}(z) + \frac{1}{2}a(z) \right\} p_G(z),$$

$$J_{22}(z) = \int_z^\infty \frac{\partial}{\partial z} \tilde{h}'_z(x) \left\{ g_{b(G)}(x) + \frac{1}{2}a(x) \right\} p_G(x) dx.$$

From (32), we have that

$$J_{21}(z) = -\frac{2}{p_F(\beta)a(\beta)} \exp\left(-\int_c^z \frac{2b(y)}{a(y)} dy\right) \times \left\{ \left(-\frac{2b(z)}{a(z)}\right) H_F(z)[1-H_F(z)] - p_F(z)H_F(z) \right\} \times \left\{ g_{b(G)}(z) + \frac{1}{2}a(z) \right\} p_G(z), \quad (34)$$

$$J_{22}(z) = \frac{2}{p_F(\beta)a(\beta)} \int_z^\infty \exp\left(-\int_\beta^x \frac{2b(y)}{a(y)} dy\right) \times \left\{ \left(-\frac{2b(x)}{a(x)}\right) [1-H_F(x)]p_F(z) - p_F(x)p_F(z) \right\} \times \left\{ g_{b(G)}(x) + \frac{1}{2}a(x) \right\} p_G(x) dx. \quad (35)$$

From (20), the differentiation of the second integral in (29) can be easily calculated as follows:

$$\begin{aligned}
 & \mathbb{E}[b(G)] \frac{\partial}{\partial z} \int_{-\infty}^{\infty} \tilde{h}_z(x) p_G(x) dx \\
 = & \mathbb{E}[b(G)] \frac{\partial}{\partial z} \int_{-\infty}^z \tilde{h}_z(x) p_G(x) dx \\
 & + \mathbb{E}[b(G)] \frac{\partial}{\partial z} \int_z^{\infty} \tilde{h}_z(x) p_G(x) dx \\
 = & \frac{2\mathbb{E}[b(G)]}{p_F(\beta)a(\beta)} \left\{ -p_F(z) \int_{-\infty}^z \exp\left(-\int_{\beta}^x \frac{2b(y)}{a(y)} dy\right) H_F(x) p_G(x) dx \right. \\
 & + (1 - H_F(z)) \exp\left(-\int_{\beta}^z \frac{2b(y)}{a(y)} dy\right) H_F(z) p_G(z) \Big\} \\
 & + \frac{2\mathbb{E}[b(G)]}{p_F(\beta)a(\beta)} \left\{ p_F(z) \int_z^{\infty} \exp\left(-\int_{\beta}^x \frac{2b(y)}{a(y)} dy\right) (1 - H_F(x)) p_G(x) dx \right. \\
 & - H_F(z) \exp\left(-\int_{\beta}^z \frac{2b(y)}{a(y)} dy\right) (1 - H_F(z)) p_G(z) \Big\} \\
 = & \frac{2p_F(z)\mathbb{E}[b(G)]}{p_F(\beta)a(\beta)} \left\{ -\int_{-\infty}^z \exp\left(-\int_{\beta}^x \frac{2b(y)}{a(y)} dy\right) H_F(x) p_G(x) dx \right. \\
 & \left. + \int_z^{\infty} \exp\left(-\int_{\beta}^x \frac{2b(y)}{a(y)} dy\right) (1 - H_F(x)) p_G(x) dx \right\}. \tag{36}
 \end{aligned}$$

Combining (31), (32), (34), (35) and (36) yields that, for  $z \in \mathbb{R}$ ,

$$\begin{aligned}
 p_G(z) - p_F(z) = & \frac{2p_F(z)}{p_F(\beta)a(\beta)} \exp\left(-\int_{\beta}^z \frac{2b(y)}{a(y)} dy\right) \left\{ g_{b(G)}(z) + \frac{1}{2}a(z) \right\} p_G(z) \\
 & + \frac{2p_F(z)}{p_F(\beta)a(\beta)} \left[ \int_{-\infty}^z \exp\left(-\int_{\beta}^x \frac{2b(y)}{a(y)} dy\right) \left(\frac{2b(x)}{a(x)}\right) H_F(x) \right. \\
 & \quad \times \left\{ g_{b(G)}(x) + \frac{1}{2}a(x) \right\} p_G(x) dx \\
 & \quad + \int_z^{\infty} \exp\left(-\int_{\beta}^x \frac{2b(y)}{a(y)} dy\right) \left(-\frac{2b(x)}{a(x)}\right) [1 - H_F(x)] \\
 & \quad \times \left\{ g_{b(G)}(x) + \frac{1}{2}a(x) \right\} p_G(x) dx \Big] \\
 & - \frac{2p_F(z)}{p_F(\beta)a(\beta)} \int_{-\infty}^{\infty} \exp\left(-\int_{\beta}^x \frac{2b(y)}{a(y)} dy\right) p_F(x) \\
 & \quad \times \left\{ g_{b(G)}(x) + \frac{1}{2}a(x) \right\} p_G(x) dx \\
 & + \frac{2p_F(z)\mathbb{E}[b(G)]}{p_F(\beta)a(\beta)} \left\{ -\int_{-\infty}^z \exp\left(-\int_{\beta}^x \frac{2b(y)}{a(y)} dy\right) H_F(x) p_G(x) dx \right. \\
 & \left. + \int_z^{\infty} \exp\left(-\int_{\beta}^x \frac{2b(y)}{a(y)} dy\right) (1 - H_F(x)) p_G(x) dx \right\}. \tag{37}
 \end{aligned}$$

Substituting  $p_F$  in (10) for  $p_F$  in the right-hand side of the equation (37), we get

$$\begin{aligned}
 & p_G(z) - p_F(z) \\
 = & \frac{2}{a(z)} \left\{ g_{b(G)}(z) + \frac{1}{2}a(z) \right\} p_G(z) \\
 & + \frac{2}{a(z)} \exp \left( \int_{\beta}^z \frac{2b(y)}{a(y)} dy \right) \left[ \int_{-\infty}^z \exp \left( - \int_{\beta}^x \frac{2b(y)}{a(y)} dy \right) \left( \frac{2b(x)}{a(x)} \right) H_F(x) \right. \\
 & \quad \times \left\{ g_{b(G)}(x) + \frac{1}{2}a(x) \right\} p_G(x) dx \\
 & \quad + \int_z^{\infty} \exp \left( - \int_{\beta}^x \frac{2b(y)}{a(y)} dy \right) \left( - \frac{2b(x)}{a(x)} \right) [1 - H_F(x)] \\
 & \quad \times \left\{ g_{b(G)}(x) + \frac{1}{2}a(x) \right\} p_G(x) dx \Bigg] \\
 & - \frac{2}{a(z)} \exp \left( \int_{\beta}^z \frac{2b(y)}{a(y)} dy \right) \int_{-\infty}^{\infty} \exp \left( - \int_{\beta}^x \frac{2b(y)}{a(y)} dy \right) p_F(x) \\
 & \quad \times \left\{ g_{b(G)}(x) + \frac{1}{2}a(x) \right\} p_G(x) dx \\
 & + \frac{2\mathbb{E}[b(G)]}{a(z)} \exp \left( \int_{\beta}^z \frac{2b(y)}{a(y)} dy \right) \left\{ - \int_{-\infty}^z \exp \left( - \int_{\beta}^x \frac{2b(y)}{a(y)} dy \right) H_F(x) p_G(x) dx \right. \\
 & \quad \left. + \int_z^{\infty} \exp \left( - \int_{\beta}^x \frac{2b(y)}{a(y)} dy \right) (1 - H_F(x)) p_G(x) dx \right\}. \tag{38}
 \end{aligned}$$

From the formula of  $p_F$  in (10) and (38), we obtain that, for some  $\beta \in \text{supp}(p_G)$ ,

$$\begin{aligned}
 & -g_{b(G)}(z)p_G(z) \\
 = & \frac{p_F(\beta)a(\beta)}{2} \exp \left( \int_{\beta}^z \frac{2b(y)}{a(y)} dy \right) \\
 & + \exp \left( \int_{\beta}^z \frac{2b(y)}{a(y)} dy \right) \left\{ \int_{-\infty}^z \exp \left( - \int_{\beta}^x \frac{2b(y)}{a(y)} dy \right) \left( \frac{2b(x)}{a(x)} \right) H_F(x) \right. \\
 & \quad \times \left\{ g_{b(G)}(x) + \frac{1}{2}a(x) \right\} p_G(x) dx \\
 & \quad + \int_z^{\infty} \exp \left( - \int_{\beta}^x \frac{2b(y)}{a(y)} dy \right) \left( - \frac{2b(x)}{a(x)} \right) [1 - H_F(x)] \\
 & \quad \times \left\{ g_{b(G)}(x) + \frac{1}{2}a(x) \right\} p_G(x) dx \Bigg\} \\
 & - \exp \left( \int_{\beta}^z \frac{2b(y)}{a(y)} dy \right) \int_{-\infty}^{\infty} \exp \left( - \int_{\beta}^x \frac{2b(y)}{a(y)} dy \right) p_F(x) \\
 & \quad \times \left\{ g_{b(G)}(x) + \frac{1}{2}a(x) \right\} p_G(x) dx \\
 & + \mathbb{E}[b(G)] \exp \left( \int_{\beta}^z \frac{2b(y)}{a(y)} dy \right) \left\{ - \int_{-\infty}^z \exp \left( - \int_{\beta}^x \frac{2b(y)}{a(y)} dy \right) \right. \\
 & \quad \times H_F(x) p_G(x) dx \\
 & \quad \left. + \int_z^{\infty} \exp \left( - \int_{\beta}^x \frac{2b(y)}{a(y)} dy \right) (1 - H_F(x)) p_G(x) dx \right\}. \tag{39}
 \end{aligned}$$

Differentiating the equation (39) with respect to  $z$  proves that

$$\begin{aligned} \frac{\partial}{\partial z} g_{b(G)}(z) p_G(z) &= \frac{2b(z)}{a(z)} g_{b(G)}(z) p_G(z) \\ &\quad - \left( \frac{2b(z)}{a(z)} \right) \left\{ g_{b(G)}(z) + \frac{1}{2} a(z) \right\} p_G(z) - \mathbb{E}[b(G)] p_G(z) \\ &= -(b(z) - \mathbb{E}[b(G)]) p_G(z). \end{aligned} \quad (40)$$

This equation (40) proves that, for almost all  $z \in \text{supp}(p_G)$ ,

$$g_{b(G)}(z) p_G(z) = - \int_{-\infty}^z (b(x) - \mathbb{E}[b(G)]) p_G(x) dx. \quad (41)$$

From (40) and (41), it follows that, for almost all  $z \in \text{supp}(p_G)$ ,

$$\frac{\frac{d}{dz}(g_{b(G)}(z) p_G(z))}{g_{b(G)}(z) p_G(z)} = - \frac{b(z) - \mathbb{E}[b(G)]}{g_{b(G)}(z)} \quad (42)$$

Hence

$$\frac{d}{dz} \log(g_{b(G)}(z) p_G(z)) = - \frac{b(z) - \mathbb{E}[b(G)]}{g_{b(G)}(z)} \quad (43)$$

By integrating both sides of (43) from  $\beta \in \text{supp}(p_G)$  to  $z$ , we have

$$\log(g_{b(G)}(z) p_G(z)) = \log(g_{b(G)}(\beta) p_G(\beta)) - \int_{\beta}^z \frac{b(x) - \mathbb{E}[b(G)]}{g_{b(G)}(x)} dx. \quad (44)$$

The above equation (44) proves that, for almost all  $z \in \text{supp}(p_G)$ ,

$$p_G(z) = \frac{g_{b(G)}(\beta) p_G(\beta)}{g_{b(G)}(z)} \exp \left( - \int_{\beta}^z \frac{b(x) - \mathbb{E}[b(G)]}{g_{b(G)}(x)} dx \right). \quad (45)$$

□

When a random variable  $G$  is general, it is not easy to find an explicit computation of  $g_{b(G)}((x))$ . In particular, when  $\langle -DL^{-1}(b(G) - \mathbb{E}[b(G)]), DG \rangle_{\mathcal{H}}$  is not measurable with respect to the  $\sigma$ -field generated by  $G$ , there are cases where it is impossible to compute the expectation. Using the above Theorem 2, we derive the explicit form of  $g_{b(G)}(x)$ . The following theorem corresponds to Theorem 2 in [9].

**Theorem 3.** A random variable  $G \in \mathbb{D}^{1,2}$ , taking its value on  $I$ , has the distribution  $\mu$  and satisfies that  $\mathbb{E}[b(G)^2] < \infty$  if and only if  $\mathbb{E}[b(G)] = 0$  and

$$g_{b(G)}(x) = -\frac{1}{2} a(x) \text{ for all } x \in I. \quad (46)$$

**Proof:** Suppose that  $\mathbb{E}[b(G)] = 0$  and the equation (46) holds true. Let  $p_F$  be a density of an invariant measure  $\mu$  corresponding to a solution of SDE (11). Then substituting  $-\frac{1}{2}a(x)$  in (46) instead of  $g_{b(G)}(x)$  in (18) gives that

$$\begin{aligned} p_G(x) &= \frac{p_G(\beta) g_{b(G)}(\beta)}{g_{b(G)}(x)} \exp \left( - \int_{\beta}^x \frac{b(y)}{g_{b(G)}(y)} dy \right) \\ &= \frac{p_G(\beta) a(\beta)}{a(x)} \exp \left( \int_{\beta}^x \frac{2b(y)}{a(y)} dy \right). \end{aligned} \quad (47)$$

Combining (10) and (47), we get

$$p_G(x) = \frac{p_G(\beta)}{p_F(\beta)} p_F(x). \quad (48)$$

This equation (48) shows that  $\text{supp}(p_G) = \text{supp}(p_F)$ . Hence integrating both sides of (48) over  $I = (l, u)$  yields that

$$\frac{p_G(\beta)}{p_F(\beta)} = 1,$$

which implies that  $p_G = p_F$  on  $I$ . If  $p_G = p_F$  on  $I$ , then  $\mathbb{E}[b(G)] = 0$ . From (9) and (41), it follows that

$$\begin{aligned} a(x) &= \frac{2 \int_l^x b(y) p_F(y) dy}{p_F(x)} \\ &= \frac{2 \int_l^x b(y) p_G(y) dy}{p_G(x)} \\ &= -2g_{b(G)}(z), \end{aligned}$$

which gives that (46) holds.  $\square$

#### 4. Examples

In this section, two examples will be given where invariant measures have the standard Gaussian and uniform distribution, respectively.

##### 4.1. The standard Gaussian distribution

When  $\mu$  is the standard Gaussian distribution, then the coefficients in (12) are given by  $a(x) = 2$  and  $b(x) = -x$ , and  $u = \infty$  and  $l = -\infty$ . Then we have, from (20), that

$$\begin{aligned} h_z &= e^{\frac{x^2}{2}} \int_{-\infty}^x [\mathbf{1}_{(-\infty, z]}(y)) - \Phi(z)] e^{-x^2/2} dy \\ &= \begin{cases} \sqrt{2\pi} e^{\frac{x^2}{2}} \Phi(x)(1 - \Phi(z)) & \text{if } x \leq z \\ \sqrt{2\pi} e^{\frac{x^2}{2}} \Phi(z)(1 - \Phi(x)) & \text{if } x > z, \end{cases} \end{aligned} \quad (49)$$

where  $\Phi(z) = \mathbb{P}(Z \leq z)$ . We have, from (21), that for  $x > z$ , taking  $\beta = 0$

$$\begin{aligned} \tilde{h}'_z(x) &= \sqrt{2\pi} x e^{\frac{x^2}{2}} \Phi(z)(1 - \Phi(x)) \\ &\quad - \sqrt{2\pi} e^{\frac{x^2}{2}} p_F(x) \Phi(z) \\ &= [\sqrt{2\pi} x e^{\frac{x^2}{2}} (1 - \Phi(x)) - 1] \Phi(z), \end{aligned} \quad (50)$$

and for  $x < z$ ,

$$\begin{aligned} \tilde{h}'_z(x) &= \sqrt{2\pi} x e^{\frac{x^2}{2}} \Phi(x)[1 - \Phi(z)] \\ &\quad + \sqrt{2\pi} e^{\frac{x^2}{2}} p_F(x)[1 - \Phi(z)] \\ &= [\sqrt{2\pi} x e^{\frac{x^2}{2}} \Phi(x) + 1][1 - \Phi(z)]. \end{aligned} \quad (51)$$

If  $G \in \mathbb{D}^{1,2}$  and the random variable  $g_{-G}(G)$  is strictly positive almost surely, then the density  $p_G$  of  $G$  can be obtained, with  $\beta = 0$ , by

$$\begin{aligned} p_G(z) &= \frac{g_{-G}(0)p_G(0)}{g_{-G}(z)} \exp\left(\int_0^z \frac{x}{g_{-G}(x)} dx\right) \\ &= \frac{g_G(0)p_G(0)}{g_G(z)} \exp\left(-\int_0^z \frac{x}{g_G(x)} dx\right). \end{aligned} \quad (52)$$

Since  $\mathbb{E}[G] = 0$ , we get, from (41), that

$$\begin{aligned} g_G(0)p_G(0) &= -g_{-G}(0)p_G(0) \\ &= -\int_0^0 x p_G(x) dx \\ &= \frac{1}{2} \mathbb{E}[|G|]. \end{aligned} \quad (53)$$

Substituting (53) into (52), we have

$$p_G(z) = \frac{\mathbb{E}[|G|]}{2g_G(z)} \exp\left(-\int_0^z \frac{x}{g_G(x)} dx\right),$$

which is the density (18) in Theorem 1. If  $g_G = (z) = 1$ ,

$$\begin{aligned} p_G(z) &= \frac{\mathbb{E}[|G|]}{2} \exp\left(-\int_0^z x dx\right) \\ &= \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right), \end{aligned}$$

which implies that Theorem 3 holds.

#### 4.2. The Uniform Distribution

When  $\mu$  is the uniform distribution, i.e.,  $F \sim \mathcal{U}([0, 1])$ , then the coefficients in (12) are given by

$$a(x) = x(1-x) \text{ and } b(x) = -\left(x - \frac{1}{2}\right) \text{ for } x \in (0, 1).$$

From (20), we have that

$$\begin{aligned} \tilde{h}_z(x) &= \frac{2}{p_F(1/2)a(1/2)} \exp\left(\int_{1/2}^x \frac{(2y-1)}{y(1-y)} dy\right) \\ &\quad \times [(x \wedge z) - zx] \\ &= 8 \exp\left(\int_{1/2}^x \frac{(2y-1)}{y(1-y)} dy\right) \times [(x \wedge z) - zx] \\ &= \frac{2x}{1-x} \times \begin{cases} z(1-x) & \text{if } x \geq z \\ x(1-z) & \text{if } x < z, \end{cases} \end{aligned} \quad (54)$$

Then the density of  $G$  is given by

$$p_G(x) = \frac{p_G(\beta)g_{b(G)}(\beta)}{g_{b(G)}(x)} \exp \left( - \int_{\beta}^x \frac{b(y) - \mathbb{E}[b(G)]}{g_{b(G)}(y)} dy \right). \quad (55)$$

Taking  $\beta = \mathbb{E}[G]$ , then

$$p_G(x) = \frac{p_G(\mathbb{E}[G])g_{b(G)}(\mathbb{E}[G])}{g_{b(G)}(x)} \exp \left( - \int_{\mathbb{E}[G]}^x \frac{b(y) - \mathbb{E}[b(G)]}{g_{b(G)}(y)} dy \right). \quad (56)$$

The relation (41) gives that

$$p_G(\mathbb{E}[G])g_{b(G)}(\mathbb{E}[G]) = -\frac{1}{2}\mathbb{E}[|G - \mathbb{E}[G]|].$$

Hence (56) can be written as

$$\begin{aligned} p_G(x) &= \frac{\mathbb{E}[|G - \mathbb{E}[G]|]}{-2g_{-G}(x)} \exp \left( \int_{\mathbb{E}[G]}^x \frac{y - \mathbb{E}[G]}{g_{-G}(y)} dy \right) \\ &= \frac{\mathbb{E}[|G - \mathbb{E}[G]|]}{2g_G(x)} \exp \left( - \int_{\mathbb{E}[G]}^x \frac{y - \mathbb{E}[G]}{g_G(y)} dy \right). \end{aligned} \quad (57)$$

Putting  $\mathbb{E}[G] = 0$ , we know, from (57), that the density  $p_G$  is identical to the density in Theorem 1. If  $g_G(x) = \frac{1}{2}x(1-x)$  for  $x \in (0, 1)$ , a direct computation yields that

$$\begin{aligned} p_G(x) &= \frac{1}{4x(1-x)} \exp \left( - \int_{1/2}^x \frac{y - \frac{1}{2}}{\frac{1}{2}y(1-y)} dy \right) \\ &= \frac{1}{4x(1-x)} \exp \left( - \int_{1/2}^x \left\{ \frac{-2(1-y)}{y(1-y)} + \frac{1}{y(1-y)} \right\} dy \right) \\ &= \frac{1}{4x(1-x)} \exp \left( \log x + \log(1-x) + \log 4 \right) \\ &= \mathbf{1}_{[0,1]}(x), \end{aligned}$$

which implies that Theorem 3 holds true.

## 5. Conclusions and Future Works

When a random variable  $F$  follows the invariant measure  $\mu$  that has a density  $p_F$ , and a random variable  $G \in \mathbb{D}^{1,2}$  also allows a density  $p_G$ , this paper find an explicit formula of the density  $p_G$  based on the coefficients in the diffusion associated with the density  $p_F$ . The significant feature of our works is that it shows that the density  $p_G$  can be obtained by connecting the diffusion with the invariant measure, and that if  $g_{b(G)}$  is equal to the diffusion coefficient, Theorem 2 in [9] can be easily proven.

Future works will be carried out in two directions: (1) Using the results worked in this paper, we plan to derive a density formula associated with an Edgeworth expansion with general terms given in [11]. (2) In the case when  $G$  is a random variable belonging to a fixed Wiener chaos, we will obtain a more rigorous formula than the formula obtained in the previous works.

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