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INSTITUT NATIONAL DE RECHERCHE EN INFORMATIQUE ET EN AUTOMATIQUE

# *A Backward Particle Interpretation of Feynman-Kac Formulae*

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# A Backward Particle Interpretation of Feynman-Kac Formulae

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**Abstract:** We design a particle interpretation of Feynman-Kac measures on path spaces based on a backward Markovian representation combined with a traditional mean field particle interpretation of the flow of their final time marginals. In contrast to traditional genealogical tree based models, these new particle algorithms can be used to compute normalized additive functionals “on-the-fly” as well as their limiting occupation measures with a given precision degree that does not depend on the final time horizon.

We provide uniform convergence results w.r.t. the time horizon parameter as well as functional central limit theorems and exponential concentration estimates, yielding what seems to be the first results of this type for this class of models. We also illustrate these results in the context of computational physics and imaginary time Schroedinger type partial differential equations, with a special interest in the numerical approximation of the invariant measure associated to  $h$ -processes.

**Key-words:** Feynman-Kac models, mean field particle algorithms, functional central limit theorems, exponential concentration, non asymptotic estimates.

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# A Backward Particle Interpretation of Feynman-Kac Formulae

**Résumé :** Nous présentons de nouvelles interprétations particulières de mesures de Feynman-Kac trajectorielles fondées sur une représentation markovienne à rebours de ces modèles, couplée avec les interprétations particulières de type champ moyen classiques du flot des mesures marginales par rapport aux temps terminaux. A la différence des algorithmes particuliers fondés sur des évolutions d'arbres généalogiques, ces nouvelles techniques permettent de calculer récursivement des fonctionnelles additives normalisées et leur mesures limites avec un degré de précision uniforme par rapport à l'horizon temporel considéré.

Nous proposons des résultats de convergence uniformes par rapport à l'horizon temporel, ainsi que des théorèmes de la limite centrale fonctionnels et des inégalités de concentration exponentielles. Ces résultats semblent être les premiers de ce type pour cette classe d'algorithmes particuliers. Nous illustrons ces résultats en physique numérique avec des approximations particulières d'équations aux dérivées partielles de type Schroedinger et le calcul effectif des mesures stationnaires associées aux  $h$ -processus.

**Mots-clés :** Modèles de Feynman-Kac, algorithmes stochastiques de type champ moyen, théorème de la limite centrale fonctionnels, inégalités de concentration exponentielle, estimations non asymptotiques

## 1 Introduction

Let  $(E_n)_{n \geq 0}$  be a sequence of measurable spaces equipped with some  $\sigma$ -fields  $(\mathcal{E}_n)_{n \geq 0}$ , and we let  $\mathcal{P}(E_n)$  be the set of all probability measures over the set  $E_n$ , with  $n \geq 0$ . We let  $X_n$  be a Markov chain with Markov transition  $M_n$  on  $E_n$ , and we consider a sequence of  $(0, 1]$ -valued potential functions  $G_n$  on the set  $E_n$ . The Feynman-Kac path measure associated with the pairs  $(M_n, G_n)$  is the probability measure  $\mathbb{Q}_n$  on the product state space  $E_{[0, n]} := (E_0 \times \dots \times E_n)$  defined by the following formula

$$d\mathbb{Q}_n := \frac{1}{\mathcal{Z}_n} \left\{ \prod_{0 \leq p < n} G_p(X_p) \right\} d\mathbb{P}_n \quad (1.1)$$

where  $\mathcal{Z}_n$  is a normalizing constant and  $\mathbb{P}_n$  is the distribution of the random paths  $(X_p)_{0 \leq p \leq n}$  of the Markov process  $X_p$  from the origin  $p = 0$ , up to the current time  $p = n$ . We also denote by  $\Gamma_n = \mathcal{Z}_n \mathbb{Q}_n$  its unnormalized version.

These distributions arise in a variety of application areas, including filtering, Bayesian inference, branching processes in biology, particle absorption problems in physics and many other instances. We refer the reader to the pair of books [4, 9] and references therein. Feynman-Kac models also play a central role in the numerical analysis of certain partial differential equations, offering a natural way to solve these functional integral models by simulating random paths of stochastic processes. These Feynman-Kac models were originally presented by Mark Kac in 1949 [11] for continuous time processes. These continuous time models are used in molecular chemistry and computational physics to calculate the ground state energy of some Hamiltonian operators associated with some potential function  $V$  describing the energy of a molecular configuration (see for instance [1, 5, 13, 16], and references therein).

To better connect these partial differential equation models with (1.1), let us assume that  $M_n(x_{n-1}, dx_n)$  is the Markov probability transition  $X_n = x_n \rightsquigarrow X_{n+1} = x_{n+1}$  coming from a discretization in time  $X_n = X'_{t_n}$  of a continuous time  $E$ -valued Markov process  $X'_t$  on a given time mesh  $(t_n)_{n \geq 0}$  with a given time step  $(t_n - t_{n-1}) = \Delta t$ . For potential functions of the form  $G_n = e^{-V \Delta t}$ , the measures  $\mathbb{Q}_n \simeq_{\Delta t \rightarrow 0} \mathbb{Q}_{t_n}$  represents the time discretization of the following distribution:

$$d\mathbb{Q}_t = \frac{1}{\mathcal{Z}_t} \exp \left( - \int_0^t V(X'_s) ds \right) d\mathbb{P}_t^{X'}$$

where  $\mathbb{P}_t^{X'}$  stands for the distribution of the random paths  $(X'_s)_{0 \leq s \leq t}$  with a given infinitesimal generator  $L$ . The marginal distributions  $\gamma_t$  at time  $t$  of the unnormalized measures  $\mathcal{Z}_t d\mathbb{Q}_t$  are the solution of the so-called imaginary time Schroedinger equation, given in weak formulation on every sufficiently regular function  $f$  by

$$\frac{d}{dt} \gamma_t(f) := \gamma_t(L^V(f)) \quad \text{with} \quad L^V = L - V$$

The errors introduced by the discretization of the time are well understood for regular models, we refer the interested reader to [6, 8, 12, 14] in the context of nonlinear filtering.

In this article, we design an numerical approximation of the distributions  $\mathbb{Q}_n$  based on the simulation of a sequence of mean field interacting particle systems. In molecular chemistry, these evolutionary type models are often interpreted as a quantum or diffusion Monte Carlo model. In this context, particles often are referred as walkers, to distinguish the virtual particle-like objects to physical particles, like electrons of atoms. In contrast to traditional genealogical tree based approximations (see for instance [4]), the particle model presented in this article can approximate additive functionals of the form

$$\bar{F}_n(x_0, \dots, x_n) = \frac{1}{(n+1)} \sum_{0 \leq p \leq n} f_p(x_p) \quad (1.2)$$

uniformly with respect to the time horizon. Moreover this computation can be done “on-the-fly”. To give a flavor of the impact of these results, we recall that the precision of the algorithm corresponds to the size  $N$  of the particle system. If  $\mathbb{Q}_n^N$  stands for the  $N$ -particle approximation of  $\mathbb{Q}_n$ , under some appropriate regularity properties, we shall prove the following uniform and non asymptotic Gaussian concentration estimates<sup>1</sup>:

$$\frac{1}{N} \log \sup_{n \geq 0} \mathbb{P} \left( \left| [\mathbb{Q}_n^N - \mathbb{Q}_n](F_n) \right| \geq \frac{b}{\sqrt{N}} + \epsilon \right) \leq -\epsilon^2 / (2b^2)$$

for any  $\epsilon > 0$ , and for some finite constant  $b < \infty$ . For time homogeneous models  $(M_n, f_n, G_n) = (M, f, G)$  associated with a lower bounded potential function  $G > \delta$ , and a  $M$ -reversible transition w.r.t. to some probability measure  $\mu$  s.t.  $M(x, \cdot) \sim \mu$  and  $(M(x, \cdot)/d\mu) \in \mathbb{L}_2(\mu)$ , it can be established that  $\mathbb{Q}_n(F_n)$  converges to  $\mu_h(f)$ , as  $n \rightarrow \infty$ , with the measure  $\mu_h$  defined below

$$\mu_h(dx) := \frac{1}{\mu(hM(h))} h(x) M(h)(x) \mu(dx)$$

In the above display,  $h$  is a positive eigenmeasure associated with the top eigenvalue of the integral operator  $Q(x, dy) = G(x)M(x, dy)$  on  $\mathbb{L}_2(\mu)$  (see for instance section 12.4 in [4]). This measure  $\mu_h$  is in fact the invariant measure of the  $h$ -process defined as the Markov chain  $X^h$  with elementary Markov transitions  $M_h(x, dy) \propto M(x, dy)h(y)$ . As the initiated reader would have certainly noticed, the above convergence result is only valid under some appropriate mixing conditions on the  $h$ -process. The long time behavior of these  $h$ -processes and their connections to various applications areas of probability, analysis, geometry and partial differential equations, have been the subject of countless papers for many years in applied probability. In our framework, using elementary manipulations, the Gaussian estimate given above can be used to calibrate the convergence of the particle estimate  $\mathbb{Q}_n^N(F_n)$  towards  $\mu_h(f)$ , as the pair of parameters  $N$  and  $n \rightarrow \infty$ .

The rest of this article is organized as follows:

In section 2, we describe the mean field particle models used to design the particle approximation measures  $\mathbb{Q}_n^N$ . In section 3, we state the main results presented in this article, including a functional central limit theorem, and non asymptotic mean error bounds. Section 4 is dedicated to a key backward Markov chain representation of the measures  $\mathbb{Q}_n$ . The analysis of our particle approximations is provided in section 5. The final two sections, section 6 and section 7, are mainly concerned with the proof of the two main theorems presented in section 3.

For the convenience of the reader, we end this introduction with some notation used in the present article. We denote respectively by  $\mathcal{M}(E)$ , and  $\mathcal{B}(E)$ , the set of all finite signed measures on some measurable space  $(E, \mathcal{E})$ , and the Banach space of all bounded and measurable functions  $f$  equipped with the uniform norm  $\|f\|$ . We let  $\mu(f) = \int \mu(dx) f(x)$ , be the Lebesgue integral of a function  $f \in \mathcal{B}(E)$ , with respect to a measure  $\mu \in \mathcal{M}(E)$ . We recall that a bounded integral kernel  $M(x, dy)$  from a measurable space  $(E, \mathcal{E})$  into an auxiliary measurable space  $(E', \mathcal{E}')$  is an operator  $f \mapsto M(f)$  from  $\mathcal{B}(E')$  into  $\mathcal{B}(E)$  such that the functions

$$x \mapsto M(f)(x) := \int_{E'} M(x, dy) f(y)$$

are  $\mathcal{E}$ -measurable and bounded, for any  $f \in \mathcal{B}(E')$ . In the above displayed formulae,  $dy$  stands for an infinitesimal neighborhood of a point  $y$  in  $E'$ . The kernel  $M$  also generates a dual operator  $\mu \mapsto \mu M$  from  $\mathcal{M}(E)$  into  $\mathcal{M}(E')$  defined by  $(\mu M)(f) := \mu(M(f))$ . A Markov kernel is a positive and bounded integral operator  $M$  with  $M(1) = 1$ . Given a pair of bounded integral operators  $(M_1, M_2)$ , we let  $(M_1 M_2)$  the composition operator defined by  $(M_1 M_2)(f) = M_1(M_2(f))$ . For time homogenous state spaces, we denote by  $M^m = M^{m-1} M = M M^{m-1}$  the  $m$ -th composition of a given bounded integral

<sup>1</sup>Consult the last paragraph of this section for a statement of the notation used in this article.

operator  $M$ , with  $m \geq 1$ . Given a positive function  $G$  on  $E$ , we let  $\Psi_G : \eta \in \mathcal{P}(E) \mapsto \Psi_G(\eta) \in \mathcal{P}(E)$ , be the Boltzmann-Gibbs transformation defined by

$$\Psi_G(\eta)(dx) := \frac{1}{\eta(G)} G(x) \eta(dx)$$

## 2 Description of the models

The numerical approximation of the path-space distributions (1.1) requires extensive calculations. The mean field particle interpretation of these models are based on the fact that the flow of the  $n$ -th time marginals  $\eta_n$  of the measures  $\mathbb{Q}_n$  satisfy a non linear evolution equation of the following form

$$\eta_{n+1}(dy) = \int \eta_n(dx) K_{n+1, \eta_n}(x, dy) \quad (2.1)$$

for some collection of Markov transitions  $K_{n+1, \eta}$ , indexed by the time parameter  $n \geq 0$  and the set of probability measures  $\mathcal{P}(E_n)$ . The mean field particle interpretation of the nonlinear measure valued model (2.1) is the  $E_n^N$ -valued Markov chain

$$\xi_n = (\xi_n^1, \xi_n^2, \dots, \xi_n^N) \in E_n^N$$

with elementary transitions defined as

$$\mathbb{P}(\xi_{n+1} \in dx \mid \xi_n) = \prod_{i=1}^N K_{n+1, \eta_n^i}(\xi_n^i, dx^i) \quad \text{with} \quad \eta_n^N := \frac{1}{N} \sum_{j=1}^N \delta_{\xi_n^j} \quad (2.2)$$

In the above displayed formula,  $dx$  stands for an infinitesimal neighborhood of the point  $x = (x^1, \dots, x^N) \in E_{n+1}^N$ . The initial system  $\xi_0$  consists of  $N$  independent and identically distributed random variables with common law  $\eta_0$ . We let  $\mathcal{F}_n^N := \sigma(\xi_0, \dots, \xi_n)$  be the natural filtration associated with the  $N$ -particle approximation model defined above. The resulting particle model coincides with a genetic type stochastic algorithm  $\xi_n \rightsquigarrow \widehat{\xi}_n \rightsquigarrow \xi_{n+1}$  with selection transitions  $\xi_n \rightsquigarrow \widehat{\xi}_n$  and mutation transitions  $\widehat{\xi}_n \rightsquigarrow \xi_{n+1}$  dictated by the potential (or fitness) functions  $G_n$  and the Markov transitions  $M_{n+1}$ .

During the selection stage  $\xi_n \rightsquigarrow \widehat{\xi}_n$ , for every index  $i$ , with a probability  $\epsilon_n G_n(\xi_n^i)$ , we set  $\widehat{\xi}_n^i = \xi_n^i$ , otherwise we replace  $\xi_n^i$  with a new individual  $\widehat{\xi}_n^i = \xi_n^j$  randomly chosen from the whole population with a probability proportional to  $G_n(\xi_n^j)$ . The parameter  $\epsilon_n \geq 0$  is a tuning parameter that must satisfy the constraint  $\epsilon_n G_n(\xi_n^i) \leq 1$ , for every  $1 \leq i \leq N$ . For  $\epsilon_n = 0$ , the resulting proportional selection transition corresponds to the so-called simple genetic model. During the mutation stage, the selected particles  $\widehat{\xi}_n^i \rightsquigarrow \xi_{n+1}^i$  evolve independently according to the Markov transitions  $M_{n+1}$ .

If we interpret the selection transition as a birth and death process, then arises the important notion of the ancestral line of a current individual. More precisely, when a particle  $\widehat{\xi}_{n-1}^i \rightarrow \xi_n^i$  evolves to a new location  $\xi_n^i$ , we can interpret  $\widehat{\xi}_{n-1}^i$  as the parent of  $\xi_n^i$ . Looking backwards in time and recalling that the particle  $\widehat{\xi}_{n-1}^i$  has selected a site  $\xi_{n-1}^j$  in the configuration at time  $(n-1)$ , we can interpret this site  $\xi_{n-1}^j$  as the parent of  $\widehat{\xi}_{n-1}^i$  and therefore as the ancestor denoted  $\xi_{n-1, n}^i$  at level  $(n-1)$  of  $\xi_n^i$ . Running backwards in time we may trace the whole ancestral line

$$\xi_{0, n}^i \leftarrow \xi_{1, n}^i \leftarrow \dots \leftarrow \xi_{n-1, n}^i \leftarrow \xi_{n, n}^i = \xi_n^i \quad (2.3)$$

More interestingly, the occupation measure of the corresponding  $N$ -genealogical tree model converges as  $N \rightarrow \infty$  to the conditional distribution  $\mathbb{Q}_n$ . For any function  $F_n$  on the path space  $E_{[0, n]}$ , we have the following convergence (to be stated precisely later) as  $N \rightarrow \infty$ ,

$$\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{i=1}^N F_n(\xi_{0, n}^i, \xi_{1, n}^i, \dots, \xi_{n, n}^i) = \int \mathbb{Q}_n(d(x_0, \dots, x_n)) F_n(x_0, \dots, x_n) \quad (2.4)$$



This convergence result can be refined in various directions. Nevertheless, the asymptotic variance  $\sigma_n^2(F_n)$  of the above occupation measure around  $\mathbb{Q}_n$  increases quadratically with the final time horizon  $n$  for additive functions of the form

$$F_n(x_0, \dots, x_n) = \sum_{0 \leq p \leq n} f_p(x_p) \Rightarrow \sigma_n^2(F_n) \simeq n^2 \quad (2.5)$$

with some collection of non negative functions  $f_p$  on  $E_p$ . To be more precise, let us examine a time homogeneous model  $(E_n, f_n, G_n, M_n) = (E, f, G, M)$  with constant potential functions  $G_n = 1$  and mutation transitions  $M$  s.t.  $\eta_0 M = \eta_0$ . For the choice of the tuning parameter  $\epsilon = 0$ , using the asymptotic variance formulae in [4, eqn. (9.13), page 304], for any function  $f$  s.t.  $\eta_0(f) = 0$  and  $\eta_0(f^2) = 1$  we prove that

$$\sigma_n^2(F_n) = \sum_{0 \leq p \leq n} \mathbb{E} \left( \left[ \sum_{0 \leq q \leq n} M^{(q-p)_+}(f)(X_q) \right]^2 \right)$$

with the positive part  $a_+ = \max(a, 0)$  and the convention  $M^0 = Id$ , the identity transition. For  $M(x, dy) = \eta_0(dy)$ , we find that

$$\sigma_n^2(F_n) = \sum_{0 \leq p \leq n} \mathbb{E} \left( \left[ \sum_{0 \leq q \leq p} f(X_q) \right]^2 \right) = (n+1)(n+2)/2 \quad (2.6)$$

We further assume that the Markov transitions  $M_n(x_{n-1}, dx_n)$  are absolutely continuous with respect to some measures  $\lambda_n(dx_n)$  on  $E_n$  and we have

$$(H) \quad \forall (x_{n-1}, x_n) \in (E_{n-1} \times E_n) \quad H_n(x_{n-1}, x_n) = \frac{dM_n(x_{n-1}, \cdot)}{d\lambda_n}(x_n) > 0$$

In this situation, we have the backward decomposition formula

$$\mathbb{Q}_n(d(x_0, \dots, x_n)) = \eta_n(dx_n) \mathcal{M}_n(x_n, d(x_0, \dots, x_{n-1})) \quad (2.7)$$

with the Markov transitions  $\mathcal{M}_n$  defined below

$$\mathcal{M}_n(x_n, d(x_0, \dots, x_{n-1})) := \prod_{q=1}^n M_{q, \eta_{q-1}}(x_q, dx_{q-1})$$

In the above display,  $M_{n+1, \eta}$  is the collection of Markov transitions defined for any  $n \geq 0$  and  $\eta \in \mathcal{P}(E_n)$  by

$$M_{n+1, \eta}(x, dy) = \frac{1}{\eta(G_n H_{n+1}(\cdot, x))} G_n(y) H_{n+1}(y, x) \eta(dy) \quad (2.8)$$

A detailed proof of this formula and its extended version is provided in section 4.

Using the representation in (2.7), one natural way to approximate  $\mathbb{Q}_n$  is to replace the measures  $\eta_n$  with their  $N$ -particle approximations  $\eta_n^N$ . The resulting particle approximation measures,  $\mathbb{Q}_n^N$ , is then

$$\mathbb{Q}_n^N(d(x_0, \dots, x_n)) := \eta_n^N(dx_n) \mathcal{M}_n^N(x_n, d(x_0, \dots, x_{n-1})) \quad (2.9)$$

with the random transitions

$$\mathcal{M}_n^N(x_n, d(x_0, \dots, x_{n-1})) := \prod_{q=1}^n M_{q, \eta_{q-1}^N}(x_q, dx_{q-1}) \quad (2.10)$$

At this point, it is convenient to recall that for any bounded measurable function  $f_n$  on  $E_n$ , the measures  $\eta_n$  can be written as follows:

$$\eta_n(f_n) := \frac{\gamma_n(f_n)}{\gamma_n(1)} \quad \text{with} \quad \gamma_n(f_n) := \mathbb{E} \left( f_n(X_n) \prod_{0 \leq p < n} G_p(X_p) \right) = \eta_n(f_n) \prod_{0 \leq p < n} \eta_p(G_p) \quad (2.11)$$

The multiplicative formula in the r.h.s. of (2.11) is easily checked using the fact that  $\gamma_{n+1}(1) = \gamma_n(G_n) = \eta_n(G_n) \gamma_n(1)$ . Mimicking the above formulae, we set

$$\Gamma_n^N = \gamma_n^N(1) \times \mathbb{Q}_n^N \quad \text{with} \quad \gamma_n^N(1) := \prod_{0 \leq p < n} \eta_p^N(G_p) \quad \text{and} \quad \gamma_n^N(dx) = \gamma_n^N(1) \times \eta_n^N(dx)$$

Notice that the  $N$ -particle approximation measures  $\mathbb{Q}_n^N$  can be computed recursively with respect to the time parameter. For instance, for linear functionals of the form (2.5), we have

$$\mathbb{Q}_n^N(F_n) = \eta_n^N(F_n^N)$$

with a sequence of random functions  $F_n^N$  on  $E_n$  that can be computed ‘‘on-the-fly’’ according to the following recursion

$$F_n^N = \sum_{0 \leq p \leq n} \left[ M_{n, \eta_{n-1}^N} \cdots M_{p+1, \eta_p^N} \right] (f_p) = f_n + M_{n, \eta_{n-1}^N} (F_{n-1}^N)$$

with the initial value  $F_0^N = f_0$ . In contrast to the genealogical tree based particle model (2.4), this new particle algorithm requires  $N^2$  computations instead of  $N$ , in the sense that:

$$\forall 1 \leq j \leq N \quad F_n^N(\xi_n^j) = f_n(\xi_n^j) + \sum_{1 \leq i \leq N} \frac{G_{n-1}(\xi_{n-1}^i) H_n(\xi_{n-1}^i, \xi_n^j)}{\sum_{1 \leq i' \leq N} G_{n-1}(\xi_{n-1}^{i'}) H_n(\xi_{n-1}^{i'}, \xi_n^j)} F_{n-1}^N(\xi_{n-1}^i)$$

The convergence analysis of the  $N$ -particle measures  $\mathbb{Q}_n^N$  towards their limiting value  $\mathbb{Q}_n$ , as  $N \rightarrow \infty$ , is intimately related to the convergence of the flow of particle measures  $(\eta_p^N)_{0 \leq p \leq n}$  towards their limiting measures  $(\eta_p)_{0 \leq p \leq n}$ . Several estimates can be easily derived more or less directly from the convergence analysis of the particle occupation measures  $\eta_n^N$  developed in [4], including  $\mathbb{L}_p$ -mean error bounds and exponential deviation estimates. It is clearly out of the scope of the present work to review all these consequences. One of the central objects in this analysis is the local sampling errors  $V_n^N$  induced by the mean field particle transitions and defined by the following stochastic perturbation formula

$$\eta_n^N = \eta_{n-1}^N K_{n, \eta_{n-1}^N} + \frac{1}{\sqrt{N}} V_n^N \quad (2.12)$$

The fluctuation and the deviations of these centered random measures  $V_n^N$  can be estimated using non asymptotic Kintchine’s type  $\mathbb{L}_r$ -inequalities, as well as Hoeffding’s or Bernstein’s type exponential deviations [4, 7]. We also proved in [3] that these random perturbations behave asymptotically as Gaussian random perturbations. More precisely, for any fixed time horizon  $n \geq 0$ , the sequence of random fields  $V_n^N$  converges in law, as the number of particles  $N$  tends to infinity, to a sequence of independent, Gaussian and centered random fields  $V_n$ ; with, for any bounded function  $f$  on  $E_n$ , and  $n \geq 0$ ,

$$\mathbb{E}(V_n(f)^2) = \int \eta_{n-1}(dx) K_{n, \eta_{n-1}}(x, dy) (f(y) - K_{n, \eta_{n-1}}(f)(x))^2 \quad (2.13)$$

In section 5, we provide some key decompositions expressing the deviation of the particle measures  $(\Gamma_n^N, \mathbb{Q}_n^N)$  around their limiting values  $(\Gamma_n, \mathbb{Q}_n)$  in terms of these local random fields models. These decomposition can be used to derive almost directly some exponential and  $\mathbb{L}_p$ -mean error bounds using the stochastic analysis developed in [4]. We shall use these functional central limit theorems and some of their variations in various places in the present article.

### 3 Statement of some results

In the present article, we have chosen to concentrate on functional central limit theorems, as well as on non asymptotic variance theorems in terms of the time horizon. To describe our results, it is necessary to introduce the following notation. Let  $\beta(M)$  denote the Dobrushin coefficient of a Markov transition  $M$  from a measurable space  $E$  into another measurable space  $E'$  which defined by the following formula

$$\beta(M) := \sup \{ \text{osc}(M(f)) ; f \in \text{Osc}_1(E') \}$$

where  $\text{Osc}_1(E')$  stands the set of  $E'$ -measurable functions  $f$  with oscillation, denoted  $\text{osc}(f) = \sup \{|f(x) - f(y)| ; x, y \in E'\}$ , less than or equal to 1. Some stochastic models discussed in the present article are based on sequences of random Markov transitions  $M^N$  that depend on some mean field particle model with  $N$  random particles. In this case,  $\beta(M^N)$  may fail to be measurable. For this type of models we shall use outer probability measures to integrate these quantities. For instance, the mean value  $\mathbb{E}(\beta(M^N))$  is to be understood as the infimum of the quantities  $\mathbb{E}(B^N)$  where  $B^N \geq \beta(M^N)$  are measurable dominating functions. We also recall that  $\gamma_n$  satisfy the linear recursive equation

$$\gamma_n = \gamma_p Q_{p,n} \quad \text{with} \quad Q_{p,n} = Q_{p+1} Q_{p+2} \dots Q_n \quad \text{and} \quad Q_n(x, dy) = G_{n-1}(x) M_n(x, dy)$$

for any  $0 \leq p \leq n$ . Using elementary manipulations, we also check that

$$\Gamma_n(F_n) = \gamma_p D_{p,n}(F_n)$$

with the bounded integral operators  $D_{p,n}$  from  $E_p$  into  $E_{[0,n]}$  defined below

$$D_{p,n}(F_n)(x_p) := \int \mathcal{M}_p(x_p, d(x_0, \dots, x_{p-1})) \mathcal{Q}_{p,n}(x_p, d(x_{p+1}, \dots, x_n)) F_n(x_0, \dots, x_n) \quad (3.1)$$

with

$$\mathcal{Q}_{p,n}(x_p, d(x_{p+1}, \dots, x_n)) := \prod_{p \leq q < n} Q_{q+1}(x_q, dx_{q+1})$$

We also let  $(G_{p,n}, P_{p,n})$  be the pair of potential functions and Markov transitions defined below

$$G_{p,n} = Q_{p,n}(1)/\eta_p Q_{p,n}(1) \quad \text{and} \quad P_{p,n}(F_n) = D_{p,n}(F_n)/D_{p,n}(1) \quad (3.2)$$

Let the mapping  $\Phi_{p,n} : \mathcal{P}(E_p) \rightarrow \mathcal{P}(E_n)$ ,  $0 \leq p \leq n$ , be defined as follows

$$\Phi_{p,n}(\mu_p) = \frac{\mu_p Q_{p,n}}{\mu_p Q_{p,n}(1)}$$

Our first main result is a functional central limit theorem for the pair of random fields on  $\mathcal{B}(E_{[0,n]})$  defined below

$$W_n^{\Gamma,N} := \sqrt{N} (\Gamma_n^N - \Gamma_n) \quad \text{and} \quad W_n^{\mathbb{Q},N} := \sqrt{N} [\mathbb{Q}_n^N - \mathbb{Q}_n]$$

$W_n^{\Gamma,N}$  is centered in the sense that  $\mathbb{E}(W_n^{\Gamma,N}(F_n)) = 0$  for any  $F_n \in \mathcal{B}(E_{[0,n]})$ . The proof of this surprising unbiasedness property can be found in corollary 5.3, in section 5.

The first main result of this article is the following multivariate fluctuation theorem.

**Theorem 3.1** *We suppose that the following regularity condition is met for any  $n \geq 1$  and for any pair of states  $(x, y) \in (E_{n-1}, E_n)$*

$$(H^+) \quad h_n^-(y) \leq H_n(x, y) \leq h_n^+(y) \quad \text{with} \quad (h_n^+/h_n^-) \in \mathbb{L}_4(\eta_n) \quad \text{and} \quad h_n^+ \in \mathbb{L}_1(\lambda_n) \quad (3.3)$$

In this situation, the sequence of random fields  $W_n^{\Gamma, N}$ , resp.  $W_n^{\mathbb{Q}, N}$ , converge in law, as  $N \rightarrow \infty$ , to the centered Gaussian fields  $W_n^\Gamma$ , resp.  $W_n^\mathbb{Q}$ , defined for any  $F_n \in \mathcal{B}(E_{[0, n]})$  by

$$\begin{aligned} W_n^\Gamma(F_n) &= \sum_{p=0}^n \gamma_p(1) V_p(D_{p, n}(F_n)) \\ W_n^\mathbb{Q}(F_n) &= \sum_{p=0}^n V_p(G_{p, n} P_{p, n}(F_n - \mathbb{Q}_n(F_n))) \end{aligned}$$

The second main result of the article is the following non asymptotic theorem.

**Theorem 3.2** For any  $r \geq 1$ ,  $n \geq 0$ ,  $F_n \in \mathcal{B}(E_{[0, n]})$  s.t.  $\|F_n\| \leq 1$

$$\sqrt{N} \mathbb{E} \left( \left| [\mathbb{Q}_n^N - \mathbb{Q}_n](F_n) \right|^r \right)^{\frac{1}{r}} \leq a_r \sum_{0 \leq p \leq n} b_{p, n}^2 c_{p, n}^N \quad (3.4)$$

for some finite constants  $a_r < \infty$  whose values only depend on the parameter  $r$ , and a pair of constants  $(b_{p, n}, c_{p, n}^N)$  such that

$$b_{p, n} \leq \sup_{x, y} (Q_{p, n}(1)(x)/Q_{p, n}(1)(y)) \quad \text{and} \quad c_{p, n}^N \leq \mathbb{E}(\beta(P_{p, n}^N))$$

In the above display,  $P_{p, n}^N$  stands for the random Markov transitions defined as  $P_{p, n}$  by replacing in (3.1) and (3.2) the transitions  $\mathcal{M}_p$  by  $\mathcal{M}_p^N$ . For linear functionals of the form (2.5), with  $f_n \in \text{Osc}_1(E_n)$ , the constant  $c_{p, n}^N$  in (3.4) can be chosen so that

$$c_{p, n}^N \leq \sum_{0 \leq q < p} \beta \left( M_{p, \eta_{p-1}^N} \dots M_{q+1, \eta_q^N} \right) + \sum_{p \leq q \leq n} b_{q, n}^2 \beta(S_{p, q}) \quad (3.5)$$

with the Markov transitions  $S_{p, q}$  from  $E_p$  into  $E_q$  defined for any function  $f \in \mathcal{B}(E_q)$  by the following formula  $S_{p, q}(f) = Q_{p, q}(f)/Q_{p, q}(1)$ .

We emphasize that the  $\mathbb{L}_r$ -mean error bounds described in the above theorem enter the stability properties of the semigroups  $S_{p, q}$  and the one associated with the backward Markov transitions  $M_{n+1, \eta_n^N}$ . In several instances, the term in the r.h.s. of (3.5) can be uniformly bounded with respect to the time horizon. For instance, in the toy example we discussed in (2.6), we have the estimates

$$b_{p, n} = 1 \quad \text{and} \quad c_{p, n}^N \leq 1 \implies \sqrt{N} \mathbb{E} \left( \left| [\mathbb{Q}_n^N - \mathbb{Q}_n](F_n) \right|^r \right)^{\frac{1}{r}} \leq a_r (n+1)$$

In more general situations, these estimates are related to the stability properties of the Feynman-Kac semigroup. To simplify the presentation, let us suppose that the pair of potential-transitions  $(G_n, M_n)$  are time homogeneous  $(G_n, H_n, M_n) = (G, H, M)$  and chosen so that the following regularity condition is satisfied

$$(M)_m \quad \forall(x, x'^2) \quad G(x) \leq \delta G(x') \quad \text{and} \quad M^m(x, dy) \leq \rho M^m(x', dy) \quad (3.6)$$

for some  $m \geq 1$  and some parameters  $(\delta, \rho) \in [1, \infty)^2$ . Under this rather strong condition, we have

$$b_{p, n} \leq \rho \delta^m \quad \text{and} \quad \beta(S_{p, q}) \leq (1 - \rho^{-2} \delta^{-m})^{\lfloor (q-p)/m \rfloor}$$

See for instance corollary 4.3.3. in [4] and the more recent article [2]. On the other hand, let us suppose that

$$\inf_{x, y, y'} (H(x, y)/H(x, y')) = \alpha(h) > 0$$

In this case, we have

$$M_{n,\eta}(x, dy) \leq \alpha(h)^{-2} M_{n,\eta}(x', dy) \implies \beta \left( M_{p,\eta_{p-1}^N} \cdots M_{q+1,\eta_q^N} \right) \leq (1 - \alpha(h)^2)^{p-q}$$

For linear functional models of the form (2.5) associated with functions  $f_n \in \text{Osc}_1(E_n)$ , it is now readily checked that

$$\sqrt{N} \mathbb{E} \left( \left| [\mathbb{Q}_n^N - \mathbb{Q}_n](F_n) \right|^r \right)^{\frac{1}{r}} \leq a_r b (n+1) \quad (3.7)$$

for some finite constant  $b < \infty$  whose values do not depend on the time parameter  $n$ . With some information on the constants  $a_r$ , these  $\mathbb{L}_r$ -mean error bounds can be turned to uniform exponential estimates w.r.t. the time parameter for normalized additive functionals of the following form

$$\bar{F}_n(x_0, \dots, x_n) := \frac{1}{n+1} \sum_{0 \leq p \leq n} f_p(x_p)$$

To be more precise, by lemma 7.3.3 in [4], the collection of constants  $a_r$  in (3.7) can be chosen so that

$$a_{2r}^{2r} \leq (2r)! 2^{-r}/r! \quad \text{and} \quad a_{2r+1}^{2r+1} \leq (2r+1)! 2^{-r}/r! \quad (3.8)$$

In this situation, it is easily checked that for any  $\epsilon > 0$ , and  $N \geq 1$ , we have the following uniform Gaussian concentration estimates:

$$\frac{1}{N} \log \sup_{n \geq 0} \mathbb{P} \left( \left| [\mathbb{Q}_n^N - \mathbb{Q}_n](\bar{F}_n) \right| \geq \frac{b}{\sqrt{N}} + \epsilon \right) \leq -\epsilon^2/(2b^2)$$

This result is a direct consequence of the fact that for any non negative random variable  $U$

$$\left( \forall r \geq 1 \quad \mathbb{E}(U^r)^{\frac{1}{r}} \leq a_r b \right) \implies \log \mathbb{P}(U \geq b + \epsilon) \leq -\epsilon^2/(2b^2)$$

To check this claim, we develop the exponential to prove that

$$\log \mathbb{E}(e^{tU}) \stackrel{\forall t \geq 0}{\leq} bt + \frac{(bt)^2}{2} \implies \log \mathbb{P}(U \geq b + \epsilon) \leq -\sup_{t \geq 0} \left( \epsilon t - \frac{(bt)^2}{2} \right)$$

## 4 A backward Markov chain formulation

This section is mainly concerned with the proof of the backward decomposition formula (2.7). Before proceeding, we recall that the measures  $(\gamma_n, \eta_n)$  satisfy the non linear equations

$$\gamma_n = \gamma_{n-1} \mathbb{Q}_n \quad \text{and} \quad \eta_{n+1} := \Phi_{n+1}(\eta_n) := \Psi_{G_n}(\eta_n) M_{n+1}$$

and their semigroups are given by

$$\gamma_n = \gamma_p \mathbb{Q}_{p,n} \quad \text{and} \quad \eta_n(f_n) := \eta_p \mathbb{Q}_{p,n}(f_n) / \eta_p \mathbb{Q}_{p,n}(1)$$

for any function  $f_n \in \mathcal{B}(E_n)$ . In this connection, we also mention that the semigroup of the pair of measures  $(\Gamma_n, \mathbb{Q}_n)$  defined in (1.1) for any  $0 \leq p \leq n$  and any  $F_n \in \mathcal{B}(E_{[0,n]})$ , we have

$$\Gamma_n(F_n) = \gamma_p D_{p,n}(F_n) \quad \text{and} \quad \mathbb{Q}_n(F_n) = \eta_p D_{p,n}(F_n) / \eta_p D_{p,n}(1) \quad (4.1)$$

These formulae are a direct consequence of the following observation

$$\eta_p D_{p,n}(F_n) = \int \mathbb{Q}_p(d(x_0, \dots, x_p)) \mathbb{Q}_{p,n}(x_p, d(x_{p+1}, \dots, x_n)) F_n(x_0, \dots, x_n)$$

**Lemma 4.1** For any  $0 \leq p < n$ , we have

$$\gamma_p(dx_p) \mathcal{Q}_{p,n}(x_p, d(x_{p+1}, \dots, x_n)) = \gamma_n(dx_n) \mathcal{M}_{n,p}(x_n, d(x_p, \dots, x_{n-1})) \quad (4.2)$$

with

$$\mathcal{M}_{n,p}(x_n, d(x_p, \dots, x_{n-1})) := \prod_{p \leq q < n} M_{q+1, \eta_q}(x_{q+1}, dx_q)$$

In particular, for any time  $n \geq 0$ , the Feynman-Kac path measures  $\mathbb{Q}_n$  defined in (1.1) can be expressed in terms of the sequence of marginal measures  $(\eta_p)_{0 \leq p \leq n}$ , with the following backward Markov chain formulation

$$\mathbb{Q}_n(d(x_0, \dots, x_n)) = \eta_n(dx_n) \mathcal{M}_{n,0}(x_n, d(x_0, \dots, x_{n-1})) : \quad (4.3)$$

Before entering into the details of the proof of this lemma, we mention that (4.3) holds true for any well defined Markov transition  $M_{n+1, \eta_n}(y, dx)$  from  $E_n$  into  $E_{n+1}$  satisfying the local backward equation

$$\Psi_{G_n}(\eta_n)(dx) M_{n+1}(x, dy) = \Phi_{n+1}(\eta_n)(dy) M_{n+1, \eta_n}(y, dx)$$

or equivalently

$$\eta_n(dx) Q_{n+1}(x, dy) = (\eta_n Q_{n+1})(dy) M_{n+1, \eta_n}(y, dx) \quad (4.4)$$

In other words, we have the duality formula

$$\Psi_{G_n}(\eta_n)(f M_{n+1}(g)) = \Phi_{n+1}(\eta_n)(g M_{n+1, \eta_n}(f)) \quad (4.5)$$

Also notice that for any pair of measures  $\mu, \nu$  on  $E_n$  s.t.  $\mu \ll \nu$ , we have  $\mu M_{n+1} \ll \nu M_{n+1}$ . Indeed, if we have  $\nu M_{n+1}(A) = 0$ , the function  $M_{n+1}(1_A)$  is null  $\nu$ -almost everywhere, and therefore  $\mu$ -almost everywhere from which we conclude that  $\mu M_{n+1}(A) = 0$ . For any bounded measurable function  $g$  on  $E_n$  we set

$$\Psi_{G_n}^g(\eta_n)(dx) = \Psi_{G_n}(\eta_n)(dx) g(x) \ll \Psi_{G_n}(\eta_n)(dx)$$

From the previous discussion, we have  $\Psi_{G_n}^g(\eta_n) M_{n+1} \ll \Psi_{G_n}(\eta_n) M_{n+1}$  and it is easily checked that

$$M_{n+1, \eta_n}(g)(y) = \frac{d\Psi_{G_n}^g(\eta_n) M_{n+1}}{d\Psi_{G_n}(\eta_n) M_{n+1}}(y)$$

is a well defined Markov transition from  $E_{n+1}$  into  $E_n$  satisfying the desired backward equation. These manipulations are rather classical in the literature on Markov chains (see for instance [15], and references therein). Under the regularity condition (H) the above transition is explicitly given by the formula (2.8).

Now, we come to the proof of lemma 4.1.

**Proof of lemma 4.1:**

We prove (4.2) using a backward induction on the parameter  $p$ . By (4.4), the formula is clearly true for  $p = (n - 1)$ . Suppose the result has been proved at rank  $p$ . Since we have

$$\begin{aligned} & \gamma_{p-1}(dx_{p-1}) \mathcal{Q}_{p-1,n}(x_{p-1}, d(x_p, \dots, x_n)) \\ &= \gamma_{p-1}(dx_{p-1}) Q_p(x_{p-1}, dx_p) \mathcal{Q}_{p,n}(x_p, d(x_{p+1}, \dots, x_n)) \end{aligned}$$

and

$$\gamma_{p-1}(dx_{p-1}) Q_p(x_{p-1}, dx_p) = \gamma_p(dx_p) M_{p, \eta_{p-1}}(x_p, dx_{p-1})$$

Using the backward induction we conclude that the desired formula is also met at rank  $(p - 1)$ . The second assertion is a direct consequence of (4.2). The end of the proof of the lemma is now completed.  $\blacksquare$

We end this section with some properties of backward Markov transitions associated with a given initial probability measure that may differ from the one associated with the Feynman-Kac measures. These mathematical objects appear in a natural way in the analysis of the  $N$ -particle approximation transitions  $\mathcal{M}_n^N$  introduced in (2.10).

**Definition 4.2** For any  $0 \leq p \leq n$  and any probability measure  $\eta \in \mathcal{P}(E_p)$ , we denote by  $\mathcal{M}_{n+1,p,\eta}$  the Markov transition from  $E_{n+1}$  into  $E_{[p,n]} = (E_p \times \dots \times E_n)$  defined by

$$\mathcal{M}_{n+1,p,\eta}(x_{n+1}, d(x_p, \dots, x_n)) = \prod_{p \leq q \leq n} M_{q+1, \Phi_{p,q}(\eta)}(x_{q+1}, dx_q)$$

Notice that this definition is consistent with the definition of the Markov transitions  $\mathcal{M}_{p,n}$  introduced in lemma 4.1:

$$\mathcal{M}_{n+1,p,\eta_p}(x_{n+1}, d(x_p, \dots, x_n)) = \mathcal{M}_{n+1,p}(x_{n+1}, d(x_p, \dots, x_n))$$

Also observe that  $\mathcal{M}_{n+1,p,\eta}$  can alternatively be defined by the pair of recursions

$$\begin{aligned} & \mathcal{M}_{n+1,p,\eta}(x_{n+1}, d(x_p, \dots, x_n)) \\ &= \mathcal{M}_{n+1,p+1, \Phi_{p+1}(\eta)}(x_{n+1}, d(x_{p+1}, \dots, x_n)) \times M_{p+1,\eta}(x_{p+1}, dx_p) \\ &= M_{n+1, \Phi_{p,n}(\eta)}(x_{n+1}, dx_n) \mathcal{M}_{n,p,\eta}(x_n, d(x_p, \dots, x_{n-1})) \end{aligned} \quad (4.6)$$

The proof of the following lemma follows the same lines of arguments as the ones used in the proof of lemma 4.1. For the convenience of the reader, the details of this proof are postponed to the appendix.

**Lemma 4.3** For any  $0 \leq p < n$  and any probability measure  $\eta \in \mathcal{P}(E_p)$ , we have

$$\eta Q_{p,n}(dx_n) \mathcal{M}_{n,p,\eta}(x_n, d(x_p, \dots, x_{n-1})) = \eta(dx_p) \mathcal{Q}_{p,n}(x_p, d(x_{p+1}, \dots, x_n))$$

In other words, we have

$$\begin{aligned} & \mathcal{M}_{n,p,\eta}(x_n, d(x_p, \dots, x_{n-1})) \\ &= \frac{(\eta \times \mathcal{Q}_{p,n-1})(d(x_p, \dots, x_{n-1})) G_{n-1}(x_{n-1}) H_n(x_{n-1}, x_n)}{(\eta Q_{p,n-1})(G_{n-1} H_n(\cdot, x_n))} \end{aligned} \quad (4.7)$$

with the measure  $(\eta \times \mathcal{Q}_{p,n-1})$  defined below

$$(\eta \times \mathcal{Q}_{p,n-1})(d(x_p, \dots, x_{n-1})) := \eta(dx_p) \mathcal{Q}_{p,n-1}(x_p, d(x_{p+1}, \dots, x_{n-1}))$$

## 5 Particle approximation models

We provide in this section some preliminary results on the convergence of the  $N$ -particle measures  $(\Gamma_n^N, \mathbb{Q}_n^N)$  to their limiting values  $(\Gamma_n, \mathbb{Q}_n)$ , as  $N \rightarrow \infty$ . Most of the forthcoming analysis is developed in terms of the following integral operators.

**Definition 5.1** For any  $0 \leq p \leq n$ , we let  $D_{p,n}^N$  be the  $\mathcal{F}_{p-1}^N$ -measurable integral operators from  $\mathcal{B}(E_{[0,n]})$  into  $\mathcal{B}(E_p)$  defined below

$$D_{p,n}^N(F_n)(x_p) := \int \mathcal{M}_p^N(x_p, d(x_0, \dots, x_{p-1})) \mathcal{Q}_{p,n}(x_p, d(x_{p+1}, \dots, x_n)) F_n(x_0, \dots, x_n)$$

with the conventions  $D_{0,n}^N = \mathcal{Q}_{0,n}$ , and resp.  $D_{p,n}^N = \mathcal{M}_n^N$ , for  $p = 0$ , and resp.  $p = n$

The main result of this section is the following theorem.

**Theorem 5.2** For any  $0 \leq p \leq n$ , and any function  $F_n$  on the path space  $E_{[0,n]}$ , we have

$$\mathbb{E}(\Gamma_n^N(F_n) \mid \mathcal{F}_p^N) = \gamma_p^N(D_{p,n}^N(F_n)) \quad \text{and} \quad W_n^{\Gamma,N}(F_n) = \sum_{p=0}^n \gamma_p^N(1) V_p^N(D_{p,n}^N(F_n))$$

**Proof of theorem 5.2:**

To prove the first assertion, we use a backward induction on the parameter  $p$ . For  $p = n$ , the result is immediate since we have

$$\Gamma_n^N(F_n) = \gamma_n^N(1) \eta_n^N(D_{n,n}^N(F_n))$$

We suppose that the formula is valid at a given rank  $p \leq n$ . In this situation, we have

$$\begin{aligned} \mathbb{E}(\Gamma_n^N(F_n) \mid \mathcal{F}_{p-1}^N) &= \gamma_p^N(1) \mathbb{E}(\eta_p^N(D_{p,n}^N(F_n)) \mid \mathcal{F}_{p-1}^N) \\ &= \gamma_{p-1}^N(1) \int \eta_{p-1}^N(G_{p-1}H_p(\cdot, x_p)) \lambda_p(dx_p) D_{p,n}^N(F_n)(x_p) \end{aligned} \quad (5.1)$$

Using the fact that

$$\gamma_{p-1}^N(1) \eta_{p-1}^N(G_{p-1}H_p(\cdot, x_p)) \lambda_p(dx_p) M_{p,\eta_{p-1}^N}(x_p, dx_{p-1}) = \gamma_{p-1}^N(dx_{p-1}) Q_p(x_{p-1}, dx_p)$$

we conclude that the r.h.s. term in (5.1) takes the form

$$\begin{aligned} &\int \gamma_{p-1}^N(dx_{p-1}) \mathcal{M}_{p-1}^N(x_{p-1}, d(x_0, \dots, x_{p-2})) \mathcal{Q}_{p-1,n}(x_{p-1}, d(x_p, \dots, x_n)) F_n(x_0, \dots, x_n) \\ &= \gamma_{p-1}^N(D_{p-1,n}^N(F_n)) \end{aligned}$$

This ends the proof of the first assertion. The proof of the second assertion is based on the following decomposition

$$\begin{aligned} (\Gamma_n^N - \Gamma_n)(F_n) &= \sum_{p=0}^n [\mathbb{E}(\Gamma_n^N(F_n) \mid \mathcal{F}_p^N) - \mathbb{E}(\Gamma_n^N(F_n) \mid \mathcal{F}_{p-1}^N)] \\ &= \sum_{p=0}^n \gamma_p^N(1) \left( \eta_p^N(D_{p,n}^N(F_n)) - \frac{1}{\eta_{p-1}^N(G_{p-1})} \eta_{p-1}^N(D_{p-1,n}^N(F_n)) \right) \end{aligned}$$

where  $\mathcal{F}_{-1}^N$  is the trivial sigma field. By definition of the random fields  $V_p^N$ , it remains to prove that

$$\eta_{p-1}^N(D_{p-1,n}^N(F_n)) = (\eta_{p-1}^N Q_p)(D_{p,n}^N(F_n))$$

To check this formula, we use the decomposition

$$\begin{aligned} &\eta_{p-1}^N(dx_{p-1}) \mathcal{M}_{p-1}^N(x_{p-1}, d(x_0, \dots, x_{p-2})) \mathcal{Q}_{p-1,n}(x_{p-1}, d(x_p, \dots, x_n)) \\ &= \eta_{p-1}^N(dx_{p-1}) Q_p(x_{p-1}, dx_p) \mathcal{M}_{p-1}^N(x_{p-1}, d(x_0, \dots, x_{p-2})) \mathcal{Q}_{p,n}(x_p, d(x_{p+1}, \dots, x_n)) \end{aligned} \quad (5.2)$$

Using the fact that

$$\eta_{p-1}^N(dx_{p-1}) Q_p(x_{p-1}, dx_p) = (\eta_{p-1}^N Q_p)(dx_p) M_{p,\eta_{p-1}^N}(x_p, dx_{p-1})$$

we conclude that the term in the r.h.s. of (5.2) is equal to

$$(\eta_{p-1}^N Q_p)(dx_p) \mathcal{M}_p^N(x_p, d(x_0, \dots, x_{p-1})) \mathcal{Q}_{p,n}(x_p, d(x_{p+1}, \dots, x_n))$$



This ends the proof of the theorem. ■

Several consequences of theorem 5.2 are now emphasized. On the one hand, using the fact that the random fields  $V_n^N$  are centered given  $\mathcal{F}_{n-1}^N$ , we find that

$$\mathbb{E}(\Gamma_n^N(F_n)) = \Gamma_n(F_n)$$

On the other hand, using the fact that

$$\frac{\gamma_p(1)}{\gamma_n(1)} = \frac{\gamma_p(1)}{\gamma_p Q_{p,n}(1)} = \frac{1}{\eta_p Q_{p,n}(1)}$$

we prove the following decomposition

$$\overline{W}_n^{\Gamma,N}(F_n) = \sqrt{N} (\overline{\gamma}_n^N(1) \mathbb{Q}_n^N - \mathbb{Q}_n)(F_n) = \sum_{p=0}^n \overline{\gamma}_p^N(1) V_p^N \left( \overline{D}_{p,n}^N(F_n) \right) \quad (5.3)$$

with the pair of parameters  $(\overline{\gamma}_n^N(1), \overline{D}_{p,n}^N)$  defined below

$$\overline{\gamma}_n^N(1) := \frac{\gamma_n^N(1)}{\gamma_n(1)} \quad \text{and} \quad \overline{D}_{p,n}^N(F_n) = \frac{D_{p,n}^N(F_n)}{\eta_p Q_{p,n}(1)} \quad (5.4)$$

Using again the fact that the random fields  $V_n^N$  are centered given  $\mathcal{F}_{n-1}^N$ , we have

$$\mathbb{E} \left( \overline{W}_n^{\Gamma,N}(F_n)^2 \right) = \sum_{p=0}^n \mathbb{E} \left( \overline{\gamma}_p^N(1)^2 \mathbb{E} \left[ V_p^N \left( \overline{D}_{p,n}^N(F_n) \right)^2 \mid \mathcal{F}_{p-1}^N \right] \right)$$

Using the estimates

$$\begin{aligned} \|D_{p,n}^N(F_n)\| &\leq \|Q_{p,n}(1)\| \|F_n\| \\ \|\overline{D}_{p,n}^N(F_n)\| &\leq \|\overline{Q}_{p,n}(1)\| \|F_n\| \quad \text{with} \quad \overline{Q}_{p,n}(1) = \frac{Q_{p,n}(1)}{\eta_p Q_{p,n}(1)} \end{aligned} \quad (5.5)$$

we prove the non asymptotic variance estimate

$$\mathbb{E} \left( \overline{W}_n^{\Gamma,N}(F_n)^2 \right) \leq \sum_{p=0}^n \mathbb{E} \left( \overline{\gamma}_p^N(1)^2 \|\overline{Q}_{p,n}(1)\|^2 \right) = \sum_{p=0}^n [1 + \mathbb{E}([\overline{\gamma}_p^N(1) - 1]^2)] \|\overline{Q}_{p,n}(1)\|^2$$

for any function  $F_n$  such that  $\|F_n\| \leq 1$ . On the other hand, using the decomposition

$$(\overline{\gamma}_n^N(1) \mathbb{Q}_n^N - \mathbb{Q}_n) = [\overline{\gamma}_n^N(1) - 1] \mathbb{Q}_n^N + (\mathbb{Q}_n^N - \mathbb{Q}_n)$$

we prove that

$$\mathbb{E} \left( [\mathbb{Q}_n^N(F_n) - \mathbb{Q}_n(F_n)]^2 \right)^{1/2} \leq \frac{1}{\sqrt{N}} \mathbb{E} (W_n^\Gamma(F_n)^2)^{1/2} + \mathbb{E} \left( [\overline{\gamma}_n^N(1) - 1]^2 \right)^{1/2}$$

Some interesting bias estimates can also be obtained using the fact that

$$\mathbb{E} (\mathbb{Q}_n^N(F_n) - \mathbb{Q}_n(F_n)) = \mathbb{E} ([1 - \overline{\gamma}_n^N(1)] [\mathbb{Q}_n^N(F_n) - \mathbb{Q}_n(F_n)])$$

and the following easily proved upper bound

$$|\mathbb{E} (\mathbb{Q}_n^N(F_n) - \mathbb{Q}_n(F_n))| \leq \mathbb{E} \left( [1 - \overline{\gamma}_n^N(1)]^2 \right)^{1/2} \mathbb{E} \left( [\mathbb{Q}_n^N(F_n) - \mathbb{Q}_n(F_n)]^2 \right)^{1/2}$$

Under the regularity condition  $(M)_m$  stated in (3.6), we proved in a recent article [2], that for any  $n \geq p \geq 0$ , and any  $N > (n+1)\rho\delta^m$  we have

$$\|\bar{Q}_{p,n}(1)\| \leq \delta^m \rho \quad \text{and} \quad N \mathbb{E} \left[ (\bar{\gamma}_n^N(1) - 1)^2 \right] \leq 4(n+1)\rho\delta^m$$

From these estimates, we readily prove the following corollary.

**Corollary 5.3** *Assume that condition  $(M)_m$  is satisfied for some parameters  $(m, \delta, \rho)$ . In this situation, for any  $n \geq p \geq 0$ , any  $F_n$  such that  $\|F_n\| \leq 1$ , and any  $N > (n+1)\rho\delta^m$  we have*

$$\mathbb{E} \left( \bar{W}_n^{\Gamma, N}(F_n) \right) = 0 \quad \text{and} \quad \mathbb{E} \left( \bar{W}_n^{\Gamma, N}(F_n)^2 \right) \leq (\delta^m \rho)^2 (n+1) \left( 1 + \frac{2}{N} \rho \delta^m (n+2) \right)$$

In addition, we have

$$N \mathbb{E} \left( \left[ \mathbb{Q}_n^N(F_n) - \mathbb{Q}_n(F_n) \right]^2 \right) \leq 2(n+1)\rho\delta^m \left( 4 + \rho\delta^m \left[ 1 + \frac{2}{N}(n+2) \right] \right)$$

and the bias estimate

$$N \left| \mathbb{E} \left( \mathbb{Q}_n^N(F_n) \right) - \mathbb{Q}_n(F_n) \right| \leq 2\sqrt{2} (n+1)\rho\delta^m \left( 4 + \rho\delta^m \left[ 1 + \frac{2}{N}(n+2) \right] \right)^{1/2}$$

## 6 Fluctuation properties

This section is mainly concerned with the proof of theorem 3.1. Unless otherwise is stated, in the further developments of this section, we assume that the regularity condition  $(H^+)$  presented in (3.3) is satisfied for some collection of functions  $(h_n^-, h_n^+)$ . Our first step to establish theorem 3.1 is the fluctuation analysis of the  $N$ -particle measures  $(\Gamma_n^N, \mathbb{Q}_n^N)$  given in proposition 6.2 whose proof relies on the following technical lemma.

**Lemma 6.1**

$$\begin{aligned} & \mathcal{M}_n^N(x_n, d(x_0, \dots, x_{n-1})) - \mathcal{M}_n(x_n, d(x_0, \dots, x_{n-1})) \\ &= \sum_{0 \leq p \leq n} \left[ \mathcal{M}_{n,p,\eta_p^N} - \mathcal{M}_{n,p,\Phi_p(\eta_{p-1}^N)} \right] (x_n, d(x_p, \dots, x_{n-1})) \mathcal{M}_p^N(x_p, d(x_0, \dots, x_{p-1})) \end{aligned}$$

The proof of this lemma follows elementary but rather tedious calculations; thus it is postponed to the appendix. We now state proposition 6.2.

**Proposition 6.2** *For any  $N \geq 1$ ,  $0 \leq p \leq n$ ,  $x_p \in E_p$ ,  $m \geq 1$ , and  $F_n \in \mathcal{B}(E_{[0,n]})$  such that  $\|F_n\| \leq 1$ , we have*

$$\sqrt{N} \mathbb{E} \left( \left| D_{p,n}^N(F_n) - D_{p,n}(F_n)(x_p) \right|^m \right)^{\frac{1}{m}} \leq a(m) b(n) \left( \frac{h_p^+}{h_p^-}(x_p) \right)^2 \quad (6.1)$$

for some finite constants  $a(m) < \infty$ , resp.  $b(n) < \infty$ , whose values only depend on the parameters  $m$ , resp. on the time horizon  $n$ .

**Proof:**

Using lemma 6.1, we find that

$$D_{p,n}^N(F_n) - D_{p,n}(F_n) = \sum_{0 \leq q \leq p} \left[ \mathcal{M}_{p,q,\eta_q^N} - \mathcal{M}_{p,q,\Phi_q(\eta_{q-1}^N)} \right] (T_{p,q,n}^N(F_n))$$

with the random function  $T_{p,q,n}^N(F_n)$  defined below

$$\begin{aligned} T_{p,q,n}^N(F_n)(x_q, \dots, x_p) \\ := \int \mathcal{Q}_{p,n}(x_p, d(x_{p+1}, \dots, x_n)) \mathcal{M}_q^N(x_q, d(x_0, \dots, x_{q-1})) F_n(x_0, \dots, x_n) \end{aligned}$$

Using formula (4.7), we prove that for any  $m \geq 1$  and any function  $F$  on  $E_{[q,p]}$

$$\sqrt{N} \mathbb{E} \left( \left| \left[ \mathcal{M}_{p,q,\eta_q^N} - \mathcal{M}_{p,q,\Phi_q(\eta_{q-1}^N)} \right] (F)(x_p) \right|^m \mid \mathcal{F}_{q-1}^N \right)^{\frac{1}{m}} \leq a(m) b(n) \|F\| \left( \frac{h_p^+}{h_p^-}(x_p) \right)^2$$

for some finite constants  $a(m) < \infty$  and  $b(n) < \infty$  whose values only depend on the parameters  $m$  and  $n$ . Using these almost sure estimates, we easily prove (6.1). This ends the proof of the proposition.  $\blacksquare$

Now, we come to the proof of theorem 3.1.

**Proof of theorem 3.1:**

Using theorem 5.2, we have the decomposition

$$W_n^{\Gamma,N}(F_n) = \sum_{p=0}^n \gamma_p^N(1) V_p^N(D_{p,n}(F_n)) + R_n^{\Gamma,N}(F_n)$$

with the second order remainder term

$$R_n^{\Gamma,N}(F_n) := \sum_{p=0}^n \gamma_p^N(1) V_p^N(F_{p,n}^N) \quad \text{and the function} \quad F_{p,n}^N := [D_{p,n}^N - D_{p,n}](F_n)$$

By Slutsky's lemma and by the continuous mapping theorem it clearly suffices to check that  $R_n^{\Gamma,N}(F_n)$  converge to 0, in probability, as  $N \rightarrow \infty$ . To prove this claim, we notice that

$$\mathbb{E} \left( V_p^N(F_{p,n}^N)^2 \mid \mathcal{F}_{p-1}^N \right) \leq \Phi_p(\eta_{p-1}^N) \left( (F_{p,n}^N)^2 \right)$$

On the other hand, we have

$$\begin{aligned} & \Phi_p(\eta_{p-1}^N) \left( (F_{p,n}^N)^2 \right) \\ &= \int \lambda_p(dx_p) \Psi_{G_{p-1}}(\eta_{p-1}^N)(H_p(\cdot, x_p)) F_{p,n}^N(x_p)^2 \\ &\leq \eta_p \left( (F_{p,n}^N)^2 \right) + \int \lambda_p(dx_p) \left| [\Psi_{G_{p-1}}(\eta_{p-1}^N) - \Psi_{G_{p-1}}(\eta_{p-1})](H_p(\cdot, x_p)) \right| F_{p,n}^N(x_p)^2 \end{aligned}$$

This yields the rather crude estimate

$$\begin{aligned} & \Phi_p(\eta_{p-1}^N) \left( (F_{p,n}^N)^2 \right) \\ &= \int \lambda_p(dx_p) \Psi_{G_{p-1}}(\eta_{p-1}^N)(H_p(\cdot, x_p)) F_{p,n}^N(x_p)^2 \\ &\leq \eta_p \left( (F_{p,n}^N)^2 \right) + 4\|Q_{p,n}(1)\|^2 \int \lambda_p(dx_p) \left| [\Psi_{G_{p-1}}(\eta_{p-1}^N) - \Psi_{G_{p-1}}(\eta_{p-1})](H_p(\cdot, x_p)) \right| \end{aligned}$$

from which we conclude that

$$\begin{aligned} & \mathbb{E} \left( V_p^N(F_{p,n}^N)^2 \right) \\ &\leq \int \eta_p(dx_p) \mathbb{E} \left[ (F_{p,n}^N(x_p))^2 \right] \\ &\quad + 4\|Q_{p,n}(1)\|^2 \int \lambda_p(dx_p) \mathbb{E} \left( \left| [\Psi_{G_{p-1}}(\eta_{p-1}^N) - \Psi_{G_{p-1}}(\eta_{p-1})](H_p(\cdot, x_p)) \right| \right) \end{aligned} \quad \text{INRIA}$$

We can establish that

$$\sqrt{N} \mathbb{E} (|[\Psi_{G_{p-1}}(\eta_{p-1}^N) - \Psi_{G_{p-1}}(\eta_{p-1})](H_p(\cdot, x_p))|) \leq b(n) h_p^+(x_p)$$

See for instance section 7.4.3, theorem 7.4.4 in [4]. Using proposition 6.2,

$$\sqrt{N} \mathbb{E} \left( V_p^N (F_{p,n}^N)^2 \right) \leq c(n) \left( \frac{1}{\sqrt{N}} \eta_p \left( \left( \frac{h_p^+}{h_p} \right)^4 \right) + \lambda_p(h_p^+) \right)$$

for some finite constant  $c(n) < \infty$ . The end of the proof of the first assertion now follows standard computations. To prove the second assertion, we use the following decomposition

$$\sqrt{N} [\mathbb{Q}_n^N - \mathbb{Q}_n](F_n) = \frac{1}{\bar{\gamma}_n^N(1)} \bar{W}_n^{\Gamma, N}(F_n - \mathbb{Q}_n(F_n))$$

with the random fields  $\bar{W}_n^{\Gamma, N}$  defined in (5.3). We complete the proof using the fact that  $\bar{\gamma}_n^N(1)$  tends to 1, almost surely, as  $N \rightarrow \infty$ . This ends the proof of the theorem.  $\blacksquare$

We end this section with some comments on the asymptotic variance associated to the Gaussian fields  $W_n^{\mathbb{Q}}$ . Using (4.1), we prove that

$$\mathbb{Q}_n = \Psi_{\bar{D}_{p,n}(1)}(\eta_p) P_{p,n}$$

with the pair of integral operators  $(\bar{D}_{p,n}, P_{p,n})$  from  $\mathcal{B}(E_{[0,n]})$  into  $\mathcal{B}(E_p)$

$$\bar{D}_{p,n}(F_n) := \frac{D_{p,n}(F_n)}{\eta_p Q_{p,n}(1)} = \frac{D_{p,n}(1)}{\eta_p Q_{p,n}(1)} P_{p,n}(F_n) \quad \text{and} \quad P_{p,n}(F_n) := \frac{D_{p,n}(F_n)}{D_{p,n}(1)}$$

from which we deduce the following formula

$$\begin{aligned} & \bar{D}_{p,n}(F_n - \mathbb{Q}_n(F_n))(x_p) \\ &= \bar{D}_{p,n}(1)(x_p) \int [P_{p,n}(F_n)(x_p) - P_{p,n}(F_n)(y_p)] \Psi_{\bar{D}_{p,n}(1)}(\eta_p)(dy_p) \end{aligned} \tag{6.2}$$

Under condition  $(M)_m$ , for any function  $F_n$  with oscillations  $\text{osc}(F_n) \leq 1$ , we prove the following estimate

$$\|\bar{D}_{p,n}(1)\| \leq \delta^m \rho \implies \mathbb{E} (W_n^{\mathbb{Q}}(F_n)^2) \leq (\delta^m \rho)^2 \sum_{p=0}^n \beta(P_{p,n})^2$$

## 7 Non asymptotic estimates

This section is mainly concerned with the proof of theorem 3.2. We follow the same semigroup techniques as the ones we used in section 7.4.3 in [4] to derive uniform estimates w.r.t. the time parameter for the  $N$ -particle measures  $\eta_n^N$ . We use the decomposition

$$[\mathbb{Q}_n^N - \mathbb{Q}_n](F_n) = \sum_{0 \leq p \leq n} \left( \frac{\eta_p^N D_{p,n}^N(F_n)}{\eta_p^N D_{p,n}^N(1)} - \frac{\eta_{p-1}^N D_{p-1,n}^N(F_n)}{\eta_{p-1}^N D_{p-1,n}^N(1)} \right)$$

with the conventions  $\eta_{-1}^N D_{-1,n}^N = \eta_0 \mathcal{Q}_{0,n}$ , for  $p = 0$ . Next, we observe that

$$\begin{aligned} & \eta_{p-1}^N D_{p-1,n}^N(F_n) \\ &= \int \eta_{p-1}^N(dx_{p-1}) \mathcal{M}_{p-1}^N(x_{p-1}, d(x_0, \dots, x_{p-2})) \mathcal{Q}_{p-1,n}(x_{p-1}, d(x_p, \dots, x_n)) F_n(x_0, \dots, x_n) \\ &= \int \eta_{p-1}^N(dx_{p-1}) \mathcal{Q}_p(x_{p-1}, dx_p) \end{aligned}$$

RR n° 7019

$$\times \mathcal{M}_{p-1}^N(x_{p-1}, d(x_0, \dots, x_{p-2})) \mathcal{Q}_{p,n}(x_p, d(x_{p+1}, \dots, x_n)) F_n(x_0, \dots, x_n)$$

On the other hand, we have

$$\eta_{p-1}^N(dx_{p-1})Q_p(x_{p-1}, dx_p) = \eta_{p-1}^N Q_p(dx_p) M_{p, \eta_{p-1}^N}(x_p, dx_{p-1})$$

from which we conclude that

$$\eta_{p-1}^N D_{p-1, n}^N(F_n) = (\eta_{p-1}^N Q_p)(D_{p, n}^N(F_n))$$

This yields the decomposition

$$[\mathbb{Q}_n^N - \mathbb{Q}_n](F_n) = \sum_{0 \leq p \leq n} \left( \frac{\eta_p^N D_{p, n}^N(F_n)}{\eta_p^N D_{p, n}^N(1)} - \frac{\Phi_p(\eta_{p-1}^N)(D_{p, n}^N(F_n))}{\Phi_p(\eta_{p-1}^N)(D_{p, n}^N(1))} \right) \quad (7.1)$$

with the convention  $\Phi_0(\eta_{-1}^N) = \eta_0$ , for  $p = 0$ . If we set

$$\tilde{F}_{p, n}^N = F_n - \frac{\Phi_p(\eta_{p-1}^N)(D_{p, n}^N(F_n))}{\Phi_p(\eta_{p-1}^N)(D_{p, n}^N(1))}$$

then every term in the r.h.s. of (7.1) takes the following form

$$\frac{\eta_p^N D_{p, n}^N(\tilde{F}_{p, n}^N)}{\eta_p^N D_{p, n}^N(1)} = \frac{\eta_p Q_{p, n}(1)}{\eta_p^N Q_{p, n}(1)} \times \left[ \eta_p^N \bar{D}_{p, n}^N(\tilde{F}_{p, n}^N) - \Phi_p(\eta_{p-1}^N) \bar{D}_{p, n}^N(\tilde{F}_{p, n}^N) \right]$$

with the integral operators  $\bar{D}_{p, n}^N$  defined in (5.4). Next, we observe that  $D_{p, n}^N(1) = Q_{p, n}(1)$ , and  $\bar{D}_{p, n}^N(1) = \bar{D}_{p, n}(1)$ . Thus, in terms of the local sampling random fields  $V_p^N$ , we have proved that

$$\frac{\eta_p^N D_{p, n}^N(\tilde{F}_{p, n}^N)}{\eta_p^N D_{p, n}^N(1)} = \frac{1}{\sqrt{N}} \times \frac{1}{\eta_p^N \bar{D}_{p, n}(1)} \times V_p^N \bar{D}_{p, n}^N(\tilde{F}_{p, n}^N) \quad (7.2)$$

and

$$\bar{D}_{p, n}^N(F_n) = \bar{D}_{p, n}(1) \times P_{p, n}^N(F_n) \quad \text{with} \quad P_{p, n}^N(F_n) := \frac{D_{p, n}^N(F_n)}{D_{p, n}^N(1)} \quad (7.3)$$

From these observations, we prove that

$$\frac{\Phi_p(\eta_{p-1}^N)(D_{p, n}^N(F_n))}{\Phi_p(\eta_{p-1}^N)(D_{p, n}^N(1))} = \frac{\Phi_p(\eta_{p-1}^N)(Q_{p, n}(1) P_{p, n}^N(F_n))}{\Phi_p(\eta_{p-1}^N)(Q_{p, n}(1))} = \Psi_{Q_{p, n}(1)}(\Phi_p(\eta_{p-1}^N)) P_{p, n}^N(F_n)$$

Arguing as in (6.2) we obtain the following decomposition

$$\begin{aligned} & \bar{D}_{p, n}^N(\tilde{F}_{p, n}^N)(x_p) \\ &= \bar{D}_{p, n}(1)(x_p) \times \int [P_{p, n}^N(F_n)(x_p) - P_{p, n}^N(F_n)(y_p)] \Psi_{Q_{p, n}(1)}(\Phi_p(\eta_{p-1}^N))(dy_p) \end{aligned}$$

and therefore

$$\left\| \bar{D}_{p, n}^N(\tilde{F}_{p, n}^N) \right\| \leq b_{p, n} \beta(P_{p, n}^N) \text{osc}(F_n) \quad \text{with} \quad b_{p, n} \leq \sup_{x_p, y_p} \frac{Q_{p, n}(1)(x_p)}{Q_{p, n}(1)(y_p)}$$

We end the proof of (3.4) using the fact that for any  $r \geq 1$ ,  $p \geq 0$ ,  $f \in \mathcal{B}(E_p)$  s.t.  $\text{osc}(f) \leq 1$  we have the almost sure Kintchine type inequality

$$\mathbb{E} \left( |V_p^N(f)|^r \mid \mathcal{F}_{p-1}^N \right)^{\frac{1}{r}} \leq a_r$$

for some finite (non random) constants  $a_r < \infty$  whose values only depend on  $r$ . Indeed, using the fact that each term in the sum of (7.1) takes the form (7.2) we prove that

$$\sqrt{N} \mathbb{E} \left( \left| [\mathbb{Q}_n^N - \mathbb{Q}_n](F_n) \right|^r \right)^{\frac{1}{r}} \leq a(r) \sum_{0 \leq p \leq n} b_{p,n}^2 \mathbb{E} (\text{osc}(P_{p,n}^N(F_n)))$$

This ends the proof of the first assertion (3.4) of theorem 3.2. For linear functionals of the form (2.5), it is easily checked that

$$D_{p,n}^N(F_n) = Q_{p,n}(1) \sum_{0 \leq q \leq p} \left[ M_{p,\eta_{p-1}^N} \cdots M_{q+1,\eta_q^N} \right] (f_q) + \sum_{p < q \leq n} Q_{p,q}(f_q) Q_{q,n}(1)$$

with the convention  $M_{p,\eta_{p-1}^N} \cdots M_{p+1,\eta_p^N} = Id$ , the identity operator, for  $q = p$ . Recalling that  $D_{p,n}^N(1) = Q_{p,n}(1)$ , we conclude that

$$P_{p,n}^N(F_n) = f_p + \sum_{0 \leq q < p} \left[ M_{p,\eta_{p-1}^N} \cdots M_{q+1,\eta_q^N} \right] (f_q) + \sum_{p < q \leq n} \frac{Q_{p,q}(Q_{q,n}(1) f_q)}{Q_{p,q}(Q_{q,n}(1))}$$

and therefore

$$P_{p,n}^N(F_n) = \sum_{0 \leq q < p} \left[ M_{p,\eta_{p-1}^N} \cdots M_{q+1,\eta_q^N} \right] (f_q) + \sum_{p \leq q \leq n} \frac{Q_{p,q}(Q_{q,n}(1) f_q)}{Q_{p,q}(Q_{q,n}(1))}$$

$$\frac{Q_{p,q}(Q_{q,n}(1) f_q)}{Q_{p,q}(Q_{q,n}(1))} = \frac{S_{p,q}(\overline{Q}_{q,n}(1) f_q)}{S_{p,q}(\overline{Q}_{q,n}(1))} \quad \text{with} \quad S_{p,q}(g) = \frac{Q_{p,q}(g)}{Q_{p,q}(1)}$$

with the potential functions  $\overline{Q}_{q,n}(1)$  defined in (5.5). After some elementary computations, we obtain the following estimates

$$\begin{aligned} & \text{osc}(P_{p,n}^N(F_n)) \\ & \leq \sum_{0 \leq q < p} \beta \left( M_{p,\eta_{p-1}^N} \cdots M_{q+1,\eta_q^N} \right) \text{osc}(f_q) + \sum_{p \leq q \leq n} b_{q,n}^2 \beta(S_{p,q}) \text{osc}(f_q) \end{aligned}$$

This ends the proof of the second assertion (3.5) of theorem 3.2.

## Appendix

### Proof of lemma 4.3

We prove the lemma by induction on the parameter  $n (> p)$ . For  $n = p + 1$ , we have

$$\mathcal{M}_{p+1,p,\eta}(x_{p+1}, dx_p) = M_{p+1,\eta}(x_{p+1}, dx_p) \quad \text{and} \quad \mathcal{Q}_{p,p+1}(x_p, dx_{p+1}) = Q_{p+1}(x_p, dx_{p+1})$$

By definition of the transitions  $M_{p+1,\eta}$ , we have

$$\eta \mathcal{Q}_{p+1}(dx_{p+1}) \mathcal{M}_{p+1,p,\eta}(x_{p+1}, dx_p) = \eta(dx_p) \mathcal{Q}_{p,p+1}(x_p, dx_{p+1})$$

We suppose that the result has been proved at rank  $n$ . In this situation, we notice that

$$\begin{aligned} & \eta(dx_p) \mathcal{Q}_{p,n+1}(x_p, d(x_{p+1}, \dots, x_{n+1})) \\ & = \eta(dx_p) \mathcal{Q}_{p,n}(x_p, d(x_{p+1}, \dots, x_n)) \mathcal{Q}_{n+1}(x_n, dx_{n+1}) \\ & = \eta \mathcal{Q}_{p,n}(dx_n) \mathcal{Q}_{n+1}(x_n, dx_{n+1}) \mathcal{M}_{n,p,\eta}(x_n, d(x_p, \dots, x_{n-1})) \end{aligned}$$

RR n° 7019

$$= \eta \mathcal{Q}_{p,n}(1) \Phi_{p,n}(\eta)(dx_n) \mathcal{Q}_{n+1}(x_n, dx_{n+1}) \mathcal{M}_{n,p,\eta}(x_n, d(x_p, \dots, x_{n-1}))$$

Using the fact that

$$\Phi_{p,n}(\eta)(dx_n) Q_{n+1}(x_n, dx_{n+1}) = \Phi_{p,n}(\eta)Q_{n+1}(dx_{n+1}) M_{n+1,\Phi_{p,n}(\eta)}(x_{n+1}, dx_n)$$

and

$$\eta Q_{p,n}(1) \Phi_{p,n}(\eta)Q_{n+1}(dx_{n+1}) = \eta Q_{p,n+1}(dx_{n+1})$$

we conclude that

$$\begin{aligned} & \eta(dx_p) Q_{p,n+1}(x_p, d(x_{p+1}, \dots, x_{n+1})) \\ &= \eta Q_{p,n+1}(dx_{n+1}) M_{n+1,\Phi_{p,n}(\eta)}(x_{n+1}, dx_n) \mathcal{M}_{n,p,\eta}(x_n, d(x_p, \dots, x_{n-1})) \\ &= \eta Q_{p,n+1}(dx_{n+1}) \mathcal{M}_{n+1,p,\eta}(x_{n+1}, d(x_p, \dots, x_n)) \end{aligned}$$

This ends the proof of the lemma. ■

## Proof of lemma 6.1:

Using the recursions (4.6), we prove that

$$\begin{aligned} & \mathcal{M}_{n+1,p,\eta_p^N}(x_{n+1}, d(x_p, \dots, x_n)) \\ &= \mathcal{M}_{n+1,p+1,\Phi_{p+1}(\eta_p^N)}(x_{n+1}, d(x_{p+1}, \dots, x_n)) \times M_{p+1,\eta_p^N}(x_{p+1}, dx_p) \end{aligned}$$

On the other hand, we also have

$$\mathcal{M}_{p+1}^N(x_{p+1}, d(x_0, \dots, x_p)) = M_{p+1,\eta_p^N}(x_{p+1}, dx_p) \mathcal{M}_p^N(x_p, d(x_0, \dots, x_{p-1}))$$

from which we conclude that

$$\begin{aligned} & \mathcal{M}_{n+1,p+1,\Phi_{p+1}(\eta_p^N)}(x_{n+1}, d(x_{p+1}, \dots, x_n)) \mathcal{M}_{p+1}^N(x_{p+1}, d(x_0, \dots, x_p)) \\ &= \mathcal{M}_{n+1,p,\eta_p^N}(x_{n+1}, d(x_p, \dots, x_n)) \mathcal{M}_p^N(x_p, d(x_0, \dots, x_{p-1})) \end{aligned}$$

The end of the proof is now a direct consequence of the following decomposition

$$\begin{aligned} & \mathcal{M}_n^N(x_n, d(x_0, \dots, x_{n-1})) - \mathcal{M}_n(x_n, d(x_0, \dots, x_{n-1})) \\ &= \sum_{1 \leq p \leq n} \left[ \mathcal{M}_{n,p,\eta_p^N}(x_n, d(x_p, \dots, x_{n-1})) \mathcal{M}_p^N(x_p, d(x_0, \dots, x_{p-1})) \right. \\ & \quad \left. - \mathcal{M}_{n,p-1,\eta_{p-1}^N}(x_n, d(x_{p-1}, \dots, x_{n-1})) \mathcal{M}_{p-1}^N(x_{p-1}, d(x_0, \dots, x_{p-2})) \right] \\ & \quad + \mathcal{M}_{n,0,\eta_0^N}(x_n, d(x_0, \dots, x_{n-1})) - \mathcal{M}_{n,0,\eta_0}(x_n, d(x_0, \dots, x_{n-1})) \end{aligned}$$

with the conventions

$$\mathcal{M}_{n,0,\eta_0^N}(x_n, d(x_0, \dots, x_{n-1})) \mathcal{M}_0^N(x_0, d(x_0, \dots, x_1)) = \mathcal{M}_{n,0,\eta_0^N}(x_n, d(x_0, \dots, x_{n-1}))$$

for  $p = 0$ , and for  $p = n$

$$\mathcal{M}_{n,n,\eta_n^N}(x_n, d(x_n, \dots, x_{n-1})) \mathcal{M}_n^N(x_n, d(x_0, \dots, x_{n-1})) = \mathcal{M}_n^N(x_n, d(x_0, \dots, x_{n-1}))$$

■

## References

- [1] E. Cancès, B. Jourdain and T. Lelièvre. Quantum Monte Carlo simulations of fermions. A mathematical analysis of the fixed-node approximation. *ESAIM: M2AN*, 16(9), pp 1403-1449 (2006).
- [2] F. Cerou, P. Del Moral, and A. Guyader. A non asymptotic variance theorem for unnormalized Feynman-Kac particle models, HAL-INRIA Research Report 6716 (2008).
- [3] P. Del Moral and L. Miclo. Branching and interacting particle systems approximations of Feynman-Kac formulae with applications to non-linear filtering. In *Séminaire de Probabilités, XXXIV*, volume 1729 of *Lecture Notes in Math.*, pages 1–145. Springer, Berlin (2000).
- [4] P. Del Moral. *Feynman-Kac formulae. Genealogical and interacting particle systems with applications*, Probability and its Applications, Springer Verlag, New York (2004).
- [5] P. Del Moral and L. Miclo. Particle approximations of Lyapunov exponents connected to Schroedinger operators and Feynman-Kac semigroups. *ESAIM: P&S*, 7, 171-208 (2003).
- [6] P. Del Moral, J. Jacod and P. Protter. The Monte-Carlo Method for filtering with discrete-time observations. *Proba. Theory Rel. Fields*, 120, 346–368 (2001).
- [7] P. Del Moral and E. Rio. Concentration inequalities for mean field particle models HAL-INRIA RR-6901 (2009).
- [8] G.B. Di Masi, M. Pratelli and W.G. Runggaldier. An approximation for the nonlinear filtering problem with error bounds. *Stochastics*, 14(4), 247-271 (1985).
- [9] A. Doucet, N. de Freitas and N. Gordon, editors. *Sequential Monte Carlo Methods in Practice*. Statistics for engineering and Information Science. Springer, New York (2001).
- [10] S.J. Godsill, A. Doucet and M. West. Monte Carlo smoothing for nonlinear time series. *J. Amer. Stat. Assoc.*, 99(465), 156-168 (2004).
- [11] M. Kac. On distributions of certain Wiener functionals. *Trans. American Math. Soc.*, 65(1), 1:13 (1949).
- [12] H. Korezlioglu and W.J. Runggaldier. Filtering for nonlinear systems driven by nonwhite noises : An approximating scheme. *Stochastics and Stochastics Rep.*, 44(1-2), 65-102 (1983).
- [13] M. El Makrini, B. Jourdain and T. Lelièvre, Diffusion Monte Carlo method: Numerical analysis in a simple case. *ESAIM: M2AN*, 41(2), 189-213 (2007).
- [14] J. Picard. Approximation of the non linear filtering problems and order of convergence. Filtering and control of random processes. *Lecture Notes in Control and Inf. Sc.*, vol.61, Springer (1984)
- [15] D. Revuz. *Markov chains*. North Holland (1975).
- [16] M. Rousset. On the control of an interacting particle approximation of Schroedinger ground states. *SIAM J. Math. Anal.*, 38 (3), 824-844 (2006).





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