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Invariant measure of duplicated diffusions and application to Richardson-Romberg extrapolation

Vincent Lemaire*, Gilles Pagès†, Fabien Panloup‡

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Abstract

With a view to numerical applications we address the following question: given an ergodic Brownian diffusion with an unique invariant measure, what are the invariant measures of the duplicated system consisting of two trajectories? We mainly focus on the interesting case where the two trajectories follow the same Brownian path. In this case, we first show that uniqueness is essentially always true in the one-dimensional case. Then, in the multidimensional case, we build some explicit counter-examples where the uniqueness property is not satisfied and then, give explicit conditions on the drift and diffusion coefficient functions (which can be interpreted as the negativity of a *non-infinitesimal Lyapunov exponent* associated with the dynamical system) to obtain uniqueness for invariant distribution of the duplicated system.

As a main application, we investigate the Richardson-Romberg extrapolation for the numerical approximation of the invariant measure of the initial ergodic Brownian diffusion.

Keywords: Invariant measure ; ergodic diffusion ; Lyapunov exponent ; Central Limit Theorem ; Euler scheme ; Richardson-Romberg extrapolation.

AMS classification (2000): 60G10, 60J60, 65C05, 60F05.

1 Introduction and motivations

When one discretizes a stochastic (or not) differential equation (SDE) by an Euler scheme with step h , a classical method to reduce the discretization error is the so-called Richardson-Romberg (*RR*) extrapolation introduced in [TT90] for diffusion processes. Roughly speaking, the idea of this method is to introduce a second Euler scheme with step $h/2$ and to choose an appropriate linear combination of the two schemes to cancel the first-order discretization error. Such an idea can be adapted to the long-time setting. More precisely, when one tries to approximate the invariant distribution of a diffusion by empirical measures based on an Euler scheme (with decreasing step) of the diffusion, it is also possible to implement the same strategy by introducing a second Euler scheme with half-step

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(see [Lem05]). In fact, tackling the rate of convergence of such a procedure involving a couple of Euler schemes of the same SDE leads to studying the long run behaviour of the underlying couple of continuous processes that we will call *duplicated diffusion*. When the two solutions only differ by the starting value and are driven by the same, say, Brownian motion, the resulting coupled process is (also known as *2-point motion* (terminology coming from the more general theory of stochastic flows, see [BS88, Car85, Kun90]). Before being more specific as concerns this motivation, let us now define precisely what we call a duplicated diffusion.

Consider the following Brownian diffusion solution to the stochastic differential equation

$$(SDE) \quad \equiv \quad dX_t = b(X_t)dt + \sigma(X_t)dW_t, \quad X_0 = x \in \mathbb{R}^d, \quad (1.1)$$

where $b : \mathbb{R}^d \rightarrow \mathbb{R}^d$ and $\sigma : \mathbb{R}^d \rightarrow \mathcal{M}(d, q, \mathbb{R})$ ($d \times q$ matrices with real valued entries) are locally Lipschitz continuous with linear growth and W is a standard q -dimensional Brownian motion defined on a filtered probability space $(\Omega, \mathcal{A}, \mathbb{P}, (\mathcal{F}_t)_{t \geq 0})$ (satisfying the usual conditions). This stochastic differential equation (SDE) has a unique strong solution denoted $X^x = (X_t^x)_{t \geq 0}$. Let $\rho \in \mathcal{M}(q, q, \mathbb{R})$ be a square matrix with transpose ρ^* such that $I_q - \rho\rho^*$ is non-negative as a symmetric matrix. We consider a filtered probability space, still denoted $(\Omega, \mathcal{A}, \mathbb{P}, (\mathcal{F}_t)_{t \geq 0})$ on which is defined a $2q$ -dimensional standard (\mathcal{F}_t) -Brownian motion denoted (W, \widetilde{W}) so that W and \widetilde{W} are two *independent* q -dimensional standard (\mathcal{F}_t) -Brownian motions. Then we define $W^{(\rho)}$ a third standard q -dimensional (\mathcal{F}_t) -Brownian motions by

$$W^{(\rho)} = \rho^*W + \sqrt{I_q - \rho^*\rho}\widetilde{W},$$

which clearly satisfies

$$\langle W^i, W^{(\rho),j} \rangle_t = \rho_{ij} t, \quad t \geq 0$$

(the square root should be understood in the set of symmetric non-negative matrices). The duplicated diffusion or “duplicated stochastic differential system” (*DSDS*) is then defined by

$$(DSDS) \quad \equiv \quad \begin{cases} dX_t = b(X_t)dt + \sigma(X_t)dW_t, & X_0 = x_1 \in \mathbb{R}^d, \\ dX_t^{(\rho)} = b(X_t^{(\rho)})dt + \sigma(X_t^{(\rho)})dW_t^{(\rho)}, & X_0^{(\rho)} = x_2 \in \mathbb{R}^d. \end{cases} \quad (1.2)$$

Under the previous assumptions on b and σ , (1.2) has a unique (strong) solution. Then both $(X_t^x)_{t \geq 0}$ and $(X_t^{x_1}, X_t^{(\rho),x_2})_{t \geq 0}$ are homogeneous Markov processes with transition (Feller) semi-groups, denoted $(P_t(x, dy))_{t \geq 0}$ and $(Q_t^{(\rho)}((x_1, x_2), (dy_1, dy_2)))_{t \geq 0}$ respectively, and defined on test Borel functions $f : \mathbb{R}^d \rightarrow \mathbb{R}$ and $g : \mathbb{R}^{2d} \rightarrow \mathbb{R}$, by

$$P_t(f)(x) = \mathbb{E}f(X_t^x) \quad \text{and} \quad Q_t^{(\rho)}(g)(x_1, x_2) = \mathbb{E}g(X_t^{x_1}, X_t^{(\rho),x_2}).$$

We will assume throughout the paper that the original diffusion X^x has an unique invariant distribution denoted ν *i.e.* satisfying $\nu P_t = \nu$ for every $t \in \mathbb{R}_+$. The first part of the paper is devoted to determining what measures are the invariant measures of $(Q_t^{(\rho)})_{t \geq 0}$ (if any) depending on the correlation matrix ρ . Thus, if $\rho = 0$, it is clear that $\nu \otimes \nu$ is invariant for $Q^{(0)}$ and if $\rho = I_q$ so is $\nu_\Delta = \nu \circ (x \mapsto (x, x))^{-1}$, but are they the only ones? To be more precise, we want to establish easily verifiable criterions on b and σ which ensure that ν_Δ is the *unique* invariant distribution of (*DSDS*). In the sequel,

we will denote by μ a generic invariant measure of $Q^{(\rho)}$. We present the problem in more details (including references to the literature at the end of this introduction).

▷ *Existence of an invariant distribution for $(Q_t^{(\rho)})_{t \geq 0}$.* First, the family of probability measures $(\mu_t^{(\rho)})_{t > 0}$ defined on $(\mathbb{R}^d \times \mathbb{R}^d, \mathcal{Bor}(\mathbb{R}^d)^{\otimes 2})$ by

$$\mu_t^{(\rho)} = \frac{1}{t} \int_0^t \nu^{\otimes 2}(dx_1, dx_2) Q_s^{(\rho)}((x_1, x_2), (dy_1, dy_2)) ds$$

is tight since both its marginals on \mathbb{R}^d are equal to ν . Furthermore, the semi-group $(Q_t^{(\rho)})_{t \geq 0}$ being Feller, one easily shows that any of its limiting distributions $\mu^{(\rho)}$ as $t \rightarrow \infty$ is an invariant distribution for $(Q_t^{(\rho)})_{t \geq 0}$ such that $\mu^{(\rho)}(dx \times \mathbb{R}^d) = \mu^{(\rho)}(\mathbb{R}^d \times dx) = \nu(dx)$. Also note that, if uniqueness fails and $(P_t)_{t \geq 0}$ has two distinct invariant distributions ν and ν' , a straightforward adaptation of the above (sketch of) proof shows that $(Q_t^{(\rho)})_{t \geq 0}$ has (at least) an invariant distribution with marginals (ν, ν') and another with (ν', ν) as marginals.

▷ *Uniqueness of the invariant distribution of $(Q_t^{(\rho)})_{t \geq 0}$.* It is clear that in full generality the couple $(X, X^{(\rho)})$ may admit several invariant distributions even if X has only one such distribution. So is the case of a fully degenerate setting ($\sigma \equiv 0$) if the flow $\Phi(x, t)$ of the *ODE* $\equiv \dot{x} = b(x)$ has 0 as a unique repulsive equilibrium and a unique invariant distribution ν on $\mathbb{R}^d \setminus \{0\}$. Then both distributions $\nu^{\otimes 2}$ and ν_Δ (defined as above) on $(\mathbb{R}^d \setminus \{0\})^2$ are invariant and if ν is not reduced to a Dirac mass (think *e.g.* to a 2-dimensional ODE with a limit cycle around 0) (*DSDS*) has at least two invariant distribution.

In the non-degenerate case ($\sigma \neq 0$) the situation is more involved and depends on the correlation structure ρ between the two Brownian motions W and $W^{(\rho)}$. The diffusion matrix $\Sigma(X_t^{x_1}, X_t^{(\rho), x_2})$ of the couple $(X^{x_1}, X^{(\rho), x_2})$ at time $t > 0$ is given by any continuous solution to the equation

$$\Sigma(\xi_1, \xi_2) \Sigma(\xi_1, \xi_2)^* = \begin{bmatrix} \sigma \sigma^*(\xi_1) & \sigma(\xi_1) \rho \sigma^*(\xi_2) \\ \sigma(\xi_2) \rho^* \sigma^*(\xi_1) & \sigma \sigma^*(\xi_2) \end{bmatrix}$$

(*e.g.* the square root in the symmetric non-negative matrices or the Choleski transform. . .).

First, note that if $I_q - \rho^* \rho$ is *positive definite* as a symmetric matrix, it is straightforward that ellipticity or uniform ellipticity of $\sigma \sigma^*$ (when $q \geq d$) for X^x is transferred to $\Sigma(X_t^{x_1}, X_t^{(\rho), x_2}) \Sigma(X_t^{x_1}, X_t^{(\rho), x_2})^*$ for the couple $(X^{x_1}, X^{(\rho), x_2})$. Now, uniform ellipticity, combined with standard regularity and growth/boundedness assumption on the coefficients b , σ and their partial derivatives, classically implies the existence for every $t > 0$ of a (strictly) positive probability density $p_t(x, y)$ for X_t^x . These additional conditions are automatically satisfied by the “duplicated coefficients” of (*DSDS*). At this stage, it is classical background that any homogeneous Markov process whose transition has a (strictly) positive density for every $t > 0$ has at most one invariant distribution (if any). Consequently, under these standard assumptions on b and σ which ensure uniqueness of the invariant distribution ν for X , we get uniqueness for the “duplicated” diffusion process $(X, X^{(\rho)})$ as well.

The *hypo-elliptic* case also implies the existence of a density for X_t^x and the uniqueness of the invariant distribution under *controllability assumptions* on a companion differential system of the SDE. This property can also be transferred to (*DSDS*), although the proof becomes significantly less straightforward than above (see Appendix B for a precise statement and a detailed proof).

The second setting of interest, $\rho = I_q$, corresponds to $W^{(\rho)} = W$ so that $X^{(\rho),x_2} = X^{x_2}$ i.e. $(DSDS)$ is the equation of the 2-point motion in the sense of [Kun90] section 4.2, [Har81]. This 2-point motion has been extensively investigated (see [Car85]) from an ergodic viewpoint, especially when the underlying diffusion, or more generally the stochastic flow $\Phi(\omega, x, t)$ lives on a (smooth) compact Riemannian manifold M . When this flow is smooth enough in x , the long run behaviour of such a flow (under its steady regime) can be classified owing to its Lyapunov spectrum. For what we are concerned with, this classification is based on the top Lyapunov exponent defined by

$$\lambda_S := \limsup_{t \rightarrow +\infty} \frac{1}{t} \log \|D_x \Phi(x, t)\|$$

where $\|D_x \Phi(x, t)\|$ denotes the operator norm of the differential (tangent) of the flow. In this compact setting and when the top Lyapunov exponent is positive, the long run behaviour of the two-point on $M^2 \setminus \Delta$ has been deeply investigated in [BS88] (see also [DKK04] for further results in this direction). Such assumption implies that Δ is somewhat repulsive.

Here, we are in fact concerned with the opposite case because, we need in some sense that the paths cluster asymptotically either in a pathwise or in a statistical sense. When $\lambda_S < 0$, such clustering result has been obtained in [Car85] (see Proposition 2.3.3) in a local form. It is shown that the ‘‘asymptotic clustering’’ holds with an arbitrarily high probability, provided the starting points are close enough. However, this result seems to be not sufficient to imply uniqueness of the invariant distribution for the two-point motion and is still in a compact setting.

We will use a somewhat similar approach in the section devoted to the multidimensional framework and obtain some sharp verifiable criterions on b and σ for uniqueness of the invariant distribution of the two-point motion. In fact, we will see that, under some conditions, these criterions can be read as the negativity, or even non-positivity, of a *non-infinitesimal Lyapunov exponent* (NILS) in the neighbourhood of the diagonal (see Section 3.4 for details).

Note that these criterions obtained in the case $\rho = I_q$ can be easily extended to the (last) case $\rho^* \rho = I_q$ using that $W^{(\rho)} = \rho W$ is still a standard B.M. (think to $\rho = -1$ when $d = 1$). For the sake of simplicity (and since it is of little interest for the practical implementation of the Richardson-Romberg extrapolation), we will not consider this case in the paper.

The second part of the paper is devoted to a first attempt in a long run ergodic setting to combine the Richardson-Romberg extrapolation with a control of the variance of this procedure (see [Pag07] in a finite horizon framework). To this end we consider two Euler schemes with decreasing steps γ_n and $\tilde{\gamma}_n$ satisfying $\tilde{\gamma}_{2n-1} = \tilde{\gamma}_{2n} = \gamma_n/2$ and ρ -correlated Brownian motion increments. We show that the optimal efficiency of the Romberg extrapolation in this framework is obtained when $\rho = 0$, at least when the above uniqueness problem for ν_Δ is satisfied. To support this claim we establish a Central Limit Theorem whose variance is analyzed as a function of ρ .

The paper is organized as follows: in Section 2, we establish a one-dimensional result which grants the uniqueness of ν_Δ as an invariant distribution for $(DSDS)$. We also prove that the paths of the $(DSDS)$ are asymptotically confluent (slightly extending by a different method a result by Has’minskii in [Has80]). Section 3, is devoted to the multidimensional framework. We first provide a simple counter-example to uniqueness and

then provide rather general but operating criterions, all based on the behavior of the one-dimensional Itô process $|X_t^{x_1} - X_t^{x_2}|$ and closely related in spirit to the Feller classification for one-dimensional diffusions. They can be seen as asymptotic weak confluence criterions. Section 4 is devoted to Richardson-Romberg extrapolation for the recursive computation of the invariant measure of a diffusion by weighted occupation measures of an Euler scheme with decreasing step: we show how to improve the (weak) rate of convergence of the procedure by implementing a Richardson-Romberg (*RR*) extrapolation involving two Euler schemes with different steps provided ν_Δ is the unique invariant distribution of the two-point motion.

NOTATIONS. • $|x| = \sqrt{xx^*}$ denotes the canonical Euclidean norm of $x \in \mathbb{R}^d$ (x^* transpose of the column vector x).

• $\|A\| = \sqrt{\text{Tr}(AA^*)}$ if $A \in \mathcal{M}(d, q, \mathbb{R})$ and A^* is the transpose of A (which is but the canonical Euclidean norm on \mathbb{R}^{d^2}).

• $\Delta_{\mathbb{R}^{2d}} = \{(x, x), x \in \mathbb{R}^d\}$ denotes the diagonal of \mathbb{R}^{2d} .

• $\mathcal{S}(d, \mathbb{R}) = \{S \in \mathcal{M}(d, d, \mathbb{R}), S^* = S\}$, $\mathcal{S}^+(d, \mathbb{R})$ the subset of $\mathcal{S}(d, \mathbb{R})$ of non-negative matrices, $\mathcal{S}^{++}(d, \mathbb{R})$ denotes the subset of positive definite such matrices and \sqrt{S} denotes the unique square root of $S \in \mathcal{S}^+(d, \mathbb{R})$ in $\mathcal{S}^{++}(d, \mathbb{R})$ (which commutes with S). $x \otimes y = xy^* = [x_i y_j] \in \mathcal{M}(d, d, \mathbb{R})$, $x, y \in \mathbb{R}^d$.

• If $S \in \mathcal{S}^{++}(d, \mathbb{R})$, we denote by $(\cdot | \cdot)_S$ and by $|\cdot|_S$, the induced inner product and norm on \mathbb{R}^d , defined by $(x|y)_S = (x|Sy)$ and $|x|_S^2 = (x|x)_S$ respectively. Finally, for $A \in \mathcal{M}(d, d, \mathbb{R})$, we set $\|A\|_S^2 = \text{Tr}(A^*SA)$.

• $\mu_n \xrightarrow{(\mathbb{R}^d)} \mu$ denotes the weak convergence of the sequence $(\mu_n)_{n \geq 1}$ of probability measures defined on $(\mathbb{R}^d, \mathcal{B}or(\mathbb{R}^d))$ toward the probability measure μ .

• For every function $f : \mathbb{R}^d \rightarrow \mathbb{R}$, define the Lipschitz coefficient of f by $[f]_{\text{Lip}} = \sup_{x \neq y} \frac{|f(x) - f(y)|}{|x - y|} \leq +\infty$.

2 The one-dimensional case

We first show that, in the one-dimensional case $d = q = 1$, uniqueness of ν implies that ν_Δ , as defined in the introduction, is the unique invariant distribution of the duplicated diffusion. The main theorem of this section is Theorem 2.1 which consists of two claims. The first one establishes this uniqueness claim using some ergodic-type arguments. Note that we do not require that σ never vanishes. The second claim is an asymptotic pathwise confluence property for the diffusion in its own scale, established under some slightly more stringent assumptions involving the scale function p , see below. This second result, under slightly less general assumptions, is originally due to Has'minskii (see [Has80], Appendix to the English edition, Theorem 2.2, p.308). It is revisited here by different techniques, mainly comparison results for one dimensional diffusions and ergodic arguments. Note that uniqueness of ν_Δ can always be retrieved from asymptotic confluence (see Remark 2.1).

Before stating the result, let us recall some definitions. We denote by M the *speed measure* of the diffusion classically defined by $M(d\xi) = \frac{d\xi}{(\sigma^2 p')(\xi)}$, where p is the *scale function* defined (up to a constant) by

$$p(x) = \int_{x_0}^x d\xi e^{-\int_{x_0}^\xi \frac{2b}{\sigma^2}(u)du}, \quad x \in \mathbb{R}.$$

Obviously, we will consider p only when it makes sense as a finite function (so is the case if b/σ^2 is locally integrable on the real line). We are now in position to state the result.

THEOREM 2.1. *Assume that b and σ are continuous functions on \mathbb{R} being such that strong existence, pathwise uniqueness and the Feller Markov property hold for (SDE) from any $x \in \mathbb{R}$. Assume furthermore that there exists $\lambda : \mathbb{R}_+ \rightarrow \mathbb{R}_+$, strictly increasing, with $\lambda(0) = 0$ and $\int_{0+} \lambda(u)^{-2} du = +\infty$ such that for all $x, y \in \mathbb{R}$, $|\sigma(y) - \sigma(x)| \leq \lambda(|x - y|)$. Then, the following claims hold true.*

(a) *If $(X_t)_{t \geq 0}$ admits a unique invariant distribution ν , the distribution $\nu_\Delta = \nu \circ (\xi \mapsto (\xi, \xi))^{-1}$ is the unique invariant measure of the duplicated diffusion $(X_t^{x_1}, X_t^{x_2})_{t \geq 0}$.*

(b) *(Has'minskii) Assume that the scale function p is well-defined as a real function on the real line and that,*

$$\lim_{x \rightarrow \pm\infty} p(x) = \pm\infty \quad \text{and} \quad M \text{ is finite.}$$

Then, $\nu = M/M(\mathbb{R})$ is the unique invariant distribution of $(X_t)_{t \geq 0}$ and $(p(X_t))_{t \geq 0}$ is pathwise confluent: \mathbb{P} -a.s., for every $x_1, x_2 \in \mathbb{R}$, $p(X_t^{x_1}) - p(X_t^{x_2})$ tends to 0 when $t \rightarrow +\infty$.

REMARK 2.1. \triangleright The general assumptions on b and σ are obviously fulfilled whenever these functions are locally Lipschitz with linear growth.

\triangleright The proofs of both claims are based on (typically one-dimensional) comparison arguments. This also explains the assumption on σ which is a classical sufficient assumption to ensure comparison of solutions, namely, if $x_1 \leq x_2$, then $X_t^{x_1} \leq X_t^{x_2}$ for every $t \geq 0$ a.s. (see [IW77]).

\triangleright The additional assumptions made in (b) imply the uniqueness of ν (see the proof below). The uniqueness of the invariant distribution ν_Δ for the duplicated diffusion follows by (a). However, it can also be viewed as a direct consequence of the asymptotic pathwise confluence of $p(X_t^{x_i})$, $i = 1, 2$ as $t \rightarrow +\infty$. Actually, if for all $x_1, x_2 \in \mathbb{R}^d$, $p(X_t^{x_1}) - p(X_t^{x_2}) \xrightarrow{t \rightarrow +\infty} 0$ a.s, we deduce that for any invariant distribution μ of (X^{x_1}, X^{x_2}) and every $K > 0$

$$\int_{\mathbb{R}} \left(|p(x_1) - p(x_2)| \wedge K \right) \mu(dx_1, dx_2) \leq \limsup_{t \rightarrow +\infty} \frac{1}{t} \int_0^t \mathbb{E}_\mu \left(|p(X_s^{x_1}) - p(X_s^{x_2})| \wedge K \right) ds = 0.$$

As a consequence, $p(x_1) = p(x_2)$ $\mu(dx_1, dx_2)$ -a.s. Since p is an increasing function, it follows that $\mu(\{(x, x), x \in \mathbb{R}\}) = 1$ and thus that $\mu = \nu_\Delta$.

\triangleright As mentioned before, (b) slightly extends a result by Has'minskii obtained in [Has80] with different methods and under the additional assumption that σ never vanishes (whereas we only need the scale function p to be finite which allows e.g. for the existence of integrable singularities of $\frac{b}{\sigma^2}$). Note however that the case of an infinite speed measure M (which corresponds to null recurrent diffusions) is also investigated in [Has80], requiring extra non-periodicity assumptions on σ .

Proof. (a) Throughout the proof we denote by $(X_t^{x_1}, X_t^{x_2})$ the duplicated diffusion at time $t \geq 0$ and by $(Q_t((x_1, x_2), dy_1, dy_2))_{t \geq 0}$ its Feller Markov semi-group. The set \mathcal{I}_{DSDS} of invariant distributions of $(Q_t)_{t \geq 0}$ is clearly nonempty, convex and weakly closed. Since any such distribution μ has ν as marginals (in the sense $\mu(dx_1 \times \mathbb{R}) = \mu(\mathbb{R} \times dx_2) = \nu$), the set \mathcal{I}_{DSDS} is tight and consequently weakly compact in the the topological vector space of signed measures on $(\mathbb{R}^2, \mathcal{B}or(\mathbb{R}^2))$ equipped with the weak topology. As a consequence

of the Krein-Millman Theorem, \mathcal{I}_{DSDS} admits extremal distributions and is the convex hull of these extremal distributions.

Let μ be such an extremal distribution and consider the following three subsets of \mathbb{R}^2 :

$$A^+ = \{(x_1, x_2), x_2 > x_1\}, A^- = \{(x_1, x_2), x_1 > x_2\} \text{ and } A_0 = \{(x, x), x \in \mathbb{R}\} = \Delta_{\mathbb{R}^2}.$$

We first want to show that if $\mu(A^+) > 0$ then the conditional distribution μ^{A^+} defined by $\mu^{A^+} = \frac{\mu(\cdot \cap A^+)}{\mu(A^+)}$ is also an invariant distribution for $(Q_t)_{t \geq 0}$. Under the above assumptions on b and σ , one derives from classical comparison theorems and strong pathwise uniqueness arguments for the solutions of (SDE) (see e.g. [IW77]) that

$$\forall (x_1, x_2) \in {}^cA^+ = \mathbb{R}^2 \setminus A^+, \quad Q_t((x_1, x_2), {}^cA^+) = 1.$$

We deduce that for every $(x_1, x_2) \in \mathbb{R}^2$ and $t \geq 0$,

$$Q_t((x_1, x_2), A^+) = \mathbb{P}((X_t^{x_1}, X_t^{x_2}) \in A^+) = \mathbf{1}_{A^+}(x_1, x_2) \mathbb{P}(\tau_{x_1, x_2} > t)$$

where $\tau_{x_1, x_2} = \inf\{t \geq 0, X_t^{x_2} \leq X_t^{x_1}\}$. The second equality follows from the pathwise uniqueness since no bifurcation can occur. Now, let $\mu \in \mathcal{I}_{DSDS}$. Integrating the above equality and letting t go to infinity implies

$$\mu(A^+) = \int_{A^+} \mu(dx_1, dx_2) \mathbb{P}(\tau_{x_1, x_2} = +\infty).$$

If $\mu(A^+) > 0$, then $\mu(dx_1, dx_2)$ -a.s. $\mathbb{P}(\tau_{x_1, x_2} = +\infty) = 1$ on A^+ i.e. $X_t^{x_2} > X_t^{x_1}$ for every $t \geq 0$ a.s.. As a consequence, $\mu(dx_1, dx_2)$ -a.s., for every $B \in \mathcal{B}(\mathbb{R}^{2d})$,

$$\mathbf{1}_{(x_1, x_2) \in A^+} Q_t((x_1, x_2), B) = \mathbf{1}_{(x_1, x_2) \in A^+} Q_t((x_1, x_2), B \cap A^+) = Q_t((x_1, x_2), B \cap A^+)$$

where we used again that $Q_t((x_1, x_2), A^+) = 0$ if $x_2 \leq x_1$. Then, since μ is invariant, we deduce from an integration of the above equality that

$$\mu(B \cap A^+) = \int_{\mathbb{R}^2} Q_t((x_1, x_2), B) \mathbf{1}_{(x_1, x_2) \in A^+} \mu(dx_1, dx_2).$$

It follows that if $\mu(A^+) > 0$, μ^{A^+} is invariant.

If $\mu(A^+) < 1$, one shows likewise that $\mu^{^cA^+}$ an invariant distribution for $(Q_t)_{t \geq 0}$ as well. Then, if $\mu(A^+) \in (0, 1)$, then μ is a convex combination of elements of \mathcal{I}_{DSDS}

$$\mu = \mu(A^+) \mu^{A^+} + \mu({}^cA^+) \mu^{^cA^+}$$

so that μ cannot be extremal. Finally $\mu(A^+) = 0$ or 1.

Assume $\mu(A^+) = 1$ so that $\mu = \mu(\cdot \cap A^+)$. This implies that $X_0^1 > X_0^2$ \mathbb{P}_μ -a.s.. But μ being invariant, both its marginals are ν i.e. X_0^1 and X_0^2 are ν -distributed. This yields a contradiction. Indeed, let φ be a bounded increasing positive function. For instance, set $\varphi(u) := 1 + \frac{u}{\sqrt{u^2+1}}$, $u \in \mathbb{R}$. Then, $\mathbb{E}[\varphi(X_0^1) - \varphi(X_0^2)] > 0$ since $X_0^1 > X_0^2$ \mathbb{P}_μ -a.s. but we also have $\mathbb{E}[\varphi(X_0^1) - \varphi(X_0^2)] = 0$ since X_0^1 and X_0^2 have the same distribution. This contradiction implies that $\mu(A^+) = 0$.

One shows likewise that $\mu(A^-) = 0$ if μ is an extremal measure. Finally any extremal distribution of \mathcal{I}_{DSDS} is supported by $A_0 = \Delta_{\mathbb{R}^2}$. Given the fact that the marginals

of μ are ν this implies that $\mu = \nu_\Delta = \nu \circ (x \mapsto (x, x))^{-1}$ which in turn implies that $\mathcal{I}_{DSDS} = \{\nu_\Delta\}$.

(b) Since the speed measure M is finite and σ never vanishes, the distribution $\nu(d\xi) = M(d\xi)/M(\mathbb{R})$ is the unique invariant measure of the diffusion. Thus, by (a), we also have the uniqueness of the invariant distribution for the duplicated diffusion. Let $x_1, x_2 \in \mathbb{R}$. If $x_1 > x_2$ then $X_t^{x_1} \geq X_t^{x_2}$, still by a comparison argument, and $p(X_t^{x_1}) \geq p(X_t^{x_2})$ since p is increasing. Consequently $M_t^{x_1, x_2} = p(X_t^{x_1}) - p(X_t^{x_2})$, $t \geq 0$, is a non-negative continuous local martingale, hence \mathbb{P} -a.s. converging toward a finite random limit $\ell_\infty^{x_1, x_2} \geq 0$. One proceeds likewise when $x_1 < x_2$ (with $\ell_\infty^{x_1, x_2} \leq 0$). When $x_1 = x_2$, $M_t = \ell_\infty^{x_1, x_2} \equiv 0$. The aim is now to show that $\ell_\infty^{x_1, x_2} = 0$ a.s. To this end, we introduce

$$\mu_t(dy_1, dy_2) := \frac{1}{t} \int_0^t Q_s((x_1, x_2), dy_1, dy_2) ds, \quad (x_1, x_2) \in \mathbb{R}^{2d}$$

and we want to check that for every $(x_1, x_2) \in \mathbb{R}^{2d}$, $(\mu_t(dy_1, dy_2))_{t \geq 1}$ converges weakly to ν_Δ . Owing to the uniqueness of ν_Δ established in (a) and to the fact that any weak limiting distribution of $(\mu_t(dy_1, dy_2))_{t \geq 1}$ is always invariant (by construction), it is enough to prove that $(\mu_t(dy_1, dy_2))_{t \geq 1}$ is tight. Since the tightness of a sequence of probability measures defined on a product space is clearly equivalent to that of its first and second marginals, it is here enough to prove the tightness of $(t^{-1} \int_0^t P_s(x_0, dy) ds)_{t \geq 1}$ for any $x_0 \in \mathbb{R}$.

Let $x_0 \in \mathbb{R}$. Owing to the comparison theorems, we have for all $t \geq 0$ and $M \in \mathbb{R}$, $P_t(x_0, [M, +\infty)) \leq P_t(x, [M, +\infty))$ if $x \geq x_0$ and $P_t(x_0, (-\infty, M]) \leq P_t(x, (-\infty, M])$ if $x_0 \geq x$. Since ν is invariant and equivalent to the Lebesgue measure, we deduce that

$$P_t(x_0, [M, +\infty)) \leq \frac{\nu([M, +\infty))}{\nu([x_0, +\infty))} \quad \text{and} \quad P_t(x_0, (-\infty, M]) \leq \frac{\nu((-\infty, M])}{\nu((-\infty, x_0])}.$$

The tightness of $(P_t(x_0, dy))_{t \geq 1}$ follows (from that of ν) and we derive from what precedes that

$$\forall (x_1, x_2) \in \mathbb{R}^{2d}, \quad \frac{1}{t} \int_0^t Q_s((x_1, x_2), dy_1, dy_2) ds \xrightarrow{(\mathbb{R}^d)} \nu_\Delta(dy_1, dy_2).$$

Now, note that for every $L \in \mathbb{N}$, the function $g_L : (y_1, y_2) \mapsto |p(y_1) - p(y_2)| \wedge L$ is continuous and bounded. Hence by Césaro's Theorem, we have that

$$\frac{1}{t} \int_0^t Q_s(g_L)(x_1, x_2) ds = \frac{1}{t} \int_0^t \mathbb{E} g_L(X_s^{x_1}, X_s^{x_2}) ds \longrightarrow \mathbb{E} (|\ell_\infty^{x_1, x_2}| \wedge L)$$

whereas, by the above weak convergence of $(\mu_t(dy_1, dy_2))_{t \geq 1}$, we get

$$\frac{1}{t} \int_0^t Q_s(g_L)(x_1, x_2) ds \longrightarrow \int_{\mathbb{R}^d} g_L(y_1, y_2) \nu_\Delta(dy_1, dy_2) = 0 \quad \text{as} \quad t \rightarrow +\infty$$

since g_L is identically 0 on $\Delta_{\mathbb{R}^{2d}}$. It follows, by letting L go to infinity, that

$$\mathbb{E} |\ell_\infty^{x_1, x_2}| = 0.$$

This implies $\ell_\infty^{x_1, x_2} = 0$ \mathbb{P} -a.s. which in turn implies that

$$\mathbb{P}\text{-a.s.} \quad p(X_t^{x_1}) - p(X_t^{x_2}) \longrightarrow 0 \quad \text{as} \quad t \rightarrow +\infty.$$

Finally, it remains to prove that we can exchange the quantifiers, i.e. that \mathbb{P} -a.s., $p(X_t^{x_1}) - p(X_t^{x_2}) \longrightarrow 0$ for every x_1, x_2 . Assume that $x_1 \geq x_2$. Again by the comparison theorem

and the fact that p increases, we have $0 \leq p(X_t^{x_1}) - p(X_t^{x_2}) \leq p(X_t^{\lfloor x_1 \rfloor + 1}) - p(X_t^{\lfloor x_2 \rfloor})$. This means that we can come down to a countable set of starting points. \square

In the continuity of the second part of Theorem 2.1(b), it is natural to wonder whether a one-dimensional diffusion is asymptotically confluent, *i.e.* when for all $x_1, x_2 \in \mathbb{R}$, $X_t^{x_1} - X_t^{x_2}$ tends to 0 *a.s.* as $t \rightarrow +\infty$. In the following corollary, we show that such property holds in a quite general setting.

COROLLARY 2.1. (a) *Assume the hypothesis of Theorem 2.1(b) hold. If furthermore,*

$$\sigma \text{ never vanishes} \quad \text{and} \quad \limsup_{|x| \rightarrow +\infty} \int_0^x \frac{b}{\sigma^2}(\xi) d\xi < +\infty$$

then, \mathbb{P} -a.s., for every $x_1, x_2 \in \mathbb{R}$,

$$X_t^{x_1} - X_t^{x_2} \longrightarrow 0 \quad \text{as} \quad t \rightarrow +\infty.$$

(b) *The above condition is in particular satisfied if there exists $M > 0$ such that for all*

$$|x| > M \implies \text{sign}(x)b(x) \leq 0.$$

Proof. (a) Under the assumptions of the theorem, p is continuously differentiable on \mathbb{R} and

$$p'(x) = e^{-\int_{x_0}^x \frac{2b}{\sigma^2}(u) du}, \quad x \in \mathbb{R}.$$

Then it is clear that $p'_{\inf} = \inf_{x \in \mathbb{R}} p'(x) > 0$ iff $\limsup_{|x| \rightarrow +\infty} \int_{x_0}^x \frac{2b}{\sigma^2}(\xi) d\xi < +\infty$. By the fundamental theorem of calculus, we know that,

$$|X_t^{x_1} - X_t^{x_2}| \leq \frac{1}{p'_{\min}} |p(X_t^{x_1}) - p(X_t^{x_2})|$$

and the result follows from Theorem 2.1(b).

(b) Since σ never vanishes, p'' is well-defined and for every $x \in \mathbb{R}$, $p''(x) = -\frac{2b(x)p'(x)}{\sigma^2(x)}$. Using that p' is positive, we deduce from the assumptions that

$$\exists M > 0 \quad \text{such that} \quad \begin{cases} p''(x) \geq 0, & x \geq M \\ p''(x) \leq 0, & x \leq -M. \end{cases}$$

Now, p' being continuous, it follows that p' attains a positive minimum $p'_{\min} > 0$. \square

Examples. 1. Let U be a positive a twice differentiable function such that $\lim_{|x| \rightarrow +\infty} U(x) = +\infty$ and consider the one-dimensional Kolmogorov equation

$$dX_t = -U'(X_t)dt + \sigma dW_t$$

where $\sigma > 0$. Then,

$$\liminf_{|x| \rightarrow +\infty} xU'(x) > \frac{\sigma^2}{2} \implies X_t^x - X_t^y \xrightarrow{t \rightarrow +\infty} 0 \text{ a.s.}$$

Note that in particular, this result holds true even if U has several local minimas.

2. Let $\sigma = \mathbb{R} \rightarrow (0, +\infty)$ be a locally Lipschitz continuous function with linear growth so that the SDE

$$dX_t = \sigma(X_t)dW_t$$

defines a (Markov) flow $(X_t^x)_{t \geq 0}$ of local martingales. If $\frac{1}{\sigma} \in L^2(\mathbb{R}, \mathcal{Bor}(\mathbb{R}), \lambda)$ then there exists a unique invariant measure $\nu(d\xi) = c_\sigma \frac{d\xi}{\sigma^2(\xi)}$ and $(X_t^{x_i})_{t \geq 0}$, $i = 1, 2$ is pathwise confluent (in the sense of Theorem 2.1(b)) since $p(x) = x$.

Note that the linear growth assumption cannot be significantly relaxed since a stationary process cannot be a true martingale which implies that ν has no (finite) first moment.

3 The multidimensional case

In this section, we begin by an example of a multidimensional Brownian diffusion (X^{x_1}, X^{x_2}) for which ν_Δ (image of ν on the diagonal) is not the only one invariant distribution. Thus, Theorem 2.1 is specific to the case $d = 1$ and we can not hope to get a similar result for the general case $d \geq 2$. It is of course closely related to the classification of two-point motion on smooth compact Riemannian manifolds since the unit circle will turn out to be a uniform attractor of the diffusion.

3.1 Counterexample in 2-dimension

Roughly speaking, saying that ν_Δ is the only one invariant distribution means in a sense that $X_t^x - X_t^y$ has a tendency to converge towards 0 when $t \rightarrow +\infty$. Thus, the idea in the counterexample below is to build a “turning” two-dimensional ergodic process where the angular difference between the two coordinates does not depend on t . Such a construction leads to a model where the distance between the two coordinates can not tend to 0 (Note that some proofs are deferred to Appendix B). We consider the 2-dimensional SDE with Lipschitz continuous coefficients defined by, $\forall x \in \mathbb{R}^2$

$$\begin{aligned} b(x) &= \left(x \mathbf{1}_{\{0 \leq |x| \leq 1\}} - \frac{x}{|x|} \mathbf{1}_{\{|x| \geq 1\}} \right) (1 - |x|) \\ \sigma(x) &= \vartheta \text{Diag}(b(x)) + \begin{bmatrix} 0 & -cx^2 \\ cx^1 & 0 \end{bmatrix} \end{aligned}$$

where $\vartheta, c \in (0, +\infty)$ are fixed parameters.

Switching to polar coordinates $X_t = (r_t \cos \varphi_t, r_t \sin \varphi_t)$, $t \in \mathbb{R}_+$, we obtain that this SDE also reads

$$dr_t = \min(r_t, 1)(1 - r_t)(dt + \vartheta dW_t^1), \quad r_0 \in \mathbb{R}_+ \quad (3.3)$$

$$d\varphi_t = c dW_t^2, \quad \varphi_0 \in [0, 2\pi), \quad (3.4)$$

where $x_0 = r_0(\cos \varphi_0, \sin \varphi_0)$ and $W = (W^1, W^2)$ is a standard 2-dimensional Brownian motion.

Standard considerations about Feller classification (see Appendix B for details) show that, if $x_0 \neq 0$ (i.e. $r_0 > 0$) and $\vartheta \in (0, \sqrt{2})$ then

$$r_t \longrightarrow 1 \quad \text{as } t \rightarrow +\infty, \quad (3.5)$$

while it is classical background that

$$\mathbb{P}\text{-a.s. } \forall \varphi_0 \in \mathbb{R}_+, \quad \frac{1}{t} \int_0^t \delta_{e^{i(\varphi_0 + \varepsilon W_s^2)}} ds \implies \lambda_{\mathcal{S}_1} \quad \text{as } t \rightarrow +\infty$$

where \mathcal{S}_1 denotes the unit circle of \mathbb{R}^2 . Combining these two results straightforwardly yields

$$\forall x \in \mathbb{R}^2 \setminus \{(0,0)\}, \mathbb{P}\text{-a.s. } \quad \frac{1}{t} \int_0^t \delta_{X_s^x} ds \xrightarrow{(\mathbb{R}^2)} \lambda_{\mathcal{S}_1} \quad \text{as } t \rightarrow +\infty.$$

On the other hand, given the form of φ_t , it is clear that if $x = r_0 e^{i\varphi_0}$ and $x' = r'_0 e^{i\varphi'_0}$, $r_0, r'_0 \neq 0$, $\varphi_0, \varphi'_0 \in [0, 2\pi)$, then

$$\lim_{t \rightarrow +\infty} |X_t^x - X_t^{x'}| = |e^{i(\varphi_0 - \varphi'_0)} - 1|$$

which in turn implies that

$$\lim_{t \rightarrow +\infty} \frac{1}{t} \int_0^t |X_s^x - X_s^{x'}| ds = |e^{i(\varphi_0 - \varphi'_0)} - 1| \quad \mathbb{P}\text{-a.s.}$$

This limit being different from 0 as soon as $\varphi_0 \neq \varphi'_0$, one derives, as a consequence, that ν_Δ cannot be the only invariant distribution. In fact, a more precise statement can be proved.

PROPOSITION 3.1. (a) *A distribution μ is invariant for the semi-group $(Q_t)_{t \geq 0}$ of the duplicated diffusion if and only if μ has the following form:*

$$\mu = \mathcal{L}(e^{i\Theta}, e^{i(\Theta+V)}) \quad (3.6)$$

where Θ is uniformly distributed over $[0, 2\pi]$ and V is a $[0, 2\pi)$ -valued random variable independent of Θ

(b) *When $V = 0$ a.s., we retrieve ν_Δ whereas, when V also has uniform distribution on $[0, 2\pi]$, we obtain $\nu \otimes \nu$. Finally, μ is extremal in the convex set of $(Q_t)_{t \geq 0}$ invariant distributions if and only if there exists $\theta_0 \in [0, 2\pi)$ such that $V = \theta_0$ a.s.*

The proof is postponed to Appendix B. However, note that the claim about extremal invariant distributions follows from the fact that for every $\theta \in [0, 2\pi)$, $(Q_t)_{t \geq 0}$ leaves the set $\Gamma_\theta := \{(e^{i\varphi}, e^{i\varphi'}) \in \mathcal{S}_1 \times \mathcal{S}_1, \varphi' - \varphi \equiv \theta \text{ mod. } 2\pi\}$ stable.

REMARK 3.2. In the above counterexample, the invariant measure of $(r_t)_{t \geq 0}$ is the Dirac measure δ_1 . In fact, setting again $x = \varepsilon_0 e^{i\varphi_0}$ and $x' = r'_0 e^{i\varphi'_0}$ and using that $X_t^x - X_t^{x'} = r_t^x \left(e^{i(\varphi_0 + W_t^2)} - e^{i(\varphi'_0 + W_t^2)} \right) + (r_t^x - r_t^{x'}) e^{i(\varphi'_0 + W_t^2)}$, an easy adaptation of the above proof shows that it can be generalized to any ergodic non-negative process $(r_t)_{t \geq 0}$ solution to an autonomous SDE and satisfying the following properties:

- Its unique invariant distribution π satisfies $\pi(\mathbb{R}_+^*) = 1$.
- For every $x, y \in (0, +\infty)$, $r_t^x - r_t^y \rightarrow 0$ a.s. as $t \rightarrow +\infty$.

For instance, let $(X_t^x)_{t \geq 0}$ be an Ornstein-Uhlenbeck process satisfying the SDE $dX_t = -X_t dt + \sigma dW_t$, $X_0 = x$. Set $r_t^x = (X_t^x)^2$ (this is a special case of the Cox-Ingersoll-Ross process). The process (r_t^x) clearly satisfies the first two properties. Furthermore, $(X_t^x)_{t \geq 0}$

satisfies *a.s.* for every $x, y \in \mathbb{R}$ and every $t \geq 0$, $|X_t^x - X_t^y| = |x - y|e^{-t}$. Then, since for every $x \in \mathbb{R}$,

$$\frac{X_t^x}{t} = -\frac{1}{t} \int_0^t X_s^x ds + \sigma \frac{W_t}{t} \rightarrow 0 \quad \textit{a.s.} \quad \textit{as} \quad t \rightarrow +\infty,$$

it follows that $(r_t^x)_{t \geq 0}$ also satisfies for all positive x, y , $r_t^x - r_t^y \rightarrow 0$ *a.s.* as $t \rightarrow +\infty$ (Many other examples can be built using Corollary 2.1).

Finally, note that if $\mu = \mathcal{L}(Re^{i\Theta}, Re^{i(\Theta+V)})$ where R, Θ and V are independent random variables such that the distributions of R and Θ are respectively π and the uniform distribution on $[0, 2\pi]$ and V takes values in $[0, 2\pi)$, then μ is an invariant distribution of the associated duplication system.

3.2 Uniqueness of the invariant measure: (S, θ) -confluence

In the sequel of this section, we propose criterions for the uniqueness of the invariant distribution of the duplicated system in the multidimensional case. The underlying idea of the criterions discussed below is to analyze the coupled diffusion process (X^{x_1}, X^{x_2}) through the squared distance process $r_t = |X_t^{x_1} - X_t^{x_2}|_S^2$ (where $|\cdot|_S$ is an Euclidean norm on \mathbb{R}^d). It is somewhat similar to that of Has'minskii's test for explosion of diffusions in \mathbb{R}^d or to the one proposed in Chen and Li's work devoted to the coupling of diffusions (see [CL89]). We begin by a general result under an assumption depending on a continuous (non-explicit) function $\theta : (0, +\infty) \rightarrow \mathbb{R}_+$. Then, more explicit criterions are derived in the next subsections. In particular one involves a kind of bi-variate non-infinitesimal Lyapunov exponent.

THEOREM 3.2. *Assume that b is continuous, σ is Lipschitz continuous and that strong existence, pathwise uniqueness and the Feller Markov property hold for (SDE) from any $x \in \mathbb{R}^d$. Assume that the set \mathcal{I}_{SDE} of invariant distributions of SDE is (nonempty, convex and) weakly compact. Furthermore, assume the SDE (1.1) is asymptotically (S, θ) -confluent in the following sense: there exists a continuous function $\theta : (0, +\infty) \rightarrow \mathbb{R}_+$ such that*

$$\left\{ \begin{array}{l} (i) \limsup_{u \rightarrow 0^+} \int_u^1 \frac{\theta(w) - 1}{w} dw < +\infty. \\ (ii) \exists S \in \mathcal{S}^{++}(d, \mathbb{R}) \text{ such that } \forall x, y \in \mathbb{R}^d, x \neq y, \\ (b(x) - b(y)|x - y)_S + \frac{1}{2} \|\sigma(x) - \sigma(y)\|_S^2 < \theta(|x - y|_S^2) \left| (\sigma^*(x) - \sigma^*(y)) \frac{S(x-y)}{|x-y|_S} \right|^2. \end{array} \right.$$

(a) Weak confluence (Uniqueness of both invariant distributions): *Then, if \mathcal{I}_{DSDS} denotes the set of invariant distributions of the duplicated system (DSDS), one has*

$$\mathcal{I}_{SDE} = \{\nu\} \quad \textit{and} \quad \mathcal{I}_{DSDS} = \{\nu_\Delta\}.$$

keeping in mind that $\nu_\Delta = \nu \circ (x \mapsto (x, x))^{-1}$.

(b) Pathwise confluence: *If furthermore, $\int_0^1 e^{\int_v^1 \frac{\theta(w)}{w} dw} dv < +\infty$ and for every $x \in \mathbb{R}^d$,*

*$\left(\frac{1}{t} \int_0^t P_s(x, dy) ds\right)_{t \geq 1}$ is tight, we have *a.s.* pathwise asymptotic confluence:*

$$\forall x_1, x_2 \in \mathbb{R}^d, \quad X_t^{x_1} - X_t^{x_2} \rightarrow 0 \quad \textit{as} \quad t \rightarrow +\infty \quad \mathbb{P}\textit{-a.s.} \quad (3.7)$$

REMARK 3.3. \triangleright If we also assume in (a), that $\left(\frac{1}{t} \int_0^t P_s(x, dy) ds\right)_{t \geq 1}$ is tight then, so is $\left(\frac{1}{t} \int_0^t Q_s(x, x', dy, dy') ds\right)_{t \geq 1}$. Since, by construction, the weak limiting distributions of this sequence as $t \rightarrow +\infty$ are invariant distributions, this implies that $\frac{1}{t} \int_0^t Q_s(x, x', dy, dy') ds$ weakly converges to ν_Δ as $t \rightarrow +\infty$. This explains the “weak confluence” terminology.

\triangleright In both statements, Assumption(ii) must be combined with an additional assumption on θ to generate some weak or pathwise confluence properties (some easier to verify criterions will be given in the next subsection). Since pathwise confluence implies uniqueness of the invariant distribution for (DSDS), one can expect that the additional condition on θ of (b) implies Assumption (i). This is true in full generality. Actually, owing to the Cauchy criterion, $\int_0^1 e^{\int_v^1 \frac{\theta(w)}{w} dw} dv < +\infty$ implies that $\int_{\frac{u}{2}}^u e^{\int_v^1 \frac{\theta(w)}{w} dw} dv \rightarrow 0$ as $u \rightarrow 0^+$. Using that $v \mapsto e^{\int_v^1 \frac{\theta(w)}{w} dw}$ is non-increasing on $(0, 1]$, it follows that $ue^{\int_u^1 \frac{\theta(w)}{w} dw} \rightarrow 0^+$ as $u \rightarrow 0$. Taking the logarithm yields $\int_u^1 \frac{\theta(w)-1}{w} dw \rightarrow -\infty$ and thus, Assumption (i).

\triangleright If b and σ are Lipschitz continuous, Kunita’s Stochastic flow theorem (see [Kun90], Section 4.5) ensures in particular that, if $x_1 \neq x_2$, the solutions $X_t^{x_1}$ and $X_t^{x_2}$ a.s. never get stuck. Taking advantage of this remark slightly shortens the proof below.

\triangleright Tightness criterions of $\left(\frac{1}{t} \int_0^t P_s(x, dy) ds\right)_{t \geq 1}$ for every $x \in \mathbb{R}^d$ usually rely on the mean-reversion property of the solutions of (SDE) usually established under various assumptions involving the existence of a so-called *Lyapunov function* V going to infinity at infinity and such that $\mathcal{A}V$ is upper-bounded and $\limsup_{|x| \rightarrow +\infty} \mathcal{A}V(x) < 0$ where \mathcal{A} denotes the infinitesimal generator of X^x (so-called *Has’minskii’s criterion*). Keep in mind that

$$\mathcal{A}V(x) = (b|\nabla V)(x) + \frac{1}{2} \text{Tr}\left(\sigma\sigma^*(x)D^2V(x)\right)$$

where $\text{Tr}(A)$ stands for the trace of the matrix A .

On the other hand, a classical criterion for pathwise asymptotic confluence (a.s. at exponential rate, see e.g. [BB92], [Lem05] and often known as *asymptotic flatness*) is

$$\forall x, y \in \mathbb{R}^d, \quad (b(x) - b(y)|x - y) + \frac{1}{2} \|\sigma(x) - \sigma(y)\|^2 < -c|x - y|^2, \quad (c > 0),$$

and, as a straightforward consequence, uniqueness of the invariant distribution ν of (SDE) (and of (DSDS) as well). Moreover, putting $y = 0$ in the above inequality straightforwardly yields real coefficients $\alpha > 0$, $\beta \geq 0$ such that $\mathcal{A}V \leq \beta - \alpha V$ with $V(x) = |x|^2$. Hence Has’minskii criterion is fulfilled, so it is also an existence criterion for the invariant distribution which (S, θ) -confluence is not.

But in fact, the (S, θ) -confluence criterion turns out to be a much weaker condition to ensure the uniqueness of the invariant distribution ν of (SDE) (and of ν_Δ for (DSDS)). This is emphasized by several operating criterions derived from this θ -confluence assumption. Finally, combined with the tightness of the occupation measure of the semi-group, it becomes a criterion for a.s. pathwise asymptotic confluence.

Proof. STEP 1: Exactly like in the beginning of the proof of Theorem 2.1(a), one checks that the set \mathcal{I}_{DSDS} of invariant distributions of $(Q_t)_{t \geq 0}$ is a nonempty, convex and weakly compact subset of $\mathcal{P}(\mathbb{R}^{2d})$. As a consequence of the Krein-Millman theorem, \mathcal{I}_{DSDS} has extremal distributions (and is their closed convex hull).

On the other hand, it follows from strong uniqueness theorem for SDE's that the semi-group $(Q_t)_{t \geq 0}$ leaves stable the diagonal $\Delta_{\mathbb{R}^{2d}}$.

Let $x_1, x_2 \in \mathbb{R}^d$, $x_1 \neq x_2$. We define the stopping time

$$\tau_{x_1, x_2} := \inf \{t \geq 0 \mid X_t^{x_1} = X_t^{x_2}\}.$$

Still by a strong uniqueness argument it is clear that $\{\tau_{x_1, x_2} > t\} = \{X_t^{x_1} \neq X_t^{x_2}\}$ so that

$$Q_t((x_1, x_2), {}^c\Delta_{\mathbb{R}^{2d}}) = \mathbf{1}_{{}^c\Delta_{\mathbb{R}^{2d}}}(x_1, x_2) \mathbb{P}(\tau_{x_1, x_2} > t)$$

and $Q_t((x_1, x_1), {}^c\Delta_{\mathbb{R}^{2d}}) = 0$.

Let $\mu \in \mathcal{I}_{DSDS}$ be an extremal invariant measure. We have, for every $t \geq 0$,

$$\mu({}^c\Delta_{\mathbb{R}^{2d}}) = \int_{{}^c\Delta_{\mathbb{R}^{2d}}} \mu(dx_1, dx_2) \mathbb{P}(\tau_{x_1, x_2} > t).$$

Letting t go to $+\infty$ yields

$$\mu({}^c\Delta_{\mathbb{R}^{2d}}) = \int_{{}^c\Delta_{\mathbb{R}^{2d}}} \mu(dx_1, dx_2) \mathbb{P}(\tau_{x_1, x_2} = +\infty)$$

so that, on ${}^c\Delta_{\mathbb{R}^{2d}}$, $\mu(dx_1, dx_2)$ -a.s., $\mathbb{P}(\tau_{x_1, x_2} = +\infty) = 1$ or equivalently the process (X^{x_1}, X^{x_2}) lives in ${}^c\Delta_{\mathbb{R}^{2d}}$. Consequently, if $\mu({}^c\Delta_{\mathbb{R}^{2d}}) \in (0, 1)$, both conditional measures $\mu^{{}^c\Delta_{\mathbb{R}^{2d}}}$ and $\mu^{\Delta_{\mathbb{R}^{2d}}}$ are invariant distributions for $(SDSD)$ as well. If so,

$$\mu = \mu({}^c\Delta_{\mathbb{R}^{2d}}) \mu^{{}^c\Delta_{\mathbb{R}^{2d}}} + \mu(\Delta_{\mathbb{R}^{2d}}) \mu^{\Delta_{\mathbb{R}^{2d}}}$$

cannot be extremal. Consequently $\mu(\Delta_{\mathbb{R}^{2d}}) = 0$ or 1 .

STEP 2: Let μ be an extremal distribution in \mathcal{I}_{DSDS} and assume that $\mu({}^c\Delta_{\mathbb{R}^{2d}}) = 1$. We will prove that this yields a contradiction under Assumptions (i) and (ii).

To this end, let us introduce the *pseudo-scale* \mathcal{C}^2 -function f_θ and its companion g_θ defined by

$$\forall u \in (0, +\infty), \quad f_\theta(u) = \int_1^u e^{\int_\xi^1 \frac{\theta(w)}{w} dw} d\xi \quad \text{and} \quad g_\theta(u) = u f'_\theta(u).$$

Note that $g_\theta \geq 0$, that Assumption (i) reads $\limsup_{u \rightarrow 0^+} g_\theta(u) < +\infty$ and that $g'_\theta(u) = f'_\theta(u)(1 - \theta(u))$. Moreover, if Assumption (ii) is fulfilled, so is the case by any continuous function $\tilde{\theta}$ satisfying $\tilde{\theta} \geq \theta$. As a consequence, we may modify θ on $[1, +\infty)$ so that θ still satisfies (ii) and $\theta \geq 1$ over $[2\varepsilon, +\infty)$. Then the function g_θ is nonincreasing on $[2, +\infty)$. Consequently, without loss of generality, we may assume in the sequel of the proof that

$$\sup_{u > 0} g_\theta(u) < +\infty. \tag{3.8}$$

We now define a (Lyapunov) function $\varphi : {}^c\Delta_{\mathbb{R}^{2d}} \rightarrow \mathbb{R}$ by

$$\varphi(y_1, y_2) := f_\theta(|y_1 - y_2|_S^2).$$

We know from Step 1 that $\mu(dx_1, dx_2)$ -a.s., $(X_t^{x_1} \neq X_t^{x_2}$ for every $t \geq 0)$ a.s.. Then, f_θ being a \mathcal{C}^2 -function, we derive from Itô's formula applied to $\varphi(X_t^{x_1}, X_t^{x_2})$ that $\mu(dx_1, dx_2)$ -a.s.,

$$\begin{aligned} \varphi(X_t^{x_1}, X_t^{x_2}) &= \varphi(x_1, x_2) + \int_0^t \mathcal{A}^{(2)} \varphi(X_s^{x_1}, X_s^{x_2}) ds \\ &\quad + \underbrace{\int_0^t f'_\theta(|X_s^{x_1} - X_s^{x_2}|_S^2) ((\sigma^*(X_s^{x_1}) - \sigma^*(X_s^{x_2})) S (X_s^{x_1} - X_s^{x_2})) |dW_s)}_{=: M_t \text{ local martingale}} \end{aligned}$$

where, for every $(x_1, x_2) \in (\mathbb{R}^d)^2$,

$$\begin{aligned} \mathcal{A}^{(2)}\varphi(x_1, x_2) &= 2\left((b(x_1) - b(x_2)|x_1 - x_2|_S + \frac{1}{2}\|\sigma(x_1) - \sigma(x_2)\|_S^2)\right) f'_\theta(|x_1 - x_2|_S^2) \\ &\quad + 2f''_\theta(|x_1 - x_2|_S^2)|(\sigma^*(x_1) - \sigma^*(x_2))S(x_1 - x_2)|^2. \end{aligned} \quad (3.9)$$

Using that f satisfies the $ODE \equiv \theta(\xi)f'_\theta(\xi) + \xi f''_\theta(\xi) = 0$, $\xi \in (0, +\infty)$ we deduce from Assumption (ii) that $\mathcal{A}^{(2)}\varphi(x_1, x_2) < 0$ if $x_1 \neq x_2$ and $= 0$ otherwise.

On the one hand, since μ is extremal and since the sign of $\mathcal{A}^{(2)}\varphi$ is constant, we can apply Birkhoff's theorem and obtain:

$$\mu(dx_1, dx_2)\text{-a.s.}, \quad \frac{1}{t} \int_0^t \mathcal{A}^{(2)}\varphi(X_s^{x_1}, X_s^{x_2}) ds \xrightarrow{t \rightarrow +\infty} \int_{{}^c\Delta_{\mathbb{R}^{2d}}} \mathcal{A}^{(2)}\varphi d\mu \in [-\infty, 0] \quad a.s.$$

In fact, $\int_{{}^c\Delta_{\mathbb{R}^{2d}}} \mathcal{A}^{(2)}\varphi d\mu$ belongs to $[-\infty, 0)$ since $\mathcal{A}^{(2)}\varphi$ is negative on ${}^c\Delta_{\mathbb{R}^{2d}}$ and $\mu({}^c\Delta_{\mathbb{R}^{2d}}) = 1$. On the other hand, using that g_θ is bounded and σ is Lipschitz continuous, it follows that $(M_t)_{t \geq 0}$ is an L^2 -martingale such that

$$\langle M \rangle_t = \int_0^t g_\theta(|X_s^{x_1} - X_s^{x_2}|_S^2) \left| \frac{(\sigma^*(X_s^{x_1}) - \sigma^*(X_s^{x_2})) S(X_s^{x_1} - X_s^{x_2})}{|X_s^{x_1} - X_s^{x_2}|_S} \right|^2 ds \leq Ct \quad \mathbb{P}_\mu\text{-a.s.} \quad (3.10)$$

where C is a deterministic positive constant so that $\frac{M_t}{t} \rightarrow 0$ \mathbb{P}_μ -a.s..

As a consequence, $\mu(dx_1, dx_2)$ -a.s.,

$$\lim_{t \rightarrow +\infty} \frac{\varphi(X_t^{x_1}, X_t^{x_2})}{t} = \int_{{}^c\Delta_{\mathbb{R}^{2d}}} \mathcal{A}^{(2)}\varphi d\mu < 0 \quad a.s..$$

Hence, $a.s.$, $f(|X_t^{x_1} - X_t^{x_2}|_S^2) = \varphi(X_t^{x_1}, X_t^{x_2}) \xrightarrow{t \rightarrow +\infty} -\infty \quad a.s.$

If $\lim_{u \rightarrow 0^+} f_\theta(u) > -\infty$, this yields a contradiction since f_θ is increasing on \mathbb{R}_+^* . Otherwise $|X_t^{x_1} - X_t^{x_2}|_S^2 \xrightarrow{t \rightarrow +\infty} 0$. But applying again Birkhoff's theorem, we obtain $\mu(dx_1, dx_2)$ -a.s.,

$$\int |y_1 - y_2|_S^2 \mu(dy_1, dy_2) = \lim_{t \rightarrow +\infty} \frac{1}{t} \int_0^t |X_s^{x_1} - X_s^{x_2}|_S^2 ds = 0 \quad a.s.,$$

which contradicts the assumption $\mu({}^c\Delta_{\mathbb{R}^{2d}}) = 1$. Consequently, for any extremal distribution μ , we have $\mu(\Delta_{\mathbb{R}^{2d}}) = 1$.

We can now prove Claim (a): by Krein-Millman's Theorem \mathcal{I}_{SDS} is the weak closure of the convex hull of its extremal distributions. Consequently, the diagonal $\Delta_{\mathbb{R}^{2d}}$ being a closed subset of \mathbb{R}^{2d} , all invariant distributions of the duplicated system are supported by this diagonal. For any such invariant distribution μ , both its marginals are invariant distributions for (SDE). If (SDE) had two distinct invariant distributions ν and ν' , we know from the introduction that \mathcal{I}_{DSDS} would contain at least a distribution μ for which the two marginals distributions are $\mu(\cdot \times \mathbb{R}^d) = \nu$ and $\mu(\mathbb{R}^d \times \cdot) = \nu'$ respectively. As a consequence, such a distribution μ could not be supported by the diagonal $\Delta_{\mathbb{R}^{2d}}$. Finally, \mathcal{I}_{SDE} is reduced to a singleton $\{\nu\}$ and $\mathcal{I}_{DSDS} = \{\nu_\Delta\}$.

STEP 3 (CLAIM (b): PROOF OF (3.7)): Under the additional assumption on θ of (b), we have $\lim_{u \rightarrow 0^+} f_\theta(u) > -\infty$ and thus, $\inf_{u > 0} f_\theta(u) > -\infty$ since f_θ is increasing. Let $x_1, x_2 \in \mathbb{R}^d$. Using again that $\mathcal{A}^{(2)}\varphi < 0$ on ${}^c\Delta_{\mathbb{R}^{2d}}$ where $\mathcal{A}^{(2)}\varphi$ is given by (3.9). It follows that $(f_\theta(|X_t^{x_1} - X_t^{x_2}|_S^2))_{t \geq 0}$ is a lower-bounded \mathbb{P} -supermartingale. Thus, it $a.s.$ converges

toward $L_\infty^{x_1, x_2} \in L^1(\mathbb{P})$. Using again that f_θ is increasing, it follows that $|X_t^{x_1} - X_t^{x_2}|_S^2$ a.s. converges toward a finite random variable $\ell_\infty^{x_1, x_2} = f_\theta^{-1}(L_\infty^{x_1, x_2})$.

Now, using that for every $x \in \mathbb{R}^d$, $\left(\frac{1}{t} \int_0^t P_s(x, dy) ds\right)_{t \geq 1}$ is tight, we derive that $\left(\frac{1}{t} \int_0^t Q_s((x_1, x_2), (dy_1, dy_2)) ds\right)_{t \geq 1}$ is tight as well. Then the uniqueness of ν_Δ as an invariant distribution of Q implies that

$$\frac{1}{t} \int_0^t Q_s((x_1, x_2), (dy_1, dy_2)) ds \xrightarrow{(\mathbb{R}^d)} \nu_\Delta.$$

Now for every bounded continuous function $g : \mathbb{R}^d \rightarrow \mathbb{R}$,

$$\frac{1}{t} \int_0^t Q_s(g(|y_1 - y_2|_S^2))(x_1, x_2) ds = \frac{1}{t} \int_0^t \mathbb{E} g(|X_s^{x_1} - X_s^{x_2}|_S^2) ds \longrightarrow \mathbb{E} g(\ell_\infty^{x_1, x_2})$$

so that

$$\mathbb{E} g(\ell_\infty^{x_1, x_2}) = \int g(|y_1 - y_2|_S^2) \nu_\Delta(dy_1, dy_2) = g(0). \quad \square$$

In Assumption (ii) of the previous theorem, we see that the function $(x, y) \mapsto |(\sigma^*(x) - \sigma^*(y))S(x - y)|$ plays an important role. In the sequel, we will obtain specific results when this function is not degenerated away from the diagonal. Such type of assumption will be called *strong* or *regular directional S-ellipticity assumption*.

In the following proposition, we first show that when such an assumption is satisfied, claim (b) of the previous theorem still holds without the tightness assumption on $\left(\frac{1}{t} \int_0^t P_s(x, dy) ds\right)_{t \geq 1}$ (although it is a not really restrictive in our framework (see the fourth item of Remark 3.3)).

PROPOSITION 3.2. *If the function θ is $(0, 1]$ -valued and σ satisfies the following strong directional S-ellipticity assumption away from the diagonal*

$$\exists \alpha_0 > 0, \forall x, y \in \mathbb{R}^d, |(\sigma^*(x) - \sigma^*(y))S(x - y)| \geq \alpha_0 |x - y|^2, \quad (3.11)$$

then the conclusion of Claim (b) in the above proposition remains true without the tightness assumption on $\left(\frac{1}{t} \int_0^t P_s(x, dy) ds\right)_{t \geq 1}$.

Proof. First, we recall that under the assumptions of (b), we recall that $(f_\theta(|X_t^{x_1} - X_t^{x_2}|_S^2))_{t \geq 0}$ is a lower-bounded \mathbb{P} -supermartingale thus convergent to an integrable random variable and that this implies that $(|X_t^{x_1} - X_t^{x_2}|_S^2)_{t \geq 0}$ is a.s. convergent to a finite random variable $\ell_\infty^{x_1, x_2}$ (since f_θ is increasing). On the other hand, since $-\mathcal{A}^{(2)}\varphi$ is positive and f_θ is lower-bounded, we also have that

$$f_\theta(|X_t^{x_1} - X_t^{x_2}|_S^2) - \int_0^t \mathcal{A}^{(2)}\varphi(X_s^{x_1}, X_s^{x_2}) ds = \varphi(x_1, x_2) + M_t$$

is a lower bounded \mathbb{P} -(local) martingale starting at a deterministic starting value, hence converging toward an integrable random variable. Owing to the computations of (3.10) (which hold for every starting points x_1, x_2), $(M_t)_{t \geq 0}$ is in fact an L^2 -convergent martingale. Thus, $\langle M \rangle_\infty < +\infty$ and taking advantage of the expression of this bracket (see (3.10)) and to Assumption (3.11), we derive that for every $\varepsilon > 0$

$$\int_0^{+\infty} (g_\theta(|X_s^{x_1} - X_s^{x_2}|_S^2))^2 \mathbf{1}_{\{|X_s^{x_1} - X_s^{x_2}|_S^2 \geq \varepsilon\}} ds < +\infty \quad a.s.$$

The function g_θ is positive on $(0, +\infty)$ and non-decreasing since $g'_\theta(u) = f'_\theta(u)(1 - \theta(u)) \geq 0$. This implies that, for every $\varepsilon > 0$,

$$\liminf_{t \rightarrow +\infty} g_\theta(|X_t^{x_1} - X_t^{x_2}|_S^2) \mathbf{1}_{\{|X_t^{x_1} - X_t^{x_2}|_S^2 \geq \varepsilon\}} = 0 \quad a.s.$$

Combined with the convergence of the squared norm this yields

$$\forall \varepsilon > 0, \quad g_\theta(\ell_\infty^{x_1, x_2}) \mathbf{1}_{\{\ell_\infty^{x_1, x_2} \geq \varepsilon\}} = 0 \quad a.s.$$

which finally implies $\ell_\infty^{x_1, x_2} = 0$ *a.s.* □

3.3 Global criterions, NILS exponent

In this section and the following, we derive several corollaries of Theorem 3.2 illustrated by different examples. For $S \in \mathcal{S}^{++}(d, \mathbb{R})$, set

$$[b]_{S,+} = \sup_{x \neq y} \frac{(b(x) - b(y)|x - y)_S}{|x - y|_S^2}.$$

Note that if $[b]_{S,+} < +\infty$ and if σ is Lipschitz continuous, strong existence, pathwise uniqueness and the Feller Markov property hold for (SDE).

PROPOSITION 3.3. *Assume $[b]_{S,+} < +\infty$, σ is Lipschitz continuous and (SDE) and \mathcal{I}_{SDS} is non empty and weakly compact. Let $\theta : (0, +\infty) \rightarrow \mathbb{R}_+$ be a continuous function such that Assumption (ii) of Theorem 3.2 holds. Then,*

- (a) *If there exists $\varepsilon_0 > 0$ such that $\theta(u) \leq 1$, $u \in (0, \varepsilon_0]$, then (SDE) (1.1) and its duplicated system have ν and ν_Δ as unique invariant distributions respectively.*
- (b) *If furthermore for every $x \in \mathbb{R}^d$, $(\frac{1}{t} \int_0^t P_s(x, dy) ds)_{t \geq 1}$ is tight and if there exists $\kappa > 1$ and $\varepsilon_0 \in (0, e^{-\frac{\kappa}{2}})$ such that*

$$\forall u \in (0, \varepsilon_0], \quad \theta(u) \leq \left(1 + \frac{\kappa}{\log u}\right), \quad (3.12)$$

the duplicated system of (SDE) is pathwise confluent in the sense of Theorem 3.2(b). This condition is in particular satisfied if there exists $\varepsilon_0 > 0$ and $\theta_0 \in (0, 1)$ such that

$$\forall u \in (0, \varepsilon_0], \quad \theta(u) \leq \theta_0.$$

Claim (a) is obvious. For (b), one checks that $\int_0^1 e^{\int_v^1 \frac{\theta(w)}{w} dw} dv < +\infty$ as soon as $\liminf_{u \rightarrow 0^+} \log(u)(\theta(u) - 1) > 1$ and the result follows.

REMARK 3.4. The simplest case where the preceding result holds is obtained when $\theta \equiv 0$. In this case, the $(S, 0)$ -confluence global condition reads:

$$\forall x, y \in \mathbb{R}^d, \quad x \neq y, \quad (b(x) - b(y)|x - y)_S + \frac{1}{2} \|\sigma(x) - \sigma(y)\|_S^2 < 0. \quad (3.13)$$

In fact, this condition is also required at every (x, y) , $x \neq y$, such that $(\sigma^*(x) - \sigma^*(y))S(x - y) = 0$, whatever θ is. In the next section, we will see that when $(\sigma^*(x) - \sigma^*(y))S(x - y)$ never vanishes away from the diagonal, one can derive a “localized” version of the criterion outside the diagonal.

The constant function $\theta \equiv 1$ clearly satisfies the assumption in (a) of the above Proposition. This leads us to introduce an important quantity of interest for our purpose.

DEFINITION 3.1. The *non-infinitesimal S-Lyapunov exponent* (NILS) is a function on $\mathbb{R}^{2d} \setminus \Delta_{\mathbb{R}^{2d}}$ defined for every $x, y \in \mathbb{R}^d$, $x \neq y$, by

$$\lambda_S(x, y) = \frac{(b(x) - b(y)|x - y)_S}{|x - y|_S^2} + \frac{1}{2} \frac{\|\sigma(x) - \sigma(y)\|_S^2}{|x - y|_S^2} - \left(\left| \frac{(\sigma^*(x) - \sigma^*(y))S(x - y)}{|x - y|_S^2} \right|^2 \right).$$

COROLLARY 3.2. Assume b and σ are like in Proposition 3.3 and \mathcal{I}_{SDE} is non empty and weakly compact.

(a) Negative NILS exponent: if

$$\forall x, y \in \mathbb{R}^d, x \neq y, \quad \lambda_S(x, y) < 0,$$

then (SDE) and its duplicated system have ν and ν_Δ as unique invariant distributions respectively.

(b) Negative NILS exponent bounded away from 0: If furthermore $(\frac{1}{t} \int_0^t P_s(x, dy) ds)_{t \geq 1}$ is tight for every $x \in \mathbb{R}^d$ or σ satisfies (3.11) and if there exists $c_0 > 0$ such that

$$\forall x, y \in \mathbb{R}^d, x \neq y, |x - y|_S^2 \leq \varepsilon_0 \implies \lambda_S(x, y) \leq -c_0 \quad (3.14)$$

then the duplicated diffusion is pathwise confluent i.e.

$$\forall x_1, x_2 \in \mathbb{R}^d, \quad X_t^{x_1} - X_t^{x_2} \longrightarrow 0 \text{ a.s. as } t \rightarrow +\infty.$$

Proof. (a) follows from claim (a) in the above proposition with $\theta \equiv 1$. (b) follows from claim (b) in the same proposition. \square

Note that in (b), Condition (3.14) can be replaced by the sharper following one: for all $x, y \in \mathbb{R}^d$, $\lambda_S(x, y) < 0$ and there exists $\kappa > 1$ and $\varepsilon_0 \in (0, e^{-\frac{\kappa}{2}})$ such that for all $x, y \in \mathbb{R}^d$ such that $|x - y|_S \leq \varepsilon_0$, $\lambda_S(x, y) \leq \frac{\kappa}{\log(|x - y|_S^2)}$.

3.4 Applications and extensions

3.4.1 Localization around the diagonal

By local we mean that the (S, θ) -confluence condition will be effective only in the neighbourhood of the diagonal $\Delta_{\mathbb{R}^{2d}}$. The price to pay is a regular directional ellipticity assumption on $\sigma(x) - \sigma(y)$ in the direction $S(x - y)$ away from the diagonal.

PROPOSITION 3.4. Assume $[b]_{S,+} < +\infty$, σ is Lipschitz continuous and (SDE) admits at least one invariant distribution ν . If there exists $\varepsilon_0 > 0$ such that

$$\left\{ \begin{array}{l} (i) \text{ Directional } S\text{-ellipticity: } \eta_0 := \inf \left\{ |(\sigma^*(x) - \sigma^*(y))S(x - y)|, |x - y|_S \geq \varepsilon_0 \right\} > 0, \\ (ii) \text{ Locally negative NILS exponent: } \forall x, y \in \mathbb{R}^d, 0 < |x - y|_S \leq \varepsilon_0, \lambda_S(x, y) < 0, \end{array} \right.$$

then (SDE) (1.1) and its duplicated system still have ν and ν_Δ as unique invariant distributions respectively.

Proof. For every $u \in (0, +\infty)$

$$\sup_{|x - y|_S = u} \frac{(b(x) - b(y)|x - y)_S + \frac{1}{2} \|\sigma(x) - \sigma(y)\|_S^2}{\left| (\sigma^*(x) - \sigma^*(y))S \frac{x - y}{|x - y|_S} \right|^2} < \theta(u)$$

where

$$\theta(u) = \begin{cases} ([b]_+ + \frac{1}{2}[\sigma]_{\text{Lip}}^2) \frac{u^4}{\eta_0^2} + \delta_0 & \text{if } u \in [\varepsilon_0, \infty), \\ 1 & \text{if } u \in (0, \varepsilon_0/2) \end{cases}$$

where δ_0 is a positive number. Consequently θ can be extended into a continuous function over $(0, +\infty)$ (e.g. by an affine extension between $\varepsilon_0/2$ and ε_0) which satisfies the condition of Proposition 3.3. \square

COROLLARY 3.3 (Smooth coefficients). *Assume the functions b and σ are continuously differentiable. Let $J_b(x) = \left[\frac{\partial b_i}{\partial x_j}(x) \right]_{1 \leq i, j \leq d}$ denote the Jacobian of b at x and let $\nabla \sigma(x) = \left[\frac{\partial \sigma_{ij}}{\partial x^k}(x) \right]_{i, j, k}$ denote the gradient of σ at x . If both $SJ_b + J_b^*S$ and $\nabla \sigma$ are Lipschitz continuous and if $\nabla \sigma$ is bounded then the NILS exponent is locally negative (condition (ii) in Proposition 3.4) as soon as*

$$\sup_{x \in \mathbb{R}^d} \sup_{|u|_S=1} \left(u^* (SJ_b(x) + J_b^*(x)S) u + \left\| (\nabla \sigma(x)|u) \right\|_S^2 - 2 \left| (\nabla \sigma^*(x)Su|u) \right|^2 \right) < 0$$

where, for every $v = (v^1, \dots, v^d) \in \mathbb{R}^d$, $(\nabla \sigma(x)|v) = \left[(\nabla \sigma_{ij}(x)|v) \right]_{1 \leq i, j \leq d}$ and $\nabla \sigma(x)v = \left[\sum_{k=1}^d \frac{\partial \sigma_{ij}}{\partial x_k}(x) v^k \right]_{1 \leq i, j \leq d}$. When $S = I_d$, this may also be written

$$\sup_{x \in \mathbb{R}^d} \sup_{|u|=1} u^* \left(J_b(x) + J_b^*(x) + \sum_{1 \leq i, j \leq d} (\nabla \sigma_{ij}(x))^{\otimes 2} - 2 \left[(\nabla \sigma_{ij}(x)|u) \right] \left[(\nabla \sigma_{ij}^*(x)|u) \right] \right) u < 0.$$

We leave the computational details to the reader.

3.4.2 The case $\lambda_S \leq 0$

The previous results require the NILS exponent to be (strictly) negative (at least near the diagonal). When the invariant distribution ν of (SDE) is unique and not degenerated, some results can be obtained when the NILS exponent is only non-positive and negative outside of a compact set.

PROPOSITION 3.5. *Assume $[b]_{S,+} < +\infty$, σ is Lipschitz continuous and (SDE) has a unique invariant distribution ν whose support is not compact. Then, uniqueness for ν_Δ holds true as soon as*

$$\forall x, y \in \mathbb{R}^d, \lambda_S(x, y) \leq 0 \text{ and } \exists R > 0 \text{ s.t. } \max(|x|_S, |y|_S) > R \implies \lambda_S(x, y) < 0. \quad (3.15)$$

Proof. Let μ be an extremal (hence ergodic) distribution μ for the duplicated system such that $\mu(\Delta_{\mathbb{R}^d}) = 1$ like in the proof of Step 2 of Theorem 3.2. Following this proof with $\theta = 1$ (so that $\varphi(x_1, x_2) = \log(|x_1 - x_2|^2)$), we still have by the ergodic theorem that

$$\mathbb{P}_{\mu\text{-a.s.}} \quad \frac{1}{t} \log |X_t^{x_1} - X_t^{x_2}|^2 \longrightarrow c_\mu := \int_{\mathbb{R}^{2d}} \lambda_S(x_1, x_2) \mu(dx_1, dx_2).$$

If $c_\mu < 0$ then both components are pathwise confluent, which implies following the proof of the theorem, that $\mu(\Delta_{\mathbb{R}^{2d}}) = 1$. Consequently $c_\mu = 0$ and then $\mu(\{\lambda_S = 0\}) = 1$

since λ_S is non-positive. Which in turn implies that μ is compactly supported owing to the assumption made on the NLS exponent. On the other hand ν being unique, both marginals of μ are equal to ν . Hence the contradiction since the support of ν is not compact. \square

REMARK 3.5. • In the particular case where σ is constant, Condition (3.15) becomes a monotony condition on b (decrease with respect to $(\cdot)_S$ at infinity), namely:

$$\begin{aligned} & \forall x, y \in \mathbb{R}^d, x \neq y \quad (b(x) - b(y)|x - y)_S \leq 0, \\ \text{and} \quad & \exists R > 0 \text{ s.t. } \max(|x|_S, |y|_S) > R \implies (b(x) - b(y)|x - y)_S < 0. \end{aligned}$$

This means that b is S -non-increasing on \mathbb{R}^d , S -decreasing outside $B_{|\cdot|_S}(0; R)^2$. For instance, if $b = -\nabla U$, the above assumption holds if U is convex and (only) strictly convex outside of a compact set.

- Note that when ∇U is only increasing outside $B_{|\cdot|_S}(0; R)$ but possibly with no specific monotony on $B_{|\cdot|_S}(0; R)$, it is still possible to find some diffusion coefficients σ such that the SDE $dX_t = -\nabla U(X_t)dt + \sigma(X_t)dW_t$ remains weakly or pathwise confluent. We refer to the next subsection for models with such *stochastically stabilizing* diffusive components.
- Finally, note that the above condition (3.15) can be also localized around the diagonal under the directional S -ellipticity assumption. To be more precise, when ν is unique and its support is not compact, Proposition 3.5 still holds if Assumption (ii) is “localized” into:

$$(ii)_{loc} \equiv \text{for every } x, y \in \mathbb{R}^d \text{ such that } 0 < |x - y| \leq \varepsilon_0, \lambda_S(x, y) \leq 0.$$

3.4.3 Local criterion on compact sets

As mentioned before, the diffusion is asymptotically $(S, 0)$ -confluent (*i.e.* (S, θ) -confluent in the sense of Theorem 3.2 with $\theta \equiv 0$), if there exists $S \in \mathcal{S}^{++}(d, \mathbb{R})$ such that (3.13) holds. One asset of this more stringent assumption is that it can be localized in two ways: first in the neighbourhood of the diagonal like in the above local criterions, but also on compact sets of \mathbb{R}^{2d} . This naturally leads to a criterion based on the differentials of b and σ when they exist.

PROPOSITION 3.6 (Criterion on compact sets). (a) Let $S \in \mathcal{S}^{++}(d, \mathbb{R})$ such that for every $R > 0$, there exists $\delta_R > 0$ such that $\forall x, y \in B_{|\cdot|_S}(0; R)$,

$$0 < |x - y|_S \leq \delta_R \implies (b(x) - b(y)|x - y)_S + \frac{1}{2}\|\sigma(x) - \sigma(y)\|_S^2 < 0. \quad (3.16)$$

Then the diffusion is asymptotically $(S, 0)$ -confluent.

(b) If b and σ are continuously differentiable, then (3.16) holds as soon as

$$(AC)^{diff} \equiv \forall x \in \mathbb{R}^d, \quad SJ_b(x) + J_b^*(x)S + \sqrt{S} \sum_{i,j} (\nabla \sigma_{ij}(x))^{\otimes 2} \sqrt{S} < 0 \text{ in } \mathcal{S}(d, \mathbb{R}).$$

Proof. (a) Let $x, y \in \mathbb{R}^d$ such that $x \neq y$. Set $R = \max(|x|_S, |y|_S)$ and

$$x_0 = x, \quad x_i = x + \frac{i}{N}(y - x), \quad i = 1, \dots, N - 1, \quad x_N = y$$

where $|y - x|_S < N\delta_R$. Then for every $i \in \{1, \dots, N\}$, $|x_i|_S \leq R$ and $|x_i - x_{i-1}|_S \leq \delta_R$. Then

$$\begin{aligned} \|\sigma(x) - \sigma(y)\|_S^2 &= \left\| \sum_{i=1}^N \sigma(x_i) - \sigma(x_{i-1}) \right\|_S^2 \leq N \sum_{i=1}^N \|\sigma(x_i) - \sigma(x_{i-1})\|_S^2 \\ &< -2N \sum_{i=1}^N (b(x_i) - b(x_{i-1}))|x_i - x_{i-1}|_S = -2 \sum_{i=1}^N (b(x_i) - b(x_{i-1}))|y - x|_S \\ &< -2(b(y) - b(x))|y - x|_S. \end{aligned}$$

(b) First, we prove the result when $S = I_d$. We note that, for every continuously differentiable function $g : \mathbb{R}^d \rightarrow \mathbb{R}$, $g(y) - g(x) = \int_0^1 (\nabla g(x + t(y - x))|y - x)dt = \int_0^1 (y - x)^* \nabla g(x + t(y - x))dt$ so that

$$(b(y) - b(x))|y - x| = \int_0^1 (y - x)^* J_b(x + t(y - x))(y - x)dt = \int_0^1 (y - x)^* J_b^*(x + t(y - x))(y - x)dt$$

and

$$\|\sigma(y) - \sigma(x)\|^2 = \sum_{i,j=1}^d \left(\int_0^1 (\nabla \sigma_{ij}(x + t(y - x))|y - x)dt \right)^2.$$

By Schwarz's Inequality and the fact that $(u|v)^2 = u^* v^{\otimes 2} u$, we deduce

$$\begin{aligned} (b(y) - b(x))|y - x| + \frac{1}{2}\|\sigma(y) - \sigma(x)\|^2 &\leq \frac{1}{2} \int_0^1 \left((y - x)^* (J_b + J_b^*)(x + t(y - x))(y - x) \right. \\ &\quad \left. + \frac{1}{2} \sum_{ij} (y - x)^* (\nabla \sigma_{ij}(x + t(y - x)))^{\otimes 2} (y - x) \right) dt. \end{aligned}$$

This completes the proof when $S = I_d$. This extends to general matrix $S \in \mathcal{S}^{++}(d, \mathbb{R})$ using that $\|\sigma(y) - \sigma(x)\|_S^2 = \|(\sqrt{S}\sigma)(y) - (\sqrt{S}\sigma)(x)\|^2$ and the fact that $(Au)^{\otimes 2} = Au^{\otimes 2}A^*$ with $A = \sqrt{S}$. \square

3.5 Examples

3.5.1 An example of confluent diffusion with increasing drift

Assume that $\sigma : \mathbb{R}^d \rightarrow \mathcal{M}(d, d, \mathbb{R})$ is defined by $\sigma(x) = x \otimes \lambda + \sigma^0$ where $\sigma^0 \in \mathcal{M}(d, d, \mathbb{R})$ and $\lambda : \mathbb{R}^d \rightarrow \mathbb{R}^d$ is a bounded Lipschitz function (such that σ is Lipschitz too). If there exists $\rho \in (0, \frac{1}{2})$ such that

$$\limsup_{|x| \rightarrow +\infty} \frac{(b(x)|x) - \rho|x|^2|\lambda(x)|^2}{(1 + |x|^2)^{\rho + \frac{1}{2}}} = -\infty \quad (3.17)$$

then the diffusion (1.1) has at least one invariant distribution ν . Thus, if

$$[b]_+^0 = \sup_{x \neq 0} \frac{(b(x) - b(0))|x|}{|x|^2} \neq +\infty,$$

the above condition is satisfied as soon as

$$\liminf_{|x| \rightarrow +\infty} |\lambda(x)|^2 > 2[b]_+^0.$$

The key is to introduce the Lyapunov function $V(x) = (a + |x|^2)^{\rho + \frac{1}{2}}$. Using that $\|(\sigma - \sigma^0)(x)\|^2 = |(\sigma - \sigma^0)^*(x)\frac{x}{|x|}|^2 = |\lambda(x)|^2|x|^2$, we deduce that

$$\frac{1}{2}\|\sigma(x)\|^2 - \left(\rho + \frac{1}{2}\right)\left|\sigma^*(x)\frac{x}{|x|}\right|^2 = -\rho|\lambda(x)|^2|x|^2 + O(1)$$

and it follows that $\limsup_{|x| \rightarrow +\infty} \mathcal{A}V(x) = -\infty$ if (3.17) is fulfilled (where \mathcal{A} denotes the infinitesimal generator of (1.1)).

If the function λ is constant, the diffusion is asymptotically pathwise confluent (so that ν is unique for (1.1) and the duplicated system has ν_Δ as unique invariant distribution) as soon as there exists $\varepsilon_0 > 0$ satisfying

$$|x - y| \leq \varepsilon_0 \implies (b(x) - b(y))|x - y| - \frac{1}{2}|\lambda|^2|x - y|^2 < 0. \quad (3.18)$$

This is a consequence of Proposition 3.4 applied with $S = I_d$ (the directional ellipticity assumption (i) is clearly true since $|(\sigma^*(x) - \sigma^*(y))(x - y)| = |\lambda||x - y|^2$). If b is smooth this condition is satisfied as soon as, for every $x \in \mathbb{R}^d$, $\frac{1}{2}(J_b + J_b^*)(x) < \frac{1}{2}|\lambda|^2 I_d$ in $\mathcal{S}(d, \mathbb{R})$ ($J_b(x)$ denotes the Jacobian matrix of b).

3.5.2 Baxendale's model

Let $\Xi_t = (X_t, Y_t)$ be the unique strong solution to the 2-dimensional SDE

$$\begin{aligned} dX_t &= \left(a - \frac{\sigma^2}{2}\right)X_t dt - (\sigma Y_t - \theta_x) dW_t \\ dY_t &= \left(b - \frac{\sigma^2}{2}\right)Y_t dt + (\sigma X_t + \theta_y) dW_t \end{aligned}$$

where W is scalar standard Brownian motion, a, b, σ are real numbers satisfying

$$ab < 0, \quad a + b < 0, \quad \sigma > \sqrt{\frac{2ab}{a+b}}.$$

and $\theta_x, \theta_y \in \mathbb{R}$. When $\theta_x = \theta_y = 0$, this system is known as Baxendale's system (see e.g. [KP92]). Its stochastic stability has been extensively investigated in connection with its Lyapunov exponent. Then set

$$\lambda = \lambda(\sigma) = \frac{b - a + \sqrt{(b - a)^2 + \sigma^4}}{\sigma^2} \in (0, 1) \quad \text{and} \quad \alpha = \sigma^2 - (a + b) - \sqrt{(a - b)^2 + \sigma^4} > 0.$$

and $|\cdot|_\lambda = |\cdot|_S$ with $S = \text{Diag}(1, \lambda)$. Itô's Lemma implies

$$d|\Xi_t|_\lambda^2 = \left(-\alpha|\Xi_t|_\lambda^2 + \theta_x(\theta_x - 2\sigma Y_t) + \lambda\theta_y(\theta_y + 2\sigma X_t)\right)dt + \Theta(\Xi_t)dW_t$$

where $\Theta(x, y) = 2((\lambda - 1)\sigma xy + \lambda\theta_y x + \theta_x y)$. It is clear that there exists $\beta \in \mathbb{R}_+$ such that

$$|\theta_x(\theta_x - 2\sigma y) + \lambda\theta_y(\theta_y + 2\sigma x)| \leq \beta|(x, y)|_\lambda.$$

Then using that $|\xi|_\lambda \leq \frac{1}{2\alpha} + \frac{\alpha}{2}|\xi|_\lambda^2$ and setting $\beta' = \beta + \frac{1}{2\alpha}$, we derive that

$$d|\Xi_t|_\lambda^2 \leq \beta' - \frac{\alpha}{2}|\Xi_t|_\lambda^2 dt + \Theta(\Xi_t)dW_t$$

where $\theta(\xi) \leq C|\xi|_\lambda$. Hence, the function $V(\xi) = |\xi|_\lambda^2$ is a Lyapunov function for the system since $AV \leq \beta' - \frac{\alpha}{2}V$. As a consequence there exists at least one invariant distribution ν for the system and any such distribution satisfies $\nu(V) \leq 2\frac{\beta'}{\alpha}$.

At this stage we can compute the non-infinitesimal S -Lyapunov exponent of the duplicated system. Tedious although elementary computations show that, for every $\xi = (x, y)$, $\xi' = (x', y') \in \mathbb{R}^2$,

$$\lambda_S(\xi, \xi') = -\frac{\alpha}{2} - (\lambda - 1)^2 \sigma^2 \frac{(x - x')^2 (y - y')^2}{|\xi - \xi'|_\lambda^4} < 0.$$

4 Application to the Richardson-Romberg extrapolation for the approximation of invariant distributions

As an application, we investigate in this section the Richardson-Romberg (RR) extrapolation for the approximation of invariant measures. Roughly speaking, the aim of a RR method is generally to improve the order of convergence of an algorithm based on an discretization scheme by cancelling the first order error term induced by the time discretization of the underlying process. However, to be efficient, such a method must be implemented with a control of its variance. We will see that in this context, this control is strongly linked to the uniqueness of the invariant distribution of the duplicated diffusion.

4.1 Setting and Background

4.1.1 Recursive computation of the invariant distribution of a diffusion: the original procedure

Following [LP02] and a series of papers cited in the introduction, we consider here a sequence of empirical measures $(\nu_n^\eta(\omega, dx))_{n \geq 1}$ built as follows: let $(\gamma_n)_{n \geq 1}$ denote a non-increasing sequence of positive *step parameters* satisfying

$$\gamma_n \xrightarrow{n \rightarrow +\infty} 0 \quad \text{and} \quad \Gamma_n = \sum_{k=1}^n \gamma_k \xrightarrow{n \rightarrow +\infty} +\infty.$$

We denote by $(\bar{X}_n)_{n \geq 0}$ the Euler scheme with step sequence $(\gamma_n)_{n \geq 1}$ defined by $\bar{X}_0 = x \in \mathbb{R}^d$ and

$$\bar{X}_{n+1} = \bar{X}_n + \gamma_{n+1} b(\bar{X}_n) + \sqrt{\gamma_{n+1}} \sigma(\bar{X}_n) U_{n+1}$$

where $(U_n)_{n \geq 1}$ is a sequence of i.i.d. centered \mathbb{R}^q -valued random vectors such that $\Sigma_{U_1} = I_q$ defined on a probability space $(\Omega, \mathcal{A}, \mathbb{P})$. The sequence of *weighted empirical measures* $(\nu_n^\eta(\omega, dx))_{n \geq 1}$ is then defined for every $n \geq 1$, by

$$\nu_n^\eta(\omega, f) = \frac{1}{H_n} \sum_{k=1}^n \eta_k \delta_{\bar{X}_{k-1}(\omega)}$$

where δ_a denotes the Dirac mass at $a \in \mathbb{R}^d$ and $(\eta_k)_{k \geq 1}$ is a sequence of positive weights such that $H_n = \sum_{k=1}^n \eta_k \xrightarrow{n \rightarrow +\infty} +\infty$. When $\eta_k = \gamma_k$ which corresponds to the genuine case, we will only write $\nu_n(\omega, dx)$ instead of $\nu_n^\eta(\omega, dx)$. For this sequence, we recall in Proposition 4.7 below in a synthesized form the main convergence results (including rates) of the sequence $(\nu_n^\eta(\omega, dx))$ to the invariant distribution ν of (X_t) . In this way, we introduce

two assumptions:

(**S_a**) : ($a > 0$) There exists a positive \mathcal{C}^2 -function $V : \mathbb{R}^d \rightarrow \mathbb{R}$ with

$$\lim_{|x| \rightarrow +\infty} V(x) = +\infty, \quad |\nabla V|^2 \leq CV, \quad \text{and} \quad \sup_{x \in \mathbb{R}^d} \|D^2V(x)\| < +\infty$$

such that there exist some positive constants C_b , β and α such that:

$$(i) \quad |b|^2 \leq C_b V^a, \quad \text{Tr}(\sigma\sigma^*)(x) = o(V^a(x)) \quad \text{as } |x| \rightarrow +\infty \quad (ii) \quad (\nabla V|b) \leq \beta - \alpha V^a.$$

This Lyapunov-type assumption is sufficient to ensure the long-time stability of the Euler scheme (in a sense made precise below) as soon as $a \in (0, 1]$. Note that the convergence can be obtained under a less restrictive mean-reverting assumption including the case $a = 0$ (see [Pan06]). The second assumption below is fundamental to establish the rate of convergence of $(\nu_n^\eta(\omega, f))$ to $\nu(f)$ for a fixed smooth enough function $f : \mathbb{R}^d \rightarrow \mathbb{R}$: we assume that f has a smooth solution to the Poisson equation (see [PV01] for results on this topic).

(**C(f, k)**): There exists a \mathcal{C}^k -function $g : \mathbb{R}^d \rightarrow \mathbb{R}$ solution to $f - \nu(f) = \mathcal{A}g$ such that f , g and its partial derivatives up to k are dominated by V^r ($r \geq 0$): $|f| \leq CV^r$ and for every $\alpha = (\alpha_1, \dots, \alpha_d) \in \mathbb{N}^d$ with $|\alpha| := \alpha_1 + \dots + \alpha_d \in \{0, \dots, k\}$, $|\partial_{x_1^{\alpha_1}, \dots, x_d^{\alpha_d}} g| \leq CV^r$.

Before recalling the results on $(\nu_n(\omega, dx))$, let us introduce further notations. We set

$$\forall r \in \mathbb{N}, \quad \Gamma_n^{(r)} = \sum_{k=1}^n \gamma_k^r$$

and for a smooth enough function $h : \mathbb{R}^d \rightarrow \mathbb{R}$ and an integer $r \geq 2$, we write:

$$D^{(r)}h(x) y_1 \otimes \dots \otimes y_r = \sum_{(i_1, \dots, i_r) \in \{1, \dots, d\}^r} \partial_{x_{i_1}, \dots, x_{i_r}}^r h(x) y_1^{i_1} \dots y_r^{i_r}.$$

PROPOSITION 4.7. *Assume (**S_a**) holds for an $a \in (0, 1]$ and $U_1 \in \cap_{p>0} L^p(\mathbb{P})$. Assume that (η_k/γ_k) is a non-increasing sequence. Then,*

(i) *For every non-increasing sequence $(\theta_n)_{n \geq 1}$ such that $\sum_{n \geq 1} \theta_n \gamma_n < +\infty$ and for every $r > 0$, $\sum_{n \geq 1} \theta_n \gamma_n \mathbb{E}[V^r(\bar{X}_n)] < +\infty$.*

(ii) *For every $r > 0$, $\sup_{n \geq 1} \nu_n^\eta(\omega, V^r) < +\infty$ a.s. In particular, $(\nu_n^\eta(\omega, dx))_{n \geq 1}$ is a.s. tight.*

(iii) *Every weak limit of $(\nu_n^\eta(\omega, dx))_{n \geq 1}$ is an invariant distribution for $(X_t)_{t \geq 0}$. Furthermore, if (SDE) has a unique invariant distribution, say ν , then $\nu_n^\eta(\omega, f) \xrightarrow{n \rightarrow +\infty} \nu(f)$ a.s. for every ν -a.s continuous function f such that $|f| \leq CV^r$ for an $r > 0$.*

(iv) *(Rate of convergence when $\eta_k = \gamma_k$): Assume that ν is unique and that $\mathbb{E}[U_1^{\otimes 3}] = 0$. Let $k \geq 1$ such that $f : \mathbb{R}^d \rightarrow \mathbb{R}$ satisfies (**C(f, k)**). Then,*

• *If $k = 4$ and $\frac{\Gamma_n^{(2)}}{\sqrt{\Gamma_n}} \xrightarrow{n \rightarrow +\infty} 0$,*

$$\sqrt{\Gamma_n} (\nu_n(\omega, f) - \nu(f)) \xrightarrow{(\mathbb{R})} \mathcal{N}\left(0; \int |\sigma^* \nabla g|^2 d\nu\right) \quad \text{as } n \rightarrow +\infty.$$

• *If $k = 5$ and $\frac{\Gamma_n^{(2)}}{\sqrt{\Gamma_n}} \xrightarrow{n \rightarrow +\infty} \tilde{\beta} \in (0, +\infty]$,*

$$\triangleright \sqrt{\Gamma_n} (\nu_n(\omega, f) - \nu(f)) \xrightarrow{(\mathbb{R})} \mathcal{N}\left(\tilde{\beta} m_g^{(1)}; \int |\sigma^* \nabla g|^2 d\nu\right) \quad \text{as } n \rightarrow +\infty \quad \text{if } \tilde{\beta} \in (0, +\infty),$$

$$\triangleright \frac{\Gamma_n}{\Gamma_n^{(2)}} (\nu_n(\omega, f) - \nu(f)) \xrightarrow{a.s.} m_g^{(1)} \quad \text{as } n \rightarrow +\infty \quad \text{if } \tilde{\beta} = +\infty$$

where $m_g^{(1)} = \int_{\mathbb{R}^d} \varphi_1 d\nu$ with

$$\varphi_1(x) = \frac{1}{2}D^2g(x)b(x)^{\otimes 2} + \frac{1}{2}\mathbb{E}[D^3g(x)b(x)(\sigma(x)U_1)^{\otimes 2}] + \frac{1}{24}\mathbb{E}[D^4g(x)(\sigma(x)U_1)^{\otimes 4}]. \quad (4.19)$$

The first three claims part (i), (ii) and (iii) of the theorem follow from [LP03] whereas the (iv) is derived from [LP02] (see Theorem 10) and [Lem05] (see Theorem V.3), in which the rate of convergence is established for a wide family of weights (η_k) .

Applying (iv) to polynomial steps of the following form: $\gamma_n = Cn^{-\mu}$, $\mu \in (0, 1]$, we observe that the optimal (weak) rate is $n^{-1/3}$ and is attained for $\mu = 1/3$. Then

$$\tilde{\beta} = \sqrt{6}C^{\frac{3}{2}} \quad \text{and} \quad \sqrt{\Gamma_n} \sim \sqrt{3C/2}n^{\frac{1}{3}}.$$

so that

$$n^{\frac{1}{3}}\left(\nu_n(\omega, f) - \nu(f)\right) \xrightarrow{(\mathbb{R})} \mathcal{N}\left(2C m_g^{(1)}; \frac{2}{3C} \int |\sigma^* \nabla g|^2 d\nu\right).$$

This corresponds to the case where the rate of convergence of the underlying diffusion toward its steady regime ($\sqrt{\Gamma_n}$ corresponding to \sqrt{t} in the continuous time setting, see [Bha82] for the CLT for the diffusion itself) and the discretization error are of the same order. From a practical point of view it seems clear that a balance should be made between the asymptotic bias and the asymptotic variance to specify the constant C . Under slightly more stringent assumptions we prove that the L^2 -norm of the error $\nu_n(\omega, f) - \nu(f)$ satisfies

$$\|\nu_n(\omega, f) - \nu(f)\|_{L^2} \sim n^{-\frac{1}{3}} \sqrt{4C^2(m_g^{(1)})^2 + \frac{2}{3C} \int |\sigma^* \nabla g|^2 d\nu}.$$

An optimisation with respect to C gives the optimal choice $C = \left(\frac{12 \int_{\mathbb{R}^d} |\sigma^* \nabla g|^2 d\nu}{(m_g^{(1)})^2}\right)^{\frac{1}{3}}$.

When $\mu \in (0, 1/3)$, the step sequence decreases too slowly and the error induced by the time discretization error becomes prominent. That is why we propose below to use an RR extrapolation in order to cancel the first-order term in the time discretization error: in practice this amount to killing the bias $m_g^{(1)}$ in order to extend the range of application of the rate $\sqrt{\Gamma_n}$ (which corresponds to the standard weak rate \sqrt{t} in Bhattacharia's *CLT*) to "slower steps".

4.1.2 The Richardson-Romberg extrapolated algorithm

As mentioned before, the starting idea is to introduce a second Euler scheme with step sequence $(\tilde{\gamma}_n)_{n \geq 1}$ defined by

$$\forall n \geq 1, \quad \tilde{\gamma}_{2(n-1)} = \tilde{\gamma}_{2n} = \frac{\gamma_n}{2}.$$

As concerns the white noise of both schemes, our aim is to make them consistent in absolute time and correlated (with correlation matrix ρ satisfying $I_q - \rho^* \rho \in \mathcal{S}^+(d, \mathbb{R})$). To achieve that we proceed as follows.

Let $(Z_n)_{n \geq 1}$ be a sequence of *i.i.d.* \mathbb{R}^q -valued random vectors lying in $\cap_{p>0} L^p(\mathbb{P})$ and satisfying

$$\mathbb{E} Z_1 = 0, \quad \Sigma_{Z_1} = I_q, \quad \mathbb{E}[Z_1^{\otimes 3}] = \mathbb{E}[Z_1^{\otimes 5}] = 0.$$

Then we devise from this sequence the white noise sequence $(U_n)_{n \geq 1}$ of the ‘‘original’’ Euler scheme with step $(\gamma_n)_{n \geq 1}$ by setting

$$\forall n \geq 1, \quad U_n = \frac{1}{\sqrt{2}} (Z_{2n-1} + Z_{2n}). \quad (4.20)$$

The white noise sequence for the second Euler scheme (with step $(\tilde{\gamma}_n)_{n \geq 1}$), denoted $Z^{(\rho)}$ is defined as follows:

$$Z_n^{(\rho)} = \rho^* Z_n + T(\rho) V_n, \quad n \geq 1, \quad (4.21)$$

where $(V_n)_{n \geq 1}$ is also a sequence of *i.i.d.* centered random variables in \mathbb{R}^q with moments of any order satisfying $\Sigma_{V_1} = I_q$ and $\mathbb{E}[V_1^{\otimes 3}] = \mathbb{E}[V_1^{\otimes 5}] = 0$, *independent* of $(Z_n)_{n \geq 1}$ and $T_q(\rho)$ is a solution to the equation

$$T_q(\rho) T_q(\rho)^* = I_q - \rho^* \rho \in \mathcal{S}^+(d, \mathbb{R}).$$

($T_q(\rho)$ can be chosen either as the commuting symmetric square root of $I_q - \rho^* \rho$ or its Choleski transform). Note that $(Z_n^{(\rho)})_{n \geq 1}$ is built in so that it satisfies

$$\Sigma_{Z_n^{(\rho)}} = I_q \quad \text{and} \quad \text{Cov}(Z_n, Z_n^{(\rho)}) = \rho.$$

Then the Euler scheme with step $\tilde{\gamma}_n$ and consistent ρ -correlated white noise $(Z_n^{(\rho)})_{n \geq 1}$, denoted $(\bar{Y}_n^{(\rho)})_{n \geq 1}$ from now on, is defined by:

$$\bar{Y}_{n+1}^{(\rho)} = \bar{Y}_n^{(\rho)} + \tilde{\gamma}_n b(\bar{Y}_n^{(\rho)}) + \sqrt{\tilde{\gamma}_n} \sigma(\bar{Y}_n^{(\rho)}) Z_{n+1}^{(\rho)}, \quad n \geq 1, \quad \bar{Y}_0 = y.$$

Also note that $(\bar{X}_n, \bar{Y}_{2n}^{(\rho)})$ is an Euler scheme at time Γ_n of the duplicated diffusion $(X_t, X_t^{(\rho)})_{t \geq 0}$.

For numerical purpose, one usually specifies the independent *i.i.d.* sequences $(Z_n)_{n \geq 1}$ and $(V_n)_{n \geq 1}$ as normally distributed so that they can be considered as the normalized increments of two independent Brownian motions W and \tilde{W} *i.e.*

$$Z_n = \frac{W_{\tilde{\Gamma}_n} - W_{\tilde{\Gamma}_{n-1}}}{\sqrt{\tilde{\gamma}_n}} \quad \text{and} \quad V_n = \frac{\tilde{W}_{\tilde{\Gamma}_n} - \tilde{W}_{\tilde{\Gamma}_{n-1}}}{\sqrt{\tilde{\gamma}_n}}, \quad n \geq 1.$$

Note that in this case, (U_n) is also a sequence of $\mathcal{N}(0, I_q)$ -random variables. This implies in particular that

$$\mathbb{E}[U_1^{\otimes 4}] = \mathbb{E}[Z_1^{\otimes 4}] \quad \text{and} \quad \mathbb{E}[U_1^{\otimes 6}] = \mathbb{E}[Z_1^{\otimes 6}]. \quad (4.22)$$

Since these properties simplify the result, we will assume them in the sequel of this section (see Remark 4.6 for extensions).

We denote $(\nu_n^{\eta, (\rho)}(\omega, dx))_{n \geq 1}$ the sequence of empirical measures related to $(\bar{Y}_n^{(\rho)}(\omega))_{n \geq 1}$ (in which the weights are adapted accordingly: $\eta_1/2, \eta_1/2, \eta_2/2, \eta_2/2, \eta_3/2, \dots$). The empirical measure $(\bar{\nu}_n^{\eta, (\rho)}(\omega, dx))_{n \geq 1}$ associated to the Richardson-Romberg extrapolation is defined by

$$\begin{aligned} \nu_n^{\eta, (\rho)}(\omega, f) &= \frac{1}{H_n} \sum_{k=1}^n \frac{\eta_k}{2} \left(f(\bar{Y}_{2(k-1)}^{(\rho)}(\omega)) + f(\bar{Y}_{2k-1}^{(\rho)}(\omega)) \right) \\ \bar{\nu}_n^{\eta, (\rho)}(\omega, f) &= (2\nu_n^{\eta, (\rho)} - \nu_n^{\eta}(\omega, f)) \\ &= \frac{1}{H_n} \sum_{k=1}^n \eta_k \left(f(\bar{Y}_{2(k-1)}^{(\rho)}(\omega)) + f(\bar{Y}_{2k-1}^{(\rho)}(\omega)) - f(\bar{X}_k(\omega)) \right). \end{aligned}$$

Under the assumptions of Proposition 4.7, it is clear that $\bar{\nu}_n^{\eta,(\rho)}(\omega, dx) \xrightarrow{n \rightarrow +\infty} \nu(dx)$ a.s..

Thus, in the next section, we propose to evaluate the effects of the Richardson-Romberg extrapolation on the rate of convergence of the procedure and to explain why the uniqueness of the invariant distribution of the duplicated diffusion plays an important role in this problem.

4.2 Rate of convergence of the extrapolated procedure

Throughout this section we assume that $\eta_k = \gamma_k$ and so we will write $\nu_n, \nu_n^{(\rho)}$ and $\bar{\nu}_n^{(\rho)}$ instead of $\nu_n^\eta, \nu_n^{\eta,(\rho)}$ and $\bar{\nu}_n^{\eta,(\rho)}$ respectively. We also set $(D^3 g_{i,\dots})_{i=1}^d = D^2(\nabla \cdot)g$ in order that the notation $\text{Tr}(\sigma^* D^2(\nabla \cdot)g\sigma)$ stands for the vector of \mathbb{R}^d defined by $\text{Tr}(\sigma^* D^2(\nabla \cdot)g\sigma) = (\text{Tr}(\sigma^* D^2(\partial_{x_i}g)\sigma))_{i=1}^d$. For a fixed matrix ρ , the main result about the RR extrapolation is Theorem 4.3 below. At this stage, we do not discuss the choice of the correlation ρ in this result. This point is tackled in Proposition 4.8 in which we will see that the optimal choice to reduce the asymptotic variance is attained with $\rho = I_q$ as soon as ν_Δ is the unique invariant distribution of the associated duplicated diffusion. This emphasizes the importance of the question of the uniqueness of the invariant distribution in this pathologic case studied in the previous part of the paper.

THEOREM 4.3. *Assume (\mathbf{S}_a) holds for an $a \in (0, 1]$. Assume that $(X_t, X_t^{(\rho)})_{t \geq 0}$ admits a unique invariant distribution $\mu^{(\rho)}$ (with marginals ν). Let $f : \mathbb{R}^d \rightarrow \mathbb{R}$ be a function satisfying $(\mathbf{C}(\mathbf{f}, \mathbf{7}))$ and such that φ_1 defined by (4.19) satisfies $(\mathbf{C}(\varphi_1, \mathbf{5}))$ with a solution to the Poisson equation denoted by g_{φ_1} . Then,*

- If $\frac{\Gamma_n^{(3)}}{\sqrt{\Gamma_n}} \xrightarrow{n \rightarrow +\infty} 0$,

$$\sqrt{\Gamma_n} \left(\nu_n^{(\rho)}(\omega, f) - \nu(f) \right) \xrightarrow{n \rightarrow +\infty} \mathcal{N}(0; \hat{\sigma}_\rho^2)$$

where

$$\hat{\sigma}_\rho^2 = 5 \int_{\mathbb{R}^d} |\sigma^* \nabla g|^2 d\nu - 4 \int_{\mathbb{R}^{2d}} ((\sigma^* \nabla g)(x) | \rho (\sigma^* \nabla g)(y)) \mu^{(\rho)}(dx, dy). \quad (4.23)$$

- If $\frac{\Gamma_n^{(3)}}{\sqrt{\Gamma_n}} \xrightarrow{n \rightarrow +\infty} \tilde{\beta} \in (0, +\infty]$, then

$$\begin{aligned} \sqrt{\Gamma_n} (\nu_n^{(\rho)}(\omega, f) - \nu(f)) &\xrightarrow{(\mathbb{R})} \mathcal{N}(\tilde{\beta} m_g^{(2)}; \hat{\sigma}_\rho^2) \quad \text{as } n \rightarrow +\infty && \text{if } \tilde{\beta} \in (0, +\infty), \\ \frac{\Gamma_n}{\Gamma_n^{(3)}} (\nu_n^{(\rho)}(\omega, f) - \nu(f)) &\xrightarrow{\mathbb{P}} m_g^{(2)} \quad \text{as } n \rightarrow +\infty && \text{if } \tilde{\beta} = +\infty, \end{aligned}$$

where $m_g^{(2)} = \frac{1}{2} \left(m_{g_{\varphi_1}} + \int_{\mathbb{R}^d} \varphi_2 d\nu \right)$ with

$$\varphi_2(x) = \sum_{k=3}^6 \frac{C_k^{2(k-3)}}{k!} \mathbb{E} [D^k g(x) b(x)^{\otimes(6-k)} (\sigma(x) U_1)^{\otimes 2(k-3)}]. \quad (4.24)$$

REMARK 4.6. \triangleright We recall that the result is stated under the assumption that the increments are normally distributed or more precisely under Assumption (4.22). When this additional assumption fails (think for instance to $Z_1 \sim (\frac{1}{2}(\delta_{-1} + \delta_1))^{\otimes q}$), the result is remains true except for the value of $m_g^{(2)}$ which becomes more complicated since it also depends on $\mathbb{E}[Z_1^{\otimes \ell}]$, $\ell = 4$ and 6).

▷ This result extends readily to general weights sequences $(\eta_n)_{n \geq 1}$. Some technical conditions appear on the choice of weights but these conditions are natural and not restrictive (see [Lem05]). In particular we can always consider the choice $\eta_n = 1$ for which we obtain the following result: if $\frac{\Gamma_n^{(2)}}{\sqrt{\Gamma_n^{(-1)}}} \xrightarrow{n \rightarrow +\infty} \tilde{\beta} \in (0, +\infty)$, then

$$\frac{n}{\sqrt{\Gamma_n^{(-1)}}} (\nu_n^{(\rho)}(\omega, f) - \nu(f)) \xrightarrow{(\mathbb{R})} \mathcal{N}(\tilde{\beta} m_g^{(2)}; \hat{\sigma}_\rho^2) \text{ as } n \rightarrow +\infty.$$

▷ POLYNOMIAL STEPS. Let $\gamma_n = Cn^{-\mu}$, $\mu \in (0, 1]$. If $\mu > \frac{1}{3}$, $\Gamma_n^{(3)} \rightarrow \Gamma_\infty^{(3)} < +\infty$ so that $\frac{\Gamma_n^{(3)}}{\sqrt{\Gamma_n}} \rightarrow 0$ as $n \rightarrow +\infty$. If $\mu < \frac{1}{3}$, $\frac{\Gamma_n^{(3)}}{\sqrt{\Gamma_n}} \asymp n^{\frac{1-5\mu}{2}}$ (and if $\mu = \frac{1}{3}$, $\frac{\Gamma_n^{(3)}}{\sqrt{\Gamma_n}} \asymp \frac{\log n}{\sqrt{n}}$). Consequently

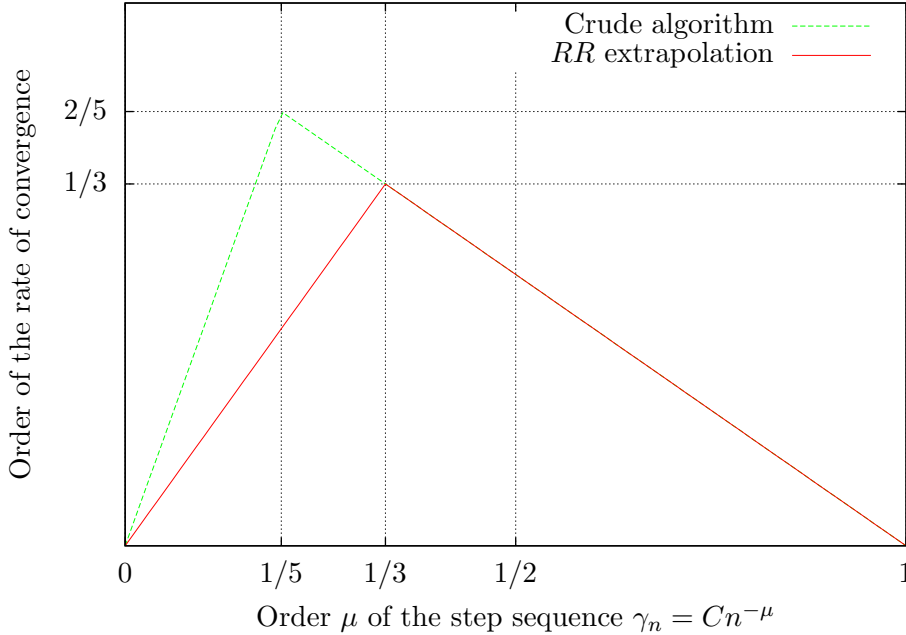
$$\frac{\Gamma_n^{(3)}}{\sqrt{\Gamma_n}} \rightarrow 0 \iff \mu > \frac{1}{5}, \quad \frac{\Gamma_n^{(3)}}{\sqrt{\Gamma_n}} \rightarrow +\infty \iff \mu < \frac{1}{5} \quad \text{and} \quad \frac{\Gamma_n^{(3)}}{\sqrt{\Gamma_n}} \rightarrow \tilde{\beta} \in (0, +\infty) \iff \mu = \frac{1}{5}.$$

When $\mu = \frac{1}{5}$, $\tilde{\beta} = C^{\frac{5}{2}} \sqrt{5}$ and $\sqrt{\Gamma_n} \sim \frac{\sqrt{5}C}{2} n^{\frac{2}{5}}$.

As a consequence, if $\gamma_n = \eta_n = Cn^{-\frac{1}{5}}$,

$$n^{\frac{2}{5}} (\nu_n^{(\rho)}(\omega, f) - \nu(f)) \xrightarrow{(\mathbb{R})} \mathcal{N}\left(2C^2 m_g^{(2)}; \frac{4}{5} \frac{\hat{\sigma}_\rho^2}{C}\right).$$

We switch from a weak rate $n^{\frac{1}{3}}$ to $n^{\frac{2}{5}}$ i.e. a “gain” of $n^{\frac{1}{15}}$ (see figure below). The second noticeable fact is that the bias is now significantly more sensitive to the constant C than in the standard setting. If we minimize the L^2 -norm of the error $\nu_n^{(\rho)}(\omega, f) - \nu(f)$ we obtain the optimal choice of C as a function of both bias and standard deviation, precisely $C = \left(\frac{\hat{\sigma}_\rho^2}{20(m_q^{(2)})^2}\right)^{\frac{1}{5}}$.



4.2.1 Optimal choice of ρ and uniqueness of $\mu^{(I_d)}$

PROPOSITION 4.8. *Let ρ be an admissible correlation matrix i.e. such that $\rho^*\rho \leq I_q$. Assume that the duplicated diffusion $(X, X^{(\rho)})$ has a unique invariant distribution $\mu^{(\rho)}$ (so that if $\rho = I_q$, $\mu^{(I_q)} = \nu_\Delta$).*

$$(a) \hat{\sigma}_\rho^2 \geq \int_{\mathbb{R}^d} |\sigma^* \nabla g|^2 d\nu.$$

$$(b) \text{ If } \rho = 0 \text{ then } \hat{\sigma}_\rho^2 = 5 \int_{\mathbb{R}^d} |\sigma^* \nabla g|^2 d\nu.$$

$$(c) \text{ If } \rho = I_q, \hat{\sigma}_\rho^2 = \int_{\mathbb{R}^d} |\sigma^* \nabla g|^2 d\nu.$$

Proof. Claims (b) and (c) being obvious thanks to (4.23), we only prove (a). Keeping in mind that both marginals $\mu^{(\rho)}(\mathbb{R}^d \times dy)$ and $\mu^{(\rho)}(dx \times \mathbb{R}^d)$ are equal to ν , one derives thanks to Schwarz's Inequality (once on \mathbb{R}^d and once on $L^2(\mu)$) from the expression (4.23) of the asymptotic variance $\hat{\sigma}_\rho^2$ that

$$\begin{aligned} \hat{\sigma}_\rho^2 &\geq 5 \int_{\mathbb{R}^d} |\sigma^* \nabla g|^2 d\nu - 4 \left[\int_{\mathbb{R}^{2d}} |\sigma^* \nabla g|^2(x) \mu^{(\rho)}(dx, dy) \right]^{\frac{1}{2}} \left[\int_{\mathbb{R}^{2d}} |\rho \sigma^* \nabla g|^2(y) \mu^{(\rho)}(dx, dy) \right]^{\frac{1}{2}} \\ &= 5 \int_{\mathbb{R}^d} |\sigma^* \nabla g|^2 d\nu - 4 \left[\int_{\mathbb{R}^d} |\sigma^* \nabla g|^2(x) \nu(dx) \right]^{\frac{1}{2}} \left[\int_{\mathbb{R}^d} |\rho \sigma^* \nabla g|^2(y) \nu(dy) \right]^{\frac{1}{2}} \\ &\geq 5 \int_{\mathbb{R}^d} |\sigma^* \nabla g|^2 d\nu - 4 \int_{\mathbb{R}^d} |\sigma^* \nabla g|^2 d\nu = \int_{\mathbb{R}^d} |\sigma^* \nabla g|^2 d\nu \end{aligned}$$

where we used in the last inequality that $|\rho u|^2 \leq |u|^2$.

The previous result says that the structural asymptotic variance of the RR estimator is always greater than that of the standard estimator but can be equal if the Brownian motions are equal. This condition is in fact almost necessary. Actually, thanks to the Pythagorean identity,

$$\begin{aligned} \sigma_\rho^2 &= 5 \int_{\mathbb{R}^d} |\sigma^* \nabla g|^2 d\nu + 2 \int_{\mathbb{R}^{2d}} |\sigma^* \nabla g(x) - \rho \sigma^* \nabla g(y)|^2 \mu^{(\rho)}(dx, dy) \\ &\quad - 2 \int_{\mathbb{R}^{2d}} |\sigma^* \nabla g(x)|^2 \nu(dx) - 2 \int_{\mathbb{R}^{2d}} |\rho \sigma^* \nabla g(y)|^2 \nu(dy). \end{aligned}$$

Then, since $\rho^*\rho \leq I_q$, a necessary condition to obtain $\sigma_\rho^2 = \int_{\mathbb{R}^d} |\sigma^* \nabla g|^2 d\nu$ is

$$|\rho \sigma^* \nabla g(y)| = |\sigma^* \nabla g(y)| \quad \nu(dy)\text{-a.e.}$$

When $\rho^*\rho < I_q$, this equality can not hold except if $\sigma^* \nabla g(y) = 0 \quad \nu(dy)\text{-a.e.}$

4.3 Proof of Theorem 4.3

4.3.1 Preliminaries

Without loss of generality, we assume that f satisfies $\nu(f) = 0$ so that $f = \mathcal{A}g$ under $(\mathbf{C}(f, \mathbf{k}))$. We denote by $\gamma^{(r)}$ the sequence defined by $\gamma_k^{(r)} = \gamma_k^r$.

LEMMA 4.1. Assume that f satisfies $(\mathbf{C}(\mathbf{f}, \mathbf{7}))$ and denote by g the solution to the Poisson equation $Ag = f$. Then,

$$\Gamma_n \bar{\nu}_n^{(\rho)}(\omega, f) = 2(g(\bar{Y}_{2n}) - g(\bar{Y}_0)) - (g(\bar{X}_n) - g(\bar{X}_0)) - \sum_{k=1}^n \sqrt{\gamma_k} (\sqrt{2} \Delta M_k^{(2)} - \Delta M_k^{(1)}) \quad (4.25)$$

$$- \mathcal{E}_n^1 - \mathcal{E}_n^2 + N_n + R_n \quad (4.26)$$

where

$$\begin{aligned} \Delta M_k^{(1)} &= (\nabla g(\bar{X}_{k-1}) | \sigma(\bar{X}_{k-1}) U_k), \\ \Delta M_k^{(2)} &= (\nabla g(\bar{Y}_{2(k-1)}) | \sigma(\bar{Y}_{2(k-1)}) Z_{2k-1}) + (\nabla g(\bar{Y}_{2k-1}) | \sigma(\bar{Y}_{2k-1}) Z_{2k}), \\ \mathcal{E}_n^1 &= 2 \sum_{k=1}^n \left(\frac{\gamma_k}{2} \right)^2 (\varphi_1(\bar{Y}_{2(k-1)}) + \mathbb{E}[\varphi_1(\bar{Y}_{2k-1}) | \mathcal{F}_{k-1}]) - \sum_{k=1}^n \gamma_k^2 \varphi_1(\bar{X}_{k-1}), \\ \mathcal{E}_n^2 &= 2 \sum_{k=1}^n \left(\frac{\gamma_k}{2} \right)^3 (\varphi_2(\bar{Y}_{2(k-1)}) + \mathbb{E}[\varphi_2(\bar{Y}_{2k-1}) | \mathcal{F}_{k-1}]) - \sum_{k=1}^n \gamma_k^3 \varphi_2(\bar{X}_{k-1}) \end{aligned}$$

with φ_1 and φ_2 defined by (4.19) and (4.24),

(N_n) is defined by

$$N_n = \sum_{k=1}^n 2 \left(\Delta N(\bar{Y}_{2(k-1)}, Z_{2k-1}, \frac{\gamma_k}{2}) + \Delta N(\bar{Y}_{2k-1}, Z_{2k}, \frac{\gamma_k}{2}) \right) - \Delta N(\bar{X}_{k-1}, Z_{2k-1}, \frac{\gamma_k}{2})$$

where $\Delta N(x, U, \gamma) = H(x, U, \gamma) - \mathbb{E}_x[H(x, U, \gamma)]$ and

$$\begin{aligned} H(x, U, \gamma) &= \frac{\gamma}{2} D^2 g(x) (\sigma(x) U)^{\otimes 2} + \frac{1}{6} \sum_{\ell=0}^2 C_3^{3-\ell} \gamma^{\frac{\ell+3}{2}} D^3 g(x) b(x)^{\otimes \ell} (\sigma(x) U)^{\otimes (3-\ell)} \\ &+ \frac{1}{24} \sum_{\ell=0}^1 \gamma^{\frac{\ell+4}{2}} C_4^{4-\ell} D^4 g(x) b(x)^{\otimes \ell} (\sigma(x) U)^{\otimes (4-\ell)} + \gamma^3 \sum_{\ell=4}^6 \frac{C_\ell^{6-\ell}}{\ell!} D^\ell g(x) b(x)^{\otimes (6-\ell)} (\sigma(x) U)^{\otimes \frac{\ell}{2}}. \end{aligned}$$

Finally, if (\mathbf{S}_a) holds, the sequence $(R_n)_{n \geq 1}$ satisfies the following property: there exists $r > 0$ such that, a.s., for every $n \geq 1$,

$$\mathbb{E}[|\Delta R_n| | \mathcal{F}_{n-1}] \leq C \gamma_n^{\frac{7}{2}} (V^r(\bar{X}_{n-1}) + V^r(\bar{Y}_{2(n-1)}) + V^r(\bar{Y}_{2n-1})) \quad (4.27)$$

where $\Delta R_n = R_n - R_{n-1}$.

REMARK 4.7. The above decomposition is built as follows: the second term of (4.25) is the main martingale component of the decomposition whereas $\mathcal{E}_{n,1}$ contains the first order discretization error. Thanks to the Richardson-Romberg extrapolation, $\mathcal{E}_{n,1}$ is in fact negligible when $n \rightarrow +\infty$. When the step sequence decreases fast (Theorem 4.3(i)), the rate of convergence is ruled by the main martingale component. In Theorem 4.3(ii), the rate is ruled by $\mathcal{E}_{n,1}$ and $\mathcal{E}_{n,2}$. Finally, N_n contains all the negligible martingale terms.

Proof. Owing to $(\mathbf{C}(\mathbf{f}, \mathbf{7}))$, to the Taylor formula and to the fact that $\mathbb{E}[D^2(x)(\sigma(x)U_1)^{\otimes 2}] = \text{Tr}(\sigma^*(x)D^2g(x)\sigma(x))$, we have

$$g(\bar{X}_k) = g(\bar{X}_{k-1}) + \gamma_k \mathcal{A}g(\bar{X}_{k-1}) + \sqrt{\gamma_k} \Delta M_{k,1} \quad (4.28)$$

$$+ \frac{1}{2} (D^2(\bar{X}_{k-1})(\sigma(\bar{X}_{k-1})U_k)^{\otimes 2} - \mathbb{E}[D^2(\bar{X}_{k-1})(\sigma(\bar{X}_{k-1})U_k)^{\otimes 2} | \mathcal{F}_{k-1}]) \quad (4.29)$$

$$+ \sum_{l=3}^5 D^l g(\bar{X}_{k-1}) (\gamma_k b(\bar{X}_{k-1}) + \sqrt{\gamma_k} \sigma(\bar{X}_{k-1}) U_k)^{\otimes l} \quad (4.30)$$

$$+ D^7 g(\xi_k) (\gamma_k b(\bar{X}_{k-1}) + \sqrt{\gamma_k} \sigma(\bar{X}_{k-1}) U_k)^{\otimes 7} \quad (4.31)$$

where $\xi_k \in [\bar{X}_{k-1}, \bar{X}_k]$. The fact that $|\nabla V|^2 \leq CV$ implies that \sqrt{V} is a Lipschitz continuous function with Lipschitz constant denoted by $[\sqrt{V}]_{\text{Lip}}$. Then, setting $\|D^7 g(x)\| = \sup_{|\alpha|=7} |\partial_\alpha g(x)|$ and using Assumption $(\mathbf{C}(\mathbf{f}, \mathbf{7}))$, we have

$$\|D^7 g(\xi_k)\| \leq C(\sqrt{V}(\xi_k))^{2r} \leq C(\sqrt{V}(\bar{X}_{k-1}) + [\sqrt{V}]_{\text{Lip}} |\Delta \bar{X}_k|)^{2r} \quad (4.32)$$

where $\Delta \bar{X}_k = \gamma_k b(\bar{X}_{k-1}) + \sqrt{\gamma_k} \sigma(\bar{X}_{k-1}) U_k$. Then, owing to the elementary inequality $|a + b|^p \leq c_p(|a|^p + |b|^p)$ and to Assumption (\mathbf{S}_a) , it follows that there exists $r > 0$ such that

$$\mathbb{E}[|\Delta R_n| | \mathcal{F}_{k-1}] \leq C \gamma_k^{\frac{7}{2}} V^r(\bar{X}_{k-1}).$$

Then we plug this control into the above Taylor expansion and to compensate the terms of (4.30) when necessary. An appropriate (tedious) grouping of the terms yields:

$$\begin{aligned} \gamma_k \mathcal{A}g(\bar{X}_{k-1}) &= g(\bar{X}_k) - g(\bar{X}_{k-1}) - \sqrt{\gamma_k} \Delta M_{k,1} \\ &\quad - \gamma_k^2 \varphi_1(\bar{X}_{k-1}) - \gamma_k^3 \varphi_2(\bar{X}_{k-1}) - \Delta N(\bar{X}_{k-1}, U_k, \gamma_k) - \Delta R_n \end{aligned}$$

where $R_{n,2}$ satisfies (4.27). Making the same development for $\mathcal{A}g(\bar{Y}_{2(k-1)})$ and for $\mathcal{A}g(\bar{Y}_{2k-1})$ and summing over n yield the announced result. \square

LEMMA 4.2. *Let $a \in (0, 1]$ such that (\mathbf{S}_a) holds. Assume that $(X_t, X_t^{(\rho)})_{t \geq 0}$ admits a unique invariant distribution $\mu^{(\rho)}$. Let g be a C^1 -function such that $|\nabla g| \leq CV^r$ where $r \in \mathbb{R}_+$. Then,*

$$\frac{1}{\sqrt{\Gamma_n}} \sum_{k=1}^n \sqrt{\gamma_k} (\sqrt{2} \Delta M_k^{(2)} - \Delta M_k^{(1)}) \xrightarrow{n \rightarrow +\infty} \hat{\sigma}_\rho^2.$$

Proof. Let $\{\xi_{k,n}, k = 1, \dots, n, n \geq 1\}$ be the triangular array of (\mathcal{F}_k) -martingale increments defined by

$$\xi_{k,n} = \sqrt{\frac{\gamma_k}{\Gamma_n}} (\sqrt{2} \Delta M_k^{(2)} - \Delta M_k^{(1)}).$$

Let us show that

$$\sum_{k=1}^n \mathbb{E}[|\xi_{k,n}|^2 | \mathcal{F}_{k-1}] \xrightarrow{n \rightarrow +\infty} \hat{\sigma}_\rho^2.$$

First, using that $\Sigma_{U_1} = I_q$, we obtain that for every $k \geq 1$,

$$\mathbb{E}[|\Delta M_k^{(1)}|^2 | \mathcal{F}_{k-1}] = |\sigma^* \nabla g(\bar{X}_{k-1})|^2.$$

Since $x \mapsto |\sigma^* \nabla g|^2(x)$ is a continuous function such that $|\sigma^* \nabla g|^2 \leq CV^r$ for a positive r , it follows from Proposition (4.7) that

$$\frac{1}{\Gamma^n} \sum_{k=1}^n \gamma_k \mathbb{E}[|\Delta M_k^{(1)}|^2 | \mathcal{F}_{k-1}] \xrightarrow{n \rightarrow +\infty} \int |\sigma^* \nabla g|^2(x) \nu(dx). \quad (4.33)$$

Similarly,

$$\mathbb{E}[|\Delta M_k^{(2)}|^2 | \mathcal{F}_{k-1}] = |\sigma^* \nabla g(\bar{Y}_{2(k-1)})|^2 + \mathbb{E}[|\sigma^* \nabla g(\bar{Y}_{2k-1})|^2 | \mathcal{F}_{k-1}].$$

It follows that

$$\frac{1}{\Gamma^n} \sum_{k=1}^n \gamma_k \mathbb{E}[|\Delta M_k^{(2)}|^2 | \mathcal{F}_{k-1}] = 2\nu^{(\rho)}(\omega, |\sigma^* \nabla g|^2) - \frac{1}{\Gamma^n} \sum_{k=1}^n \zeta_k \quad (4.34)$$

where (ζ_k) is a sequence of (\mathcal{F}_k) -martingale increments defined by

$$\zeta_k = \gamma_k (|\sigma^* \nabla g(\bar{Y}_{2k-1})|^2 - \mathbb{E}[|\sigma^* \nabla g(\bar{Y}_{2k-1})|^2 | \mathcal{F}_{k-1}]).$$

Using that $|\sigma^* \nabla g|^2 \leq CV^r$ for a positive real number r , we obtain by similar arguments to those used in (4.32) that $\mathbb{E}[|\zeta_k|^2 | \mathcal{F}_{k-1}] \leq CV^{2r}(\bar{Y}_{2(k-1)})$. We derive from Proposition 4.7(i) applied with $\theta_k = \frac{1}{\Gamma_k^2}$ that

$$\sum_{k=1}^{+\infty} \mathbb{E}\left[\left|\frac{\zeta_k}{\Gamma_k}\right|^2 \middle| \mathcal{F}_{k-1}\right] \leq C\gamma_1 \sum_{k=1}^{+\infty} \frac{\gamma_k}{\Gamma_k^2} V^{2r}(\bar{Y}_{2(k-1)}) < +\infty$$

since

$$\sum_{k \geq 1} \frac{\gamma_k}{\Gamma_k^2} \leq 1 + \sum_{k=2}^{+\infty} \int_{\Gamma_{k-1}}^{\Gamma_k} \frac{ds}{s^2} \leq 1 + \int_{\Gamma_1}^{+\infty} \frac{ds}{s^2} < +\infty.$$

As a consequence $(\sum_{k=1}^n \frac{\zeta_k}{\Gamma_k})_{n \geq 1}$ is a convergent martingale and the Kronecker Lemma then implies that $\frac{1}{\Gamma^n} \sum_{k=1}^n \zeta_k \xrightarrow{n \rightarrow +\infty} 0$ a.s. Thus, we deduce from (4.34) combined with Proposition 4.7 that

$$\frac{1}{\Gamma^n} \sum_{k=1}^n \gamma_k \mathbb{E}[|\Delta M_k^{(2)}|^2 | \mathcal{F}_{k-1}] \xrightarrow{n \rightarrow +\infty} 2\nu(|\sigma^* \nabla g|^2) \quad a.s. \quad (4.35)$$

Finally, we have to manage the cross-product: keeping in mind the construction of the noises of the Euler schemes (see (4.20) and (4.21)), we have:

$$\begin{aligned} \sqrt{2} \mathbb{E}[\Delta M_k^{(1)} \Delta M_{k,2} | \mathcal{F}_{k-1}] &= ((\sigma^* \nabla g)(\bar{X}_{k-1}) | \rho(\sigma^* \nabla g)(\bar{Y}_{2(k-1)})) \\ &+ ((\sigma^* \nabla g)(\bar{X}_{k-1}) | \rho(\sigma^* \nabla g)(\bar{Y}_{2k-1})) - \gamma_k^{-1} \zeta_k^{(2)} \end{aligned}$$

where

$$\zeta_k^{(2)} = \gamma_k (((\sigma^* \nabla g)(\bar{X}_{k-1}) | \rho(\sigma^* \nabla g)(\bar{Y}_{2k-1})) - \mathbb{E}[(\sigma^* \nabla g)(\bar{X}_{k-1}) | \rho(\sigma^* \nabla g)(\bar{Y}_{2k-1}) | \mathcal{F}_{k-1}])$$

so that

$$\frac{1}{\Gamma^n} \sum_{k=1}^n \sqrt{2} \mathbb{E}[\Delta M_k^{(1)} \Delta M_{k,2} | \mathcal{F}_{k-1}] = \mu_n^{(1)}(\psi) + \mu_n^{(2)}(\psi) - \frac{1}{\Gamma^n} \sum_{k=1}^n \zeta_k^{(2)} \quad (4.36)$$

where $\psi : \mathbb{R}^{2d} \rightarrow \mathbb{R}$ is defined by $\psi(x, y) = (\sigma^* \nabla g(x) | \rho(\sigma^* \nabla g)(y))$ and for every Borel function $f : \mathbb{R}^{2d} \rightarrow \mathbb{R}$,

$$\mu_n^{(1)}(f) = \frac{1}{\Gamma_n} \sum_{k=1}^n \gamma_k f(\bar{X}_{k-1}, \bar{Y}_{2(k-1)}) \quad \text{and} \quad \mu_n^{(2)}(f) = \frac{1}{\Gamma_n} \sum_{k=1}^n \gamma_k f(\bar{X}_{k-1}, \bar{Y}_{2k-1}).$$

By straightforward adaptations of the proof of Proposition 4.7, we can show that if $(X_t, X_t^{(\rho)})$ has a unique invariant distribution $\mu^{(\rho)}$ then, for every continuous function f such that $f \leq CV^r$ with $r > 0$,

$$\mu_n^{(i)}(\omega, f) \xrightarrow{n \rightarrow +\infty} \mu^{(\rho)}(f) \quad a.s. \quad \text{with } i = 1, 2.$$

As a consequence, $\mu_n^{(1)}(\psi) + \mu_n^{(2)}(\psi) \xrightarrow{n \rightarrow +\infty} 2\mu(\psi)$ a.s. Finally, by martingale arguments similar to those used for (ζ_k) , one checks that $\Gamma_n^{-1} \sum_{k=1}^n \zeta_k^{(2)} \xrightarrow{n \rightarrow +\infty} 0$ a.s. Thus, by (4.33), (4.35) and (4.36), we obtain that

$$\sum_{k=1}^n \mathbb{E}[|\xi_{k,n}|^2 | \mathcal{F}_{k-1}] \xrightarrow{n \rightarrow +\infty} 5\nu(|\sigma^* \nabla g|^2) - 4\mu(\psi) = \hat{\sigma}_\rho^2.$$

Then, the result follows from the CLT for arrays of martingale increments provided that a Lindeberg-type condition is satisfied (see [HH80], Corollary 3.1). To be precise, it is enough to prove that there exists $\delta > 0$ such that

$$\sum_{k=1}^n \mathbb{E}[|\xi_{k,n}|^{2+\delta} | \mathcal{F}_{k-1}] \xrightarrow{n \rightarrow +\infty} 0 \quad a.s. \quad (4.37)$$

Using Assumption **(S_a)** and the fact $|\nabla g| \leq CV^r$ ($r > 0$), one can check that there exists $r > 0$ such that

$$\mathbb{E}[|\xi_{k,n}|^{2+\delta} | \mathcal{F}_{k-1}] \leq C \frac{\gamma_k^{1+\delta}}{\Gamma_n^{1+\delta}} (V^r(\bar{X}_{k-1}) + V^r(\bar{Y}_{2k-1}) + V^r(\bar{Y}_{2(k-1)})).$$

Thus,

$$\sum_{k=1}^n \mathbb{E}[|\xi_{k,n}|^{2+\delta} | \mathcal{F}_{k-1}] \leq C \frac{\Gamma_n^{(1+\delta)}}{\Gamma_n^{1+\delta}} \left(\nu_n^{\gamma^{(1+\delta)}}(V^r) + \nu_n^{\gamma^{(1+\delta)}, (\rho)}(V^r) \right).$$

Checking easily that $\frac{\Gamma_n^{(1+\delta)}}{\Gamma_n^{1+\delta}} \xrightarrow{n \rightarrow +\infty} 0$, (4.37) follows from Proposition 4.7(ii). \square

LEMMA 4.3. *Let $a \in (0, 1]$ such that **(S_a)** holds. Assume that (X_t) admits a unique invariant distribution ν . Assume **(C(f, k))** and that $\Gamma_n^{(3)} \xrightarrow{n \rightarrow +\infty} +\infty$. Then,*

(i) *If φ_1 defined by (4.19) satisfies **(C(φ₁, 5))** then,*

$$\frac{1}{\Gamma_n^{(3)}} \mathcal{E}_{n,1} \xrightarrow{\rightarrow +\infty} -\frac{1}{2} m_{g_{\varphi_1}}^{(1)} \quad a.s.$$

(ii) *If the derivatives of g up to order 6 are continuous and dominated by V^r (with $r > 0$),*

$$\frac{1}{\Gamma_n^{(3)}} \mathcal{E}_{n,2} \xrightarrow{\rightarrow +\infty} -\frac{1}{2} \nu(\varphi_2) \quad a.s.$$

Proof. (i) Writing

$$2 \sum_{k=1}^n \left(\frac{\gamma_k}{2}\right)^2 (\varphi_1(\bar{Y}_{2(k-1)}) + \mathbb{E}[\varphi_1(\bar{Y}_{2k-1})|\mathcal{F}_{k-1}]) = \sum_{k=1}^n \frac{\gamma_k^2}{2} (\varphi_1(\bar{Y}_{2(k-1)}) + \varphi_1(\bar{Y}_{2k-1})) + \sum_{k=1}^n \frac{\gamma_k^2}{2} \Delta T_k$$

with ΔT_k being a martingale increment defined by $\Delta T_k = \mathbb{E}[\varphi_1(\bar{Y}_{2k-1})|\mathcal{F}_{k-1}] - \varphi_1(\bar{Y}_{2k-1})$, one obtains that

$$\mathcal{E}_{n,1} = \Gamma_n^{(2)} \left[(\nu_n^{\gamma^{(2)},(\rho)} - \nu)(\varphi_1) - (\nu_n^{\gamma^{(2)}} - \nu)(\varphi_1) \right] + \sum_{k=1}^n \frac{\gamma_k^2}{2} \Delta T_k.$$

Applying Theorem V.3 of [Lem05] (which is an extension of Proposition 4.7(iv) to general weights) with $\eta_k = \gamma_k^2$ and $q^* = 4$, we obtain that

$$\frac{\Gamma_n^{(2)}}{\Gamma_n^{(3)}} (\nu_n^{\gamma^{(2)}} - \nu)(\varphi_1) \xrightarrow{n \rightarrow +\infty} m_{g_{\varphi_1}} \in \mathbb{R} \quad \text{in probability.}$$

Similarly, applying this result to the Euler scheme with half-step, we have:

$$\frac{\Gamma_n^{(2)}}{\Gamma_n^{(3)}} [(\nu_n^{\gamma^{(2)},(\rho)} - \nu)(\varphi_1)] = \frac{1}{2} \frac{\Gamma_n^{(2)}}{\sum_{k=1}^n \gamma_k^2 \cdot \frac{\gamma_k}{2}} [(\nu_n^{\gamma^{(2)},(\rho)} - \nu)(\varphi_1)] \xrightarrow{n \rightarrow +\infty} \frac{1}{2} m_{g_{\varphi_1}} \in \mathbb{R} \quad \text{in probability.}$$

Thus, it remains to show that the martingale term is negligible. We set $\theta_k = \frac{\gamma_k^3}{\Gamma_k^{(3)^2}}$. Using that (γ_k) is non-increasing, one checks that (θ_n) is non-increasing and that $\sum \theta_k \gamma_k < +\infty$. Since $|\varphi_1| \leq CV^r$ with $r > 0$, it follows from Proposition 4.7 that

$$\sum_{k \geq 1} \frac{\gamma_k^4}{(\Gamma_k^{(3)})^2} \mathbb{E}[|\varphi_1|^2(\bar{Y}_{2k-1})] < +\infty.$$

This implies that the martingale $\sum \frac{\gamma_k^2}{\Gamma_k^{(3)}} \Delta T_k$ is *a.s.* convergent so that the Kronecker lemma yields $\frac{1}{\Gamma_n^{(3)}} \sum_{k=1}^n \gamma_k^2 \Delta T_k \xrightarrow{n \rightarrow +\infty} 0$ *a.s.*. The first assertion follows.

(ii) Remark that

$$\mathcal{E}_{n,2} = \frac{1}{2} \nu_n^{\gamma^{(3)},(\rho)} - \nu_n^{\gamma^{(3)}}(\omega, \varphi_2) + \sum_{k=1}^n \frac{\gamma_k^3}{4} T_k.$$

Under the assumptions, φ_2 is continuous and dominated by V^r with a positive r . Then, since $\Gamma_n^{(3)} \xrightarrow{n \rightarrow +\infty} +\infty$, $(\nu_n^{\gamma^{(3)},(\rho)}(\varphi_2))_{n \geq 1}$ and $(\nu_n^{\gamma^{(3)}}(\omega, \varphi_2))_{n \geq 1}$ converge to $\nu(\varphi_2)$. With some similar arguments as previously, one checks that the martingale term is negligible and the second assertion follows. \square

4.3.2 Proof of Theorem 4.3

For the sake of simplicity, we choose to give the proof of Theorem 4.3 only when $\Gamma_n^{(3)} \xrightarrow{n \rightarrow +\infty} +\infty$. Note that if $\gamma_n = Cn^{-\mu}$, this corresponds to $\mu \leq 1/3$, *i.e.* the case where the Romberg extrapolation really increases the rate of convergence (see Remark 4.6).

By the decomposition of Lemma 4.1 and the convergences established in Lemmas 4.2 and 4.3, one checks that it is now enough to prove the following points:

$$\frac{\Theta_n}{\Gamma_n} (2(g(\bar{Y}_{2n}) - g(\bar{Y}_0)) - (g(\bar{X}_n) - \bar{X}_0)) \xrightarrow{\mathbb{P}} 0 \quad \text{as } n \rightarrow +\infty, \quad (4.38)$$

$$\frac{\Theta_n}{\Gamma_n} N_n \xrightarrow{\mathbb{P}} 0 \quad \text{and} \quad \frac{\Theta_n}{\Gamma_n} R_n \xrightarrow{\mathbb{P}} 0 \quad \text{as } n \rightarrow +\infty \quad (4.39)$$

with $\Theta_n = \sqrt{\Gamma_n} \vee \frac{\Gamma_n}{\Gamma_n^{(3)}}$.

For (4.38), the result is obvious when g is bounded. Otherwise, we use Lemma 3 of [LP03] which implies in particular that for every $p > 0$, $\mathbb{E}[V^p(\bar{X}_n)] \leq C_p \Gamma_n$. By Jensen's inequality, this implies that for every $r > 0$ and $\alpha \in (0, 1]$, there exists a constant $C > 0$ such that

$$\forall n \geq 1, \quad \mathbb{E}[V^r(\bar{X}_n)] \leq (\mathbb{E}[V^{\frac{r}{\alpha}}(\bar{X}_n)])^\alpha \leq C \frac{\alpha}{r} \Gamma_n^\alpha.$$

Thus, since the same property holds for the (\bar{Y}_n) and since $|g| \leq CV^r$ with $r > 0$, (4.39) follows taking $\alpha \in (0, 1/2)$.

For the first assertion of (4.39), we use a martingale argument. We denote by $\{\pi_{k,n}, k = 1, \dots, n, n \geq 1\}$ the triangular array of (\mathcal{F}_k) -martingale increments defined by

$$\pi_{k,n} = \frac{\Delta N_k}{\sqrt{\Gamma_n}}.$$

Then, in order to prove the convergence in probability of $(N_n/\sqrt{\Gamma_n})$ to 0, we use the CLT for martingale increments which says that, since a Lindeberg-type condition holds (we do not prove this point, see Proof of Lemma 4.2 for a similar argument), it is enough to show that

$$\sum_{k=1}^n \mathbb{E}[|\pi_{k,n}|^2 | \mathcal{F}_{k-1}] \xrightarrow{n \rightarrow +\infty} 0 \quad a.s. \quad (4.40)$$

Under the assumptions on g and on the coefficients, one checks that there exists $r > 0$ such that

$$\sum_{k=1}^n \mathbb{E}[|\pi_{k,n}|^2 | \mathcal{F}_{k-1}] \leq C \frac{1}{\Gamma_n} \sum_{k=1}^n \gamma_k^2 (V^r(\bar{X}_{k-1}) + V^r(\bar{Y}_{2(k-1)}) + V^r(\bar{Y}_{2k-1})).$$

By Proposition 4.7, $\sup_{n \geq 1} (\nu_n(\omega, V^r) + \nu_n^{(\rho)}(\omega, V^r)) < +\infty$. Assertion (4.40) follows.

As concerns R_n , it follows from a martingale argument that

$$\frac{1}{\Gamma_n^{(3)}} \sum_{k=1}^n (\Delta R_k - \mathbb{E}[\Delta R_k | \mathcal{F}_{k-1}]) \xrightarrow{\mathbb{P}} 0 \quad \text{as } n \rightarrow +\infty.$$

Now, since $\sup_{n \geq 1} (\nu_n^{\gamma^3}(\omega, V^r) + \nu_n^{\gamma^3, (\rho)}(\omega, V^r)) < +\infty$ *a.s.* and since $\gamma_n \xrightarrow{n \rightarrow +\infty} 0$, we deduce that

$$\frac{1}{\Gamma_n^{(3)}} \sum_{k=1}^n \mathbb{E}[\Delta R_k | \mathcal{F}_{k-1}] \xrightarrow{\mathbb{P}} 0.$$

The last assertion follows.

A Hypo-ellipticity of the correlated duplicated system

It is a well-known fact that, for a Markov process, the strong Feller property combined with some irreducibility of the transitions implies uniqueness of the invariant distribution (see *e.g.* [DPZ96], Theorem 4.2.1). For a diffusion process with smooth coefficients, such properties hold if it satisfies the hypoelliptic Hörmander assumption (see [Hör67, Hör85]) and if the deterministic system related to the stochastic differential system (written in the Stratanovich sense) is controllable. In fact, both properties can be transferred from the original *SDE* to the duplicated system so that its invariant distribution is also unique. The main result of this section is Proposition A.9. Before, we need to introduce some Hörmander-type notations. First, written in a Stratanovich way, X is a solution to

$$dX_t = A_0(X_t)dt + \sum_{j=1}^q A_j(X_t) \circ dW_t^j \quad (\text{A.41})$$

where A_0, \dots, A_q are vectors fields on \mathbb{R}^d defined by¹:

$$A_0(x) = \sum_{i=1}^d \left[b_i(x) - \frac{1}{2} \sum_{l,j} \sigma_{l,j}(x) \partial_{x_j} \sigma_{i,l}(x) \right] \partial_{x_i}$$

and for every $j \in \{1, \dots, q\}$:

$$A_j(x) = \sum_{i=1}^d \sigma_{i,j}(x) \partial_{x_i}.$$

For the sake of simplicity, we assume that b and σ are C^∞ on \mathbb{R}^d with bounded derivatives. We will also assume the following Hörmander condition at each point: there exists $N \in \mathbb{N}^*$ such that $\forall x \in \mathbb{R}^d$,

$$\dim(\text{Span}\{A_1(x), A_2(x), \dots, A_q(x), \text{L. B. of length} \leq N \text{ of the } A_j(x)\text{'s}, 0 \leq j \leq q\}) = d \quad (\text{A.42})$$

where “L.B.” stands for Lie Brackets. The above assumptions imply that for every $t > 0$ and $x \in \mathbb{R}^d$, $P_t(x, \cdot)$ admits a density $p_t(x, \cdot)$ *w.r.t.* the Lebesgue measure and that $(x, y) \mapsto p_t(x, y)$ is C^∞ on $\mathbb{R}^d \times \mathbb{R}^d$ (see *e.g.* [Cat92], Theorem 2.9). In particular, $x \mapsto P_t(x, \cdot)$ is a strong Feller semi-group. Assume also that the control system (associated with (A.41))

$$\dot{x}^{(u)} = A_0(x^{(u)}) + \sum_{j=1}^q A_j(x^{(u)})u_j, \quad (\text{A.43})$$

is *approximatively*-controllable:

There exists $T > 0$ such that for every $\varepsilon > 0$, $x_1, x_2 \in \mathbb{R}^d$, there exists $u \in L^2([0, T], \mathbb{R}^d)$ such that $(x^{(u)}(t))$ solution to (A.43) satisfies $x(0) = x_1$ and $|x(T) - x_2| \leq \varepsilon$. (A.44)

Under Assumptions (A.42) and (A.44), the diffusion has a unique invariant distribution ν . Actually, the controllability assumption combined with the Support Theorem implies

¹With a standard abuse of notation, we identify the vectors fields and the associated differential operators.

that for every non-empty open set O , for every $x \in \mathbb{R}^d$, $P_T(x, O) > 0$. The semi-group (P_t) is then irreducible. Owing to the strong Feller property, it follows classically that (P_t) admits a unique invariant distribution (see *e.g.* [DPZ96], Proposition 4.1.1. and Theorem 4.2.1.).

Furthermore, ν is absolutely continuous with respect to the Lebesgue measure on \mathbb{R}^d and its topological support is \mathbb{R}^d (since for every open set O of \mathbb{R}^d , $\nu(O) = \int P_T(x, 0)\nu(dx) > 0$). Let us now consider the duplicated diffusion $(X_t, X_t^{(\rho)})$. Setting $Z_t^{(\rho)} = (X_t, X_t^{(\rho)})$ and using the preceding notations, (1.2) can be written:

$$dZ_t^{(\rho)} = \tilde{A}_0(Z_t^{(\rho)})dt + \sum_{j=1}^q \tilde{A}_j(Z_t^{(\rho)})dW_t^j + \sum_{j=1}^q \tilde{A}_{d+j}(Z_t^{(\rho)})d\tilde{W}_t^j$$

where $\tilde{A}_0(z) = (A_0(x), A_0(y))^T$ (with $A_0(y) = \sum_{i=1}^d \left[b_i(y) - \frac{1}{2} \sum_{l,j} \sigma_{l,j}(y) \partial_{y_j} \sigma_{i,l}(y) \right] \partial_{y_i}$ and $z = (x, y)$), \tilde{W} is a d -dimensional Brownian Motion independent of W such that $W^{(\rho)} = \rho^*W + (I_q - \rho^*\rho)^{\frac{1}{2}}\tilde{W}$ and for every $j \in \{1, \dots, q\}$,

$$\tilde{A}_j(z) = A_j(x) + A_j^{(\rho)}(y) \quad \text{and} \quad \tilde{A}_{q+j}(z) = A_j^{((I_q - \rho^*\rho)^{\frac{1}{2}})}(y) \quad (\text{A.45})$$

where for a $q \times q$ matrix B , $A_j^{(B)}(y) = \sum_{i=1}^d (\sigma(y)B)_{i,j} \partial_{y_i}$. Then, the following property holds.

PROPOSITION A.9. *Let $\rho \in \mathbb{M}_{q,q}(\mathbb{R})$ such that $\rho^*\rho < I_q$. Assume that b and σ are C^∞ on \mathbb{R}^d with bounded derivatives. Assume (A.42) and (A.44). Then, uniqueness holds for the invariant distribution $\nu^{(\rho)}$ of the duplicated diffusion $(X_t, X_t^{(\rho)})$. Furthermore, if $\nu^{(\rho)}$ exists, then $\nu^{(\rho)}$ has a density $p^{(\rho)}$ (w.r.t. λ_{2d}) which is a.s. positive.*

Proof. First, let us check the Hörmander conditions for $(X_t, X_t^{(\rho)})_{t \geq 0}$. Setting $S = (I_q - \rho^*\rho)^{\frac{1}{2}}$, standard computations yield

$$\forall j \in \{1, \dots, q\}, \quad \tilde{A}_{q+j}(z) = \sum_{l=1}^q S_{l,j} A_l(y).$$

Since S is invertible, we deduce that $\{A_l(y), l = 1, \dots, q\}$ belongs to $\text{Span}\{\tilde{A}_{q+j}(z), j = 1, \dots, q\}$. Similarly, checking that for every $j \in \{1, \dots, q\}$,

$$[\tilde{A}_0(z), \tilde{A}_{q+j}(z)] = [A_0(y), A_j^{(S)}(y)] = \sum_{l=1}^q S_{l,j} [A_0(y), A_l(y)]$$

one deduces from the invertibility of S that $\{[A_0(y), A_l(y)], l = 1, \dots, q\}$ is included in $\text{Span}\{[\tilde{A}_0(z), \tilde{A}_{q+j}(z)], j = 1, \dots, q\}$. Owing to (A.42), it follows that $\text{Span}\{\partial_{y_1}, \dots, \partial_{y_d}\}$ is included in

$$V = \text{Span} \left\{ \tilde{A}_1(z), \tilde{A}_2(z), \dots, \tilde{A}_q(z), \text{ Lie Brackets of length} \leq N \text{ of the } \tilde{A}_j(z)\text{'s}, 0 \leq j \leq q \right\}.$$

Now, let us show that $\text{Span}\{\partial_{x_1}, \dots, \partial_{x_d}\}$ is included in V . Since $\text{Span}\{\partial_{y_1}, \dots, \partial_{y_d}\}$ is included in V , it is clear that for every $x \in \mathbb{R}^d$, $A_j(x) = A_j^{(\rho)}(y) - \tilde{A}_j(z)$ also belongs to V . Since

$$[\tilde{A}_0(z), \tilde{A}_j(z)] = [A_0(x), A_j(x)] + [A_0(y), A_j^{(\rho)}(y)],$$

$[A_0(x), A_j(x)]$ has the same property. Using again (A.42), we deduce that $\text{Span}\{\partial_{x_1}, \dots, \partial_{x_d}\}$ is included in V and thus that $\dim(V) = 2d$. As a consequence, for every $z \in \mathbb{R}^{2d}$ and $t > 0$, $Q_t^{(\rho)}(z, \cdot)$ admits a density $q_t(z, \cdot)$ w.r.t. λ_{2d} such that $(z, z') \mapsto q_t(z, z')$ is \mathcal{C}^∞ on $\mathbb{R}^{2d} \times \mathbb{R}^{2d}$.

In order to obtain uniqueness for the invariant distribution, it remains to show that there exists $T > 0$ such that for every $z \in \mathbb{R}^{2d}$, for every non-empty open set O of \mathbb{R}^{2d} , $Q_T(z, O) > 0$. Owing to (A.44), it is clear that for every $z_1 = (x_1, y_1)$ and $z_2 = (x_2, y_2)$, for every $\varepsilon > 0$, there exist u and $\tilde{u} \in L^2([0, T], \mathbb{R}^d)$ such that $z(t) = (x^{(u)}(t), x^{(\tilde{u})}(t))$, where $x^{(u)}$ and $x^{(\tilde{u})}$ are solutions to (A.43) starting from x_1 and y_1 , satisfies $|z(T) - z_2| \leq \varepsilon$. Furthermore, since S is invertible, we can assume that $\tilde{u} = \rho u + S\omega$ with $\omega \in L^2([0, T], \mathbb{R}^d)$. Then, the support Theorem can be applied to obtain that for every z_1, z_2, ε $Q_T(z_1, B(z_2, \frac{\varepsilon}{2})) > 0$ and thus to conclude that for every $z \in \mathbb{R}^{2d}$ and every non-empty open set O , $Q_T(z, O) > 0$. \square

B Additional proofs about the two-dimensional counterexample

Proof of (3.5): For the sake of completeness, we show that $r_t \rightarrow 1$ a.s. as soon as $r_0 > 0$. First, note that uniqueness holds for the solution of the SDE (3.3) since the coefficients are Lipschitz continuous. In particular, (r_t^1) defined a.s. by $r_t^1 = 1$ for every $t \geq 0$ is the unique solution starting from $r_0 = 1$. Owing to the strong Markov property, this implies that if $\tau^1 := \inf\{t \geq 0, r_t = 1\}$, then $r_t = 1$ on $\{\tau \leq t\}$. The same property holds at 0. We deduce that $(r_t)_{t \geq 0}$ lives in $[1, +\infty)$ if $r_0 > 1$ and in $[0, 1]$ if $r_0 \in [0, 1]$. Moreover, if $r_0 > 1$, we have $d(r_t - 1) = -(r_t - 1)(dt + \vartheta dW_t)$ so that

$$r_t - 1 = e^{-(1 + \frac{\vartheta^2}{2})t + \vartheta W_t}.$$

It follows that $\lim_{t \rightarrow +\infty} r_t = 1$ since $\lim_{t \rightarrow +\infty} \frac{W_t}{t} = 0$ a.s.. Now, if $r_0 \in [0, 1]$, we have

$$dr_t = r_t(1 - r_t)(dt + \vartheta dW_t).$$

Thus, (r_t) is a $[0, 1]$ -valued submartingale. In particular, r_t converges a.s. to a $[0, 1]$ -valued random variable r_∞ . Since

$$\forall t \geq 0, \quad \mathbb{E}[r_t] = r_0 + \mathbb{E}\left(\int_0^t r_s(1 - r_s)ds\right),$$

it follows that $\mathbb{E}[\int_0^{+\infty} r_s(1 - r_s)ds]$ which in turn implies that $\int_0^{+\infty} r_s(1 - r_s)ds < +\infty$ a.s. As a consequence $\liminf_{t \rightarrow +\infty} r_t(1 - r_t) = 0$ a.s.. The process (r_t) being a.s. convergent to r_∞ , it follows that $r_\infty \in \{0, 1\}$ a.s.. It remains to prove that $\mathbb{P}(r_\infty = 0) = 0$. Denote by p the scale function of (r_t) null at $r = 1/2$. For every $r \in (0, 1)$,

$$p(r) = \int_{\frac{1}{2}}^r e^{-\int_{\frac{1}{2}}^\xi \frac{2}{\vartheta^2 u(1-u)} du} d\xi = \int_{\frac{1}{2}}^r \left(\frac{1-\xi}{\xi}\right)^{\frac{2}{\vartheta^2}} d\xi.$$

As a consequence, if $\vartheta \in (0, \sqrt{2}]$, $\lim_{r \rightarrow +\infty} p(r) = +\infty$. This means that 0 is a repulsive point and that, as a consequence (see e.g. [KT81], Lemma 6.1 p. 228),

$$\forall b \in (0, 1) \quad \mathbb{P}\left(\lim_{a \rightarrow 0^+} \tau_a < \tau_b\right) := \lim_{a \rightarrow 0^+} \mathbb{P}(\tau_a < \tau_b) = 0$$

where $\tau_a = \inf\{t \geq 0 \mid r_t = a\}$, $y \in [0, 1]$. We deduce that $\mathbb{P}(r_\infty = 0) = 0$. This completes the proof. \square

Proof of (3.6): We want to prove that μ is invariant for $(X_t^x, X_t^{x'})$ if and only if μ can be represented by (3.6). First, since the unique invariant distribution of (X_t^x) is λ_{S_1} , it is clear that $\mu = \mathcal{L}(e^{i\Theta_0}, e^{i(\Theta_0+V_0)})$ where Θ_0 has uniform distribution on $[0, 2\pi]$ and V_0 is a random variable with values in $[0, 2\pi)$. One can check that if V_0 is independent of Θ_0 , μ is invariant. Thus, it remains to prove that it is a necessary condition or equivalently that $K(\theta, dv) := \mathcal{L}(e^{iV_0} \mid e^{i\Theta_0} = e^{i\theta})$ does not depend on θ . Denote by $(e^{i\Theta_t}, e^{i(\Theta_t+V_t)})$ the (stationary) duplicated diffusion starting from $(e^{i\Theta_0}, e^{i(\Theta_0+V_0)})$. Since μ is invariant, we have for every $t \geq 0$

$$\mathcal{L}(e^{iV_t} \mid e^{i\Theta_t} = e^{i\theta}) = K(\theta, dv)$$

but thanks to the construction, for every $t \geq 0$, $\Theta_t = \Theta_0 + W_t$ and $V_t = V_0$ (the angular difference between the two coordinates does not change) so that

$$\mathcal{L}(e^{iV_t} \mid e^{i\Theta_t} = e^{i\theta}) = \int K(\theta', dv) \rho_t(\theta, d\theta')$$

where $\rho_t(\theta, d\theta') = \mathcal{L}(e^{i(\theta+W_t)})$. But $\rho_t(\theta, d\theta')$ converges weakly to λ_{S_1} when $t \rightarrow +\infty$. From the two previous equations it follows that $K(\theta, dv)$ does not depend on θ since $\forall \theta \geq 0$, $K(\theta, dv) = \int K(\theta', dv) \lambda_{S_1}(d\theta')$. \square

References

- [BB92] G. K. Basak and R. N. Bhattacharya. Stability in distribution for a class of singular diffusions. *Ann. Probab.*, 20(1):312–321, 1992.
- [Bha82] R. N. Bhattacharya. On the functional central limit theorem and the law of the iterated logarithm for Markov processes. *Z. Wahrsch. Verw. Gebiete*, 60(2):185–201, 1982.
- [BS88] P. H. Baxendale and D. W. Stroock. Large deviations and stochastic flows of diffeomorphisms. *Probab. Theory Related Fields*, 80(2):169–215, 1988.
- [Car85] Andrew Carverhill. Flows of stochastic dynamical systems: ergodic theory. *Stochastics*, 14(4):273–317, 1985.
- [Cat92] P. Cattiaux. Stochastic calculus and degenerate boundary value problems. *Ann. Inst. Fourier (Grenoble)*, 42(3):541–624, 1992.
- [CL89] M. F. Chen and S. F. Li. Coupling methods for multidimensional diffusion processes. *Ann. Probab.*, 17(1):151–177, 1989.
- [DKK04] Dmitry Dolgopyat, Vadim Kaloshin, and Leonid Korolov. Sample path properties of the stochastic flows. *Ann. Probab.*, 32(1A):1–27, 2004.
- [DPZ96] G. Da Prato and J. Zabczyk. *Ergodicity for infinite-dimensional systems*, volume 229 of *London Mathematical Society Lecture Note Series*. Cambridge University Press, Cambridge, 1996.
- [Har81] T. E. Harris. Brownian motions on the homeomorphisms of the plane. *Ann. Probab.*, 9(2):232–254, 1981.
- [Has80] R. Z. Has'minskiĭ. *Stochastic stability of differential equations*, volume 7 of *Monographs and Textbooks on Mechanics of Solids and Fluids: Mechanics and Analysis*. Sijthoff & Noordhoff, Alphen aan den Rijn, 1980. Translated from the Russian by D. Louvish.

- [HH80] P. Hall and C. C. Heyde. *Martingale limit theory and its application*. Academic Press Inc. [Harcourt Brace Jovanovich Publishers], New York, 1980. Probability and Mathematical Statistics.
- [Hör67] L. Hörmander. Hypocoelliptic second order differential equations. *Acta Math.*, 119:147–171, 1967.
- [Hör85] L. Hörmander. *The analysis of linear partial differential operators 1-4.*, volume 275 of *Grundlehren der Mathematischen Wissenschaften [Fundamental Principles of Mathematical Sciences]*. Springer-Verlag, Berlin, 1985.
- [IW77] N. Ikeda and S. Watanabe. A comparison theorem for solutions of stochastic differential equations and its applications. *Osaka J. Math.*, 14(3):619–633, 1977.
- [KP92] Peter E. Kloeden and Eckhard Platen. *Numerical solution of stochastic differential equations*, volume 23 of *Applications of Mathematics (New York)*. Springer-Verlag, Berlin, 1992.
- [KT81] S. Karlin and H. M. Taylor. *A second course in stochastic processes*. Academic Press Inc. [Harcourt Brace Jovanovich Publishers], New York, 1981.
- [Kun90] H. Kunita. *Stochastic flows and stochastic differential equations*, volume 24 of *Cambridge Studies in Advanced Mathematics*. Cambridge University Press, Cambridge, 1990.
- [Lem05] V. Lemaire. *Estimation récursive de la mesure invariante d'un processus de diffusion*. Thèse de doctorat, Université de Marne-la-Vallée (France), 2005.
- [LP02] D. Lamberton and G. Pagès. Recursive computation of the invariant distribution of a diffusion. *Bernoulli*, 8(3):367–405, 2002.
- [LP03] D. Lamberton and G. Pagès. Recursive computation of the invariant distribution of a diffusion: the case of a weakly mean reverting drift. *Stoch. Dyn.*, 3(4):435–451, 2003.
- [Pag07] G. Pagès. Multi-step Richardson-Romberg extrapolation: remarks on variance control and complexity. *Monte Carlo Methods Appl.*, 13(1):37–70, 2007.
- [Pan06] F. Panloup. *Approximation récursive du régime stationnaire d'une Equation Différentielle Stochastique avec sauts*. Thèse de doctorat, Université Pierre et Marie Curie (Paris 6, France), 2006.
- [PV01] E. Pardoux and A. Yu. Veretennikov. On the Poisson equation and diffusion approximation. I. *Ann. Probab.*, 29(3):1061–1085, 2001.
- [TT90] D. Talay and L. Tubaro. Expansion of the global error for numerical schemes solving stochastic differential equations. *Stochastic Anal. Appl.*, 8(4):483–509 (1991), 1990.