

Weak Convergence Approach for Parabolic Equations with Large, Highly Oscillatory, Random Potential

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Abstract

This paper concerns the macroscopic behavior of solutions to parabolic equations with large, highly oscillatory, random potential. When the correlation function of the random potential satisfies a specific integrability condition, we show that the random solution converges, as the correlation length of the medium tends to zero, to the deterministic solution of a homogenized equation in dimension $d \geq 3$. Our derivation is based on a Feynman-Kac probabilistic representation and the Kipnis-Varadhan method applied to weak convergence of Brownian motions in random sceneries. For sufficiently mixing coefficients, we also provide an optimal rate of convergence to the homogenized limit using a quantitative martingale central limit theorem. As soon as the above integrability condition fails, the solution is expected to remain stochastic in the limit of a vanishing correlation length. For a large class of potentials given as functionals of Gaussian fields, we show the convergence of solutions to stochastic partial differential equations (SPDE) with multiplicative noise. The Feynman-Kac representation and the corresponding weak convergence of Brownian motions in random sceneries allows us to explain the transition from deterministic to stochastic limits as a function of the correlation function of the random potential.

1 Introduction

Solutions of partial differential equations with small scale structures arise in many aspects of physical and applied sciences. Homogenization theory has proved to be useful, both from the theoretical and numerical points of view, to provide macroscopic descriptions for such solutions. We consider here the setting of a parabolic equation with a large and highly oscillatory random potential. One of the salient features of such models is that the properties of the limiting macroscopic model strongly depend on the correlation properties of the random medium. When an integrability condition on the correlation function is met, then the stochastic solution converges in the limit of vanishing correlation length to a deterministic, homogenized solution. However, when that condition is not satisfied, the random solution remains stochastic in that limit and converges to the solution of a stochastic partial differential equation (SPDE) with multiplicative noise. The main objective of this paper is to provide a derivation of such results and an understanding of the transition from

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deterministic to stochastic limits from a probabilistic point of view. When the solution converges to a deterministic limit, we also derive optimal rates of convergence provided the potential satisfies certain mixing conditions.

Similar such equations have been analyzed recently. When the random potential is Gaussian, a Duhamel infinite series expansions and combinatorial techniques allows us to understand such a convergence for a relatively large class of parabolic equations including parabolic Anderson and Schrödinger models; see [3, 4, 5, 35, 36]. These explicit methods do not seem to extend to non-Gaussian potentials. In the one-dimensional setting of the heat equation, the convergence to a stochastic limit in the mixing case was addressed in [29] using the same probabilistic (Feynman-Kac formula) representation we consider in this paper. The convergence to deterministic limits for time-dependent potentials (not considered in this paper) has been considered in [30, 18].

In this paper, we adapt the Feynman-Kac approach to analyze a parabolic equation in dimension $d \geq 3$ of the form

$$\partial_t u_\varepsilon = \frac{1}{2} \Delta u_\varepsilon + iV_\varepsilon u_\varepsilon, \quad (1.1)$$

where $V_\varepsilon(x) = \varepsilon^{-\gamma} V(x/\varepsilon)$ is a large, time-independent, highly oscillatory, random potential. An imaginary potential is introduced to obtain a uniform bound on the energy of the solution, which considerably simplifies the analysis of exponential functionals of Brownian motion and the passage to the limit as $\varepsilon \rightarrow 0$. The corresponding heat equation (with iV_ε replaced by V_ε) might be analyzed using techniques developed in [18] but this problem is not considered further here. Note that the scalar equation of the form $\partial_t u = \frac{1}{2} \Delta u + iV u$ may be recast as the system

$$\partial_t \begin{pmatrix} u_1 \\ u_2 \end{pmatrix} = \begin{pmatrix} \frac{1}{2} \Delta & 0 \\ 0 & \frac{1}{2} \Delta \end{pmatrix} \begin{pmatrix} u_1 \\ u_2 \end{pmatrix} + \begin{pmatrix} 0 & -V \\ V & 0 \end{pmatrix} \begin{pmatrix} u_1 \\ u_2 \end{pmatrix}, \quad (1.2)$$

with $u = u_1 + iu_2$. Here, V may model a conservative process of interaction between two components otherwise satisfying independent diffusions. We obtain (1.1) by looking at the long time, large distance asymptotic limit $u_\varepsilon(t, x) = u(t/\varepsilon^2, x/\varepsilon)$ for $\varepsilon \ll 1$. To obtain nontrivial effects from the potential, it suffices to impose on V a weak amplitude ε^ζ with $\zeta > 0$ to be determined. Deriving the equation of $u_\varepsilon(t, x)$ leads to (1.1) with $\gamma = 2 - \zeta$. We analyze the asymptotic behavior of u_ε as $\varepsilon \rightarrow 0$, and prove homogenization and convergence to SPDE under different assumptions on $V(x)$.

There is a large body of literature on stochastic homogenization, starting from the work of Kozlov [24] and Papanicolaou-Varadhan [28], where elliptic operators of the form $\nabla \cdot a(\frac{\cdot}{\varepsilon}) \nabla$ are considered for stationary and ergodic coefficients. Homogenization results show that as $\varepsilon \rightarrow 0$ the elliptic operator converges in an appropriate sense to a homogenized operator with constant coefficients. The rates of convergence are less well understood. Yurinskii [34] provided the first quantitative estimates for the statistical error. Discrete cases have been analyzed in [12, 15, 26, 27], using analytic and probabilistic approaches respectively. For the fully-nonlinear case, see [11, 1]. When $d = 1$, an explicit solution is available, which simplifies the analysis of the statistical fluctuations and allows to derive central limits for the random fluctuations, see [10, 7, 16]. In the setting of bounded random potentials, [14, 2, 8, 6] analyzed elliptic equations and derived central limit results.

From a probabilistic point of view, different realizations of the random differential operator $\nabla \cdot a(\frac{\cdot}{\varepsilon}) \nabla$ correspond to families of diffusion processes, so that homogenization may be recast as a problem of weak convergence of random motions in random environments; see [22] and the

references therein. For the heat equation considered here, our setting is that of a Brownian motion propagating in random sceneries. It is the continuous counterpart of Kesten’s model of random walk in random scenery, for which the invariance principle has been proved in [20, 9]. The weak convergence of Brownian motion in random scenery is based on the Kipnis-Varadhan approach [21]. We apply to the homogenization setting the point of view of the medium seen from an observer and their methods of corrector equation and martingale decomposition. The same probabilistic approach was used in [25] to handle equations in more general forms with random potentials written as derivatives of bounded processes.

Theorem 2.2 below provides a convergence result for the most general class of potentials for which such a convergence is expected; see Assumption 2.1 below. Using the probabilistic representation, the difference between the heterogeneous and homogenized solutions is approximately reduced to the Wasserstein distance between martingales and Brownian motions. We use the quantitative martingale central limit theorem developed in [27] to estimate the Wasserstein distance and obtain the optimal convergence rates when the random potential satisfies additional mixing conditions in Theorem 2.6. The mixing property is only used in moment estimation. While this imposes the constraint that the random potentials be sufficiently short-range-correlated, we apply the same quantitative martingale central limit theorem and extend the result to long-range-correlated Gaussian potentials; see Theorem 2.9 below.

When Assumption 2.1 below is not satisfied, we do not expect convergence to a deterministic homogenized solution. Exhibiting all possible macroscopic limits in this case seems to be out of reach. From the analysis of the simpler setting of random fluctuations beyond homogenization [7, 6, 16], we expect the class of possible limits to be rather large. We consider here a large class of random potentials with covariance function decaying sufficiently slowly so that Assumption 2.1 is violated and prove a result of convergence to SPDE in Theorem 2.11. A sharp transition to stochasticity is thus observed beyond Assumption 2.1. In the long-range-correlation setting, these results relate to limit theorems of sum of strongly correlated random variables, where non-Gaussian limit might appear in certain circumstances [32]. Our random coefficients are chosen as functionals of Gaussian processes and we obtain a SPDE driven by multiplicative Gaussian noise in the limit. Similar type of limiting equation is analyzed in [19] by Feynman-Kac formula. In [23], the heat equation with long-range correlated Gaussian potential is studied with a similar type of limiting equation as in [19].

The rest of paper is organized as follows. We state our main results in Section 2 and discuss possible extensions in Section 2.3. We then prove convergence to homogenized limit and error estimate under different assumptions in Section 3. The result of convergence to SPDE is proved in Section 4. We present some technical lemmas in the Appendix.

Here are notations used throughout the paper. In the product probability space, we use \mathbb{E} to denote the expectation only with respect to random coefficients and \mathbb{E}_B the expectation only with respect to the Brownian motion starting from the origin. Joint expectation is denoted by $\mathbb{E}\mathbb{E}_B$. $a \lesssim b$ stands for $a \leq Cb$ for some ε -independent constant $C > 0$. We use $a \wedge b = \min(a, b)$. $N(\mu, \sigma^2)$ is the Gaussian distribution with mean μ and variance σ^2 , and $q_t(x)$ denotes the density function of $N(0, t)$. When we write $\Psi(r) \lesssim 1 \wedge r^{-\beta}$ for any $\beta > 0$, the constant of proportionality might depend on β .

2 Main results

We rely on the Feynman-Kac representation for the solution to (1.1). Assuming the initial condition $u_\varepsilon(0, x) = f(x)$ for $f \in \mathcal{C}_b(\mathbb{R}^d)$, the Feynman-Kac solution is given by

$$u_\varepsilon(t, x) = \mathbb{E}_B \left\{ f(x + B_t) \exp\left(i \int_0^t V_\varepsilon(x + B_s) ds\right) \right\}. \quad (2.1)$$

Without any regularity assumption on V_ε , (1.1) is not always solvable in the classical sense, and the solution given by (2.1) is not necessarily a classical solution. In Proposition A.1, we show that it is indeed a weak solution almost surely provided $V(x)$ has locally bounded sample path.

Since $V(x)$ may be unbounded, proving uniqueness of the solution to (1.1) is a difficult task. Such a task becomes easy when the equation is posed on a bounded domain since V is then bounded almost surely. But calculations with the corresponding Brownian motion on bounded domains involve standard complications which we wish to avoid here. When we refer to "the" solution to (1.1), we therefore mean the weak solution given by the Feynman-Kac probabilistic representation in the rest of the paper.

In the following, we state the main results of homogenization and convergence to SPDE respectively.

2.1 Convergence to homogenized limit and error estimate

Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a *random medium* associated with a group of measure-preserving, ergodic transformation $\{\tau_x, x \in \mathbb{R}^d\}$. Let $\mathbb{V} \in L^2(\Omega)$ with $\int_\Omega \mathbb{V}(\omega) \mathbb{P}(d\omega) = 0$. Define $V(x, \omega) = \mathbb{V}(\tau_x \omega)$ and we consider the equation when $d \geq 3$

$$\partial_t u_\varepsilon(t, x, \omega) = \frac{1}{2} \Delta u_\varepsilon(t, x, \omega) + i \frac{1}{\varepsilon} V\left(\frac{x}{\varepsilon}, \omega\right) u_\varepsilon(t, x, \omega), \quad (2.2)$$

with initial condition $u_\varepsilon(t, x, \omega) = f(x)$ for $f \in \mathcal{C}_b(\mathbb{R}^d)$, i.e., in (1.1) we choose $\gamma = 1$. For detailed setup of random medium, we refer to e.g. [28, 22]. We will write $u_\varepsilon(t, x)$ and $V(x)$ from now on.

Let $\{D_k, k = 1, \dots, d\}$ be the $L^2(\Omega)$ generator of τ_x , and Laplacian operator $L = \frac{1}{2} \sum_{k=1}^d D_k^2$. We use $\langle \cdot, \cdot \rangle$ to denote the inner product in $L^2(\Omega)$ and $\|\cdot\|$ the $L^2(\Omega)$ norm, and assume that

Assumption 2.1.

$$\langle \mathbb{V}, -L^{-1} \mathbb{V} \rangle < \infty. \quad (2.3)$$

By defining T_x on $L^2(\Omega)$ as $T_x f(\omega) = f(\tau_x \omega)$ and assuming it is strongly continuous in $L^2(\Omega)$, we obtain the spectral resolution

$$T_x = \int_{\mathbb{R}^d} e^{i\xi x} U(d\xi), \quad (2.4)$$

where $U(d\xi)$ is the associated projection valued measure. Then Assumption 2.1 is equivalent to

$$\int_{\mathbb{R}^d} \frac{\hat{R}(\xi)}{|\xi|^2} d\xi < \infty, \quad (2.5)$$

where $\hat{R}(\xi)$ is the power spectrum associated with \mathbb{V} , i.e., $\hat{R}(\xi)d\xi = (2\pi)^d \langle U(d\xi)\mathbb{V}, \mathbb{V} \rangle$. We also have that

$$R(x) := \langle T_x \mathbb{V}, \mathbb{V} \rangle = \frac{1}{(2\pi)^d} \int_{\mathbb{R}^d} e^{i\xi x} \hat{R}(\xi) d\xi. \quad (2.6)$$

Defining

$$\sigma^2 = 2 \langle \mathbb{V}, -L^{-1}\mathbb{V} \rangle = \frac{4}{(2\pi)^d} \int_{\mathbb{R}^d} \frac{\hat{R}(\xi)}{|\xi|^2} d\xi,$$

and $u_{hom}(t, x)$ such that

$$\partial_t u_{hom}(t, x) = \frac{1}{2} \Delta u_{hom}(t, x) - \frac{1}{2} \sigma^2 u_{hom}(t, x) \quad (2.7)$$

with same initial condition $u_0(0, x) = f(x)$, we have the following theorem:

Theorem 2.2 (*Homogenization*). *Under Assumption 2.1, $u_\varepsilon(t, x) \rightarrow u_{hom}(t, x)$ in probability as $\varepsilon \rightarrow 0$.*

Remark 2.3. Clearly, Assumption 2.1 merely ensures σ^2 , i.e., the homogenized constant, to be well-defined. Since u_ε and u_0 are both bounded, moment convergence holds as well. Furthermore, if $f \in L^1(\mathbb{R}^d)$, $|u_\varepsilon(t, \cdot)|, |u_0(t, \cdot)|$ are both bounded by $\mathcal{U}(t, \cdot) \in L^2(\mathbb{R}^d)$, which solves $\partial_t \mathcal{U} = \frac{1}{2} \Delta \mathcal{U}$ with initial condition $\mathcal{U}(0, x) = |f(x)|$, so $\int_{\mathbb{R}^d} \mathbb{E}\{|u_\varepsilon(t, x) - u_0(t, x)|^2\} dx \rightarrow 0$ as $\varepsilon \rightarrow 0$.

We are also interested in the convergence rate of $u_\varepsilon \rightarrow u_0$. To give error estimate, one possible assumption we need is the following strongly mixing property of the random potential $V(x)$:

Assumption 2.4. $\mathbb{E}\{V^6(x)\} < \infty$ and there exists a mixing coefficient $\rho(r)$ decreasing in $r \in [0, \infty)$ such that for any $\beta > 0$, $\rho(r) \leq C_\beta(1 \wedge r^{-\beta})$ for some $C_\beta > 0$ and the following bound holds

$$\mathbb{E}\{\phi_1(V)\phi_2(V)\} \leq \rho(r) \sqrt{\mathbb{E}\{\phi_1^2(V)\}\mathbb{E}\{\phi_2^2(V)\}} \quad (2.8)$$

for any two compact sets K_1, K_2 with $d(K_1, K_2) = \inf_{x_1 \in K_1, x_2 \in K_2} \{|x_1 - x_2|\} \geq r$ and any random variables $\phi_1(V), \phi_2(V)$ with $\phi_i(V)$ being \mathcal{F}_{K_i} -measurable and $\mathbb{E}\{\phi_i(V)\} = 0$.

Remark 2.5. Under Assumption 2.4, we have $|R(x)| = |\mathbb{E}\{V(0)V(x)\}| \leq C_\beta(1 \wedge |x|^{-\beta})$ for any $\beta > 0$. Note that

$$\sigma^2 = \frac{4}{(2\pi)^d} \int_{\mathbb{R}^d} \frac{\hat{R}(\xi)}{|\xi|^2} d\xi = \frac{1}{\pi^{\frac{d}{2}}} \Gamma\left(\frac{d}{2} - 1\right) \int_{\mathbb{R}^d} \frac{R(x)}{|x|^{d-2}} dx, \quad (2.9)$$

so the strongly mixing assumption implies finiteness of the homogenization constant.

The following is the result of convergence rate for strongly mixing potentials:

Theorem 2.6 (*Error estimate for strongly mixing potentials*). *Under Assumption 2.4, if $f \in C_c^\infty(\mathbb{R}^d)$, the following error estimates hold:*

$$\mathbb{E}\{|u_\varepsilon(t, x) - u_{hom}(t, x)|\} \leq (1+t)C_{d,f,\rho} \begin{cases} \sqrt{\varepsilon} & d = 3, \\ \varepsilon \sqrt{|\log \varepsilon|} & d = 4, \\ \varepsilon & d > 4. \end{cases} \quad (2.10)$$

Remark 2.7. As suggested by the notation, $C_{d,f,\rho}$ only depends on the dimension, initial condition and mixing coefficient. If we follow the proof, it is easy to check that we only need to assume $\rho(r) \lesssim 1 \wedge r^{-\beta}$ for sufficiently large β , and the regularity assumption on f could be improved as well.

The error estimate given in Theorem 2.6 is universal in the sense that it is independent of the potential as long as Assumption 2.4 holds. The strongly mixing property is only used when estimating moments of $V(x)$ and controlling relevant integrals. For Gaussian potentials, the calculation of moments is straightforward, and this enables us to extend the error estimate to long-range-correlation setting.

Assumption 2.8. $V(x)$ is a zero-mean Gaussian random field with auto-covariance function $R(x) \sim |x|^{-\beta}$ as $x \rightarrow \infty$ for $\beta \in (2, d)$.

The condition $\beta > 2$ ensures that $R(x)|x|^{2-d}$ is integrable so Assumption 2.1 holds. On the other hand, $\beta < d$ so $R(x)$ is not integrable and it is the long-range-correlated case. The following theorem is a precise description of how the homogenization error depends on the interaction between the dimension d and the decay rate β of auto-covariance function.

Theorem 2.9 (*Error estimate for long-range-correlated Gaussian potentials*). *Under Assumption 2.8, if $f \in C_c^\infty(\mathbb{R}^d)$, the following error estimates hold:*

- when $d = 3, 4$,

$$\mathbb{E}\{|u_\varepsilon(t, x) - u_{hom}(t, x)|\} \leq (1+t)C_{d,f,\beta}\varepsilon^{\frac{\beta}{2}-1}, \quad (2.11)$$

- when $d > 4$,

$$\mathbb{E}\{|u_\varepsilon(t, x) - u_{hom}(t, x)|\} \leq (1+t)C_{d,f,\beta} \begin{cases} \varepsilon^{\frac{\beta}{2}-1} & \beta \in (2, 4), \\ \varepsilon\sqrt{|\log \varepsilon|} & \beta = 4, \\ \varepsilon & \beta \in (4, d). \end{cases} \quad (2.12)$$

The result shows that for sufficiently long-range-correlated random potentials, the convergence rate in homogenization could be potential-dependent, e.g., when $\beta \rightarrow 2$, the error is of order $\varepsilon^{\frac{\beta}{2}-1}$ and could be arbitrarily close to $O(1)$. On the other hand, when the covariance function is integrable, i.e., $\beta > d$, we recover the result for strongly mixing potentials.

2.2 Convergence to SPDE

Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a probability space. The following is our assumption on random coefficient $V(x) = V(x, \omega)$ with $\omega \in \Omega$ labeling the particular realization.

Assumption 2.10. $V(x) = \Phi(g(x))$, where

- $g(x)$ is a stationary Gaussian field with zero mean and unit variance. The auto-covariance function $R_g(x) = \mathbb{E}\{g(0)g(x)\}$ satisfies that $|R_g(x)| \lesssim \prod_{i=1}^d \min(1, |x_i|^{-\alpha_i})$ with $\alpha_i \in (0, 1)$ and $R_g(x) \sim c_d \prod_{i=1}^d |x_i|^{-\alpha_i}$ as $\min_{i=1, \dots, d} |x_i| \rightarrow \infty$. $\alpha := \sum_{i=1}^d \alpha_i \in (0, 2)$.

- Φ is a deterministic function with Hermite rank 1, i.e., $\int_{\mathbb{R}} \Phi^2(x) \frac{1}{\sqrt{2\pi}} \exp(-\frac{x^2}{2}) dx < \infty$ and if we define $V_k = \mathbb{E}\{\Phi(g)H_k(g)\}$ with $H_k(x) = (-1)^k \exp(x^2/2) \frac{d^k}{dx^k} \exp(-x^2/2)$ the k -th Hermite polynomial, then $V_0 = 0, V_1 \neq 0$.

We will see later that $R(x) = \mathbb{E}\{V(0)V(x)\} \sim V_1^2 c_d \prod_{i=1}^d |x_i|^{-\alpha_i}$, and since $\alpha = \sum_{i=1}^d \alpha_i < 2$, $R(x)|x|^{2-d}$ is not integrable, hence homogenization does not occur. We consider the equation when $d \geq 3$

$$\partial_t u_\varepsilon(t, x, \omega) = \frac{1}{2} \Delta u_\varepsilon(t, x, \omega) + i \frac{1}{\varepsilon^{\alpha/2}} V\left(\frac{x}{\varepsilon}, \omega\right) u_\varepsilon(t, x, \omega), \quad (2.13)$$

with initial condition $u_\varepsilon(0, x, \omega) = f(x)$ for $f \in \mathcal{C}_b(\mathbb{R}^d)$, i.e., in (1.1), we choose $\gamma = \frac{\alpha}{2} < 1$. The following is the result of convergence to SPDE.

Theorem 2.11. *Under Assumption 2.10, we have $u_\varepsilon(t, x) \rightarrow u_{spde}(t, x)$ in distribution, with u_{spde} solving the SPDE with multiplicative noise:*

$$\partial_t u_{spde} = \frac{1}{2} \Delta u_{spde} + i V_1 \sqrt{c_d} \dot{W} u_{spde}, \quad (2.14)$$

where $\dot{W}(x)$ is a generalized Gaussian random field with covariance function $\mathbb{E}\{\dot{W}(x)\dot{W}(y)\} = \prod_{i=1}^d |x_i - y_i|^{-\alpha_i}$.

Remark 2.12. The proof of Theorem 2.11 also holds for $d = 1, 2$. When $d = 2$, since $\alpha_1, \alpha_2 \in (0, 1)$, $\alpha = \alpha_1 + \alpha_2 \in (0, 2)$ is automatically satisfied. When $d = 1$, we have $\alpha = \alpha_1 \in (0, 1)$.

2.3 Remarks

One of the main ingredients in the proof of both homogenization and convergence to SPDE is the weak convergence of Brownian motion in random scenery. In the homogenization setting, Kipnis-Varadhan's result implies $\frac{1}{\varepsilon} \int_0^t V\left(\frac{B_s}{\varepsilon}\right) ds \Rightarrow \sigma W_t$ in $\mathcal{C}([0, T])$ in \mathbb{P} -probability, with only necessary assumptions of stationarity, ergodicity, and finiteness of asymptotic variance. In the SPDE setting, Proposition 4.7 below shows $\frac{1}{\varepsilon^{\alpha/2}} \int_0^t V\left(\frac{B_s}{\varepsilon}\right) ds \Rightarrow V_1 \sqrt{c_d} \int_0^t \dot{W}(B_s) ds$ in the annealed sense, where V is chosen as functionals of stationary Gaussian process. The difference between the results of weak convergence sheds light on the transition from homogenization to stochasticity from a probabilistic point of view.

To obtain optimal error estimate, a quantification of ergodicity is in need and we assume a strong mixing of the random potential. Ergodicity is quantified by controlling the tail of the mixing coefficient and is used only to estimate the fourth-order moment of the random potential. When the fourth-order moment can be estimated explicitly without any mixing condition, then similar error estimates can be derived. We considered here the example of long-range-correlated Gaussian potential and derived convergence rate depending on its decorrelation rate.

In the homogenization setting of low dimensions, when $d = 2$, weak convergence of Brownian motion in random scenery has been proved for specific types of short-range-correlated potentials in the annealed sense, including Gaussian, Poissonian [17] and piecewise-constant cases [31]. The size of potentials then includes a logarithm correction. It is not clear whether Kipnis-Varadhan's approach works to obtain weak convergence in probability. With the annealed weak convergence,

homogenization could be derived by showing the convergence of $\mathbb{E}\{u_\varepsilon(t, x)\}$ and $\mathbb{E}\{|u_\varepsilon(t, x)|^2\}$ respectively. When $d = 1$, [29] derived a stochastic limit for short-range-correlated potentials.

Intuitively, Theorem 2.2 of homogenization corresponds to law of large numbers while Theorem 2.6 and 2.9 relate to variance estimate, thus it is natural to inquire about central limit type result, i.e., the weak convergence of $\varepsilon^{-\delta}(u_\varepsilon(t, x) - u_0(t, x))$ for appropriate $\delta > 0$. In [4], for the same type of equations, central limit type of result is derived by a different approach for Gaussian potentials. The probabilistic approach is currently under study.

3 Proof of homogenization and error estimate

3.1 Feynman-Kac formula, medium seen from the observer and auxiliary equation

The solution to (2.2) is written as

$$u_\varepsilon(t, x) = \mathbb{E}_B\left\{f(x + B_t) \exp\left(i\frac{1}{\varepsilon} \int_0^t V\left(\frac{x + B_s}{\varepsilon}\right) ds\right)\right\}, \quad (3.1)$$

with Brownian motion B_s starting from the origin.

By the scaling property of Brownian motion,

$$u_\varepsilon(t, x) = \mathbb{E}_B\left\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp\left(i\varepsilon \int_0^{t/\varepsilon^2} V\left(\frac{x}{\varepsilon} + B_s\right) ds\right)\right\}.$$

Since u_0 is deterministic, by stationarity of V , the difference between the solutions to the heterogeneous and homogenized equations can be written as

$$\begin{aligned} & \mathbb{E}\{|u_\varepsilon(t, x) - u_0(t, x)|\} \\ &= \mathbb{E}\left\{\left|\mathbb{E}_B\left\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp\left(i\varepsilon \int_0^{t/\varepsilon^2} V(B_s) ds\right)\right\} - \mathbb{E}_B\left\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp\left(-\frac{1}{2}\sigma^2 t\right)\right\}\right|\right\}. \end{aligned} \quad (3.2)$$

Now we look at $X_\varepsilon(t) := \varepsilon \int_0^{t/\varepsilon^2} \nabla(\tau_{B_s} \omega) ds = \varepsilon \int_0^{t/\varepsilon^2} V(B_s) ds$. For $y_s := \tau_{B_s} \omega$, it is a stationary, ergodic Markov process taking values in Ω with invariant measure \mathbb{P} , and the generator of y_s is given by $L = \frac{1}{2} \sum_{k=1}^d D_k^2$, see e.g. [22].

We define the corrector function Φ_λ for any $\lambda > 0$ such that

$$(\lambda I - L)\Phi_\lambda = \mathbb{V}, \quad (3.3)$$

then the following proposition holds.

Proposition 3.1.

$$\Phi_\lambda = \int_{\mathbb{R}^d} \frac{1}{\lambda + \frac{1}{2}|\xi|^2} U(d\xi) \mathbb{V}. \quad (3.4)$$

Under Assumption 2.1, $\lambda\langle\Phi_\lambda, \Phi_\lambda\rangle \rightarrow 0$ as $\lambda \rightarrow 0$.

Under Assumption 2.4,

$$\lambda \langle \Phi_\lambda, \Phi_\lambda \rangle \lesssim \begin{cases} \sqrt{\lambda} & d = 3, \\ \lambda |\log \lambda| & d = 4, \\ \lambda & d > 4. \end{cases} \quad (3.5)$$

Under Assumption 2.8,

$$\lambda \langle \Phi_\lambda, \Phi_\lambda \rangle \lesssim \begin{cases} \lambda^{\frac{\beta}{2}-1} & \beta \in (2, 4), \\ \lambda |\log \lambda| & \beta = 4, \\ \lambda & \beta > 4. \end{cases} \quad (3.6)$$

If we define

$$\eta_k = \int_{\mathbb{R}^d} \frac{2i\xi_k}{|\xi|^2} U(d\xi) \mathbb{V} \quad (3.7)$$

for $k = 1, \dots, d$, $\sigma^2 = \sum_{k=1}^d \|\eta_k\|^2$. Defining $\sigma_\lambda^2 = \sum_{k=1}^d \|D_k \Phi_\lambda\|^2$, the following proposition holds.

Proposition 3.2. *Under Assumption 2.1, $D_k \Phi_\lambda \rightarrow \eta_k$ in $L^2(\Omega)$ as $\lambda \rightarrow 0$.*

Under Assumption 2.4,

$$|\sigma_\lambda^2 - \sigma^2| \lesssim \begin{cases} \sqrt{\lambda} & d = 3, \\ \lambda |\log \lambda| & d = 4, \\ \lambda & d > 4. \end{cases} \quad (3.8)$$

Under Assumption 2.8,

$$|\sigma_\lambda^2 - \sigma^2| \lesssim \begin{cases} \lambda^{\frac{\beta}{2}-1} & \beta \in (2, 4), \\ \lambda |\log \lambda| & \beta = 4, \\ \lambda & \beta > 4. \end{cases} \quad (3.9)$$

Proof of Proposition 3.1.

First, we have

$$\lambda \langle \Phi_\lambda, \Phi_\lambda \rangle = \int_{\mathbb{R}^d} \frac{\lambda}{\lambda + \frac{1}{2}|\xi|^2} \frac{\hat{R}(\xi)}{\lambda + \frac{1}{2}|\xi|^2} d\xi \lesssim \int_{\mathbb{R}^d} \frac{\lambda}{\lambda + |\xi|^2} \frac{\hat{R}(\xi)}{|\xi|^2} d\xi \quad (3.10)$$

Under Assumption 2.1, i.e., $\hat{R}(\xi)|\xi|^{-2}$ is integrable, by the dominated convergence theorem, $\lambda \langle \Phi_\lambda, \Phi_\lambda \rangle \rightarrow 0$ as $\lambda \rightarrow 0$.

If Assumption 2.4 holds, $\hat{R}(\xi)$ is bounded, and we obtain by direct calculation:

$$\begin{aligned} \lambda \langle \Phi_\lambda, \Phi_\lambda \rangle &\lesssim \lambda^{\frac{d}{2}-1} \int_{\mathbb{R}^d} \frac{1}{1 + |\xi|^2} \frac{\hat{R}(\sqrt{\lambda}\xi)}{|\xi|^2} d\xi \\ &\lesssim \lambda^{\frac{d}{2}-1} \int_{\sqrt{\lambda}|\xi| < 1} \frac{1}{1 + |\xi|^2} \frac{1}{|\xi|^2} d\xi + \lambda \int_{|\xi| > 1} \frac{\hat{R}(\xi)}{|\xi|^4} d\xi \\ &\lesssim \lambda^{\frac{d}{2}-1} \int_0^{\frac{1}{\sqrt{\lambda}}} \frac{r^{d-3}}{1 + r^2} dr + \lambda, \end{aligned} \quad (3.11)$$

so when $d = 3$, $\lambda\langle\Phi_\lambda, \Phi_\lambda\rangle \lesssim \sqrt{\lambda}$. When $d = 4$, $\lambda\langle\Phi_\lambda, \Phi_\lambda\rangle \lesssim \lambda|\log \lambda|$. When $d > 4$, $\lambda\langle\Phi_\lambda, \Phi_\lambda\rangle \lesssim \lambda$.

If Assumption 2.8 holds, $\hat{R}(\xi) \lesssim |\xi|^{\beta-d}$ at the origin, and the proof is similar. \square

Proof of Proposition 3.2. Since

$$\|D_k\Phi_\lambda - \eta_k\|^2 = \int_{\mathbb{R}^d} \frac{\lambda^2 \xi_k^2}{(\lambda + \frac{1}{2}|\xi|^2)^2 \frac{1}{4}|\xi|^4} \hat{R}(\xi) d\xi \lesssim \int_{\mathbb{R}^d} \frac{\lambda^2}{\lambda^2 + |\xi|^4} \frac{\hat{R}(\xi)}{|\xi|^2} d\xi, \quad (3.12)$$

and

$$\sigma_\lambda^2 - \sigma^2 = -16 \int_{\mathbb{R}^d} \frac{(\lambda^2 + \lambda|\xi|^2)}{|\xi|^2(2\lambda + |\xi|^2)^2} \hat{R}(\xi) d\xi, \quad (3.13)$$

we obtain the result as in the proof of Proposition 3.1. \square

Now we are ready to prove the main theorems. We choose $\lambda = \varepsilon^2$ from now on.

By Itô's formula, the process of Brownian motion in random scenery can be decomposed as

$$X_\varepsilon(t) = \varepsilon \int_0^{t/\varepsilon^2} \nabla(\tau_{B_s}\omega) ds = R_t^\varepsilon + M_t^\varepsilon, \quad (3.14)$$

where

$$R_t^\varepsilon := \varepsilon \int_0^{t/\varepsilon^2} \lambda \Phi_\lambda(y_s) ds - \varepsilon \Phi_\lambda(y_{t/\varepsilon^2}) + \varepsilon \Phi_\lambda(y_0), \quad (3.15)$$

$$M_t^\varepsilon := \varepsilon \int_0^{t/\varepsilon^2} \sum_{k=1}^d D_k \Phi_\lambda(y_s) dB_s^k. \quad (3.16)$$

Therefore, the error is decomposed correspondingly as $u_\varepsilon(t, x) - u_{hom}(t, x) = (i) + (ii)$, where

$$(i) = \mathbb{E}_B\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp(iR_t^\varepsilon + iM_t^\varepsilon)\} - \mathbb{E}_B\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp(iM_t^\varepsilon)\}, \quad (3.17)$$

$$(ii) = \mathbb{E}_B\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp(iM_t^\varepsilon)\} - \mathbb{E}_B\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp(-\frac{1}{2}\sigma^2 t)\}. \quad (3.18)$$

We see (i) is caused by the residue R_t^ε , i.e., a measure of how close $X_\varepsilon(t)$ is to a martingale, while (ii) relates to convergence of martingale M_t^ε , i.e., a measure of how close the martingale is to a Brownian motion. Since f is bounded, we have the estimate $\mathbb{E}\{|(i)|\} \lesssim \mathbb{E}\mathbb{E}_B\{|R_t^\varepsilon|\}$. It is straightforward to check that

$$\mathbb{E}\{|(i)|\} \lesssim \mathbb{E}\mathbb{E}_B\{|R_t^\varepsilon|\} \lesssim \sqrt{\lambda\langle\Phi_\lambda, \Phi_\lambda\rangle}(1+t). \quad (3.19)$$

In the following, we estimate the convergence of M_t^ε to a Brownian motion in different ways to prove homogenization and error estimate respectively.

3.2 Homogenization: proof of Theorem 2.2

We rewrite

$$M_t^\varepsilon = \varepsilon \int_0^{t/\varepsilon^2} \sum_{k=1}^d (D_k \Phi_\lambda - \eta_k)(y_s) dB_s^k + \varepsilon \int_0^{t/\varepsilon^2} \sum_{k=1}^d \eta_k(y_s) dB_s^k := (I) + (II),$$

so

$$\begin{aligned}
|(ii)| &= |\mathbb{E}_B\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp(iM_t^\varepsilon)\} - \mathbb{E}_B\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp(i(II))\}| \\
&\quad + |\mathbb{E}_B\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp(i(II))\} - \mathbb{E}_B\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp(-\frac{1}{2}\sigma^2 t)\}| \\
&\lesssim \mathbb{E}_B\{|(I)|\} + \mathbb{E}_B\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp(i(II))\} - \mathbb{E}_B\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp(-\frac{1}{2}\sigma^2 t)\}.
\end{aligned} \tag{3.20}$$

We clearly have that

$$\mathbb{E}\mathbb{E}_B\{|(I)|\} \leq \sqrt{t \sum_{k=1}^d \|D_k \Phi_\lambda - \eta_k\|^2} \tag{3.21}$$

On the other hand, by martingale central limit theorem [13], ergodic theorem, the fact that $\mathbb{E}\{\eta_k\} = 0$ for $k = 1, \dots, d$, and $\sum_{k=1}^d \|\eta_k\|^2 = \sigma^2$, we have that for almost every $\omega \in \Omega$:

$$(\varepsilon B_{t/\varepsilon^2}, \varepsilon \int_0^{t/\varepsilon^2} \sum_{k=1}^d \eta_k(\tau_{B_s} \omega) dB_s^k) \Rightarrow (W_t^1, \sigma W_t^2), \tag{3.22}$$

where W_t^1 is a d -dimensional Brownian motion and W_t^2 is an independent 1-dimensional Brownian motion. Therefore,

$$\mathbb{E}_B\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp(i(II))\} - \mathbb{E}_B\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp(-\frac{1}{2}\sigma^2 t)\} \rightarrow 0 \tag{3.23}$$

as $\varepsilon \rightarrow 0$ almost surely.

To summarize, we have

$$\begin{aligned}
\mathbb{E}\{|u_\varepsilon(t, x) - u_0(t, x)|\} &\lesssim \sqrt{\lambda \langle \Phi_\lambda, \Phi_\lambda \rangle} (1+t) + \sqrt{t \sum_{k=1}^d \|D_k \Phi_\lambda - \eta_k\|^2} \\
&\quad + \mathbb{E}\{|\mathbb{E}_B\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp(i(II))\} - \mathbb{E}_B\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp(-\frac{1}{2}\sigma^2 t)\}|\}.
\end{aligned} \tag{3.24}$$

By Proposition 3.1 and 3.2, and the dominated convergence theorem, the proof of Theorem 2.2 is complete.

3.3 Error estimate: proof of Theorem 2.6 and 2.9

Defining $\hat{f}(\xi) = \int_{\mathbb{R}^d} f(x) e^{-i\xi \cdot x} dx$, we can write (ii) as

$$\begin{aligned}
(ii) &= \mathbb{E}_B\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp(iM_t^\varepsilon)\} - \mathbb{E}_B\{f(x + \varepsilon B_{t/\varepsilon^2}) \exp(-\frac{1}{2}\sigma^2 t)\} \\
&= \frac{1}{(2\pi)^d} \int_{\mathbb{R}^d} \hat{f}(\xi) e^{i\xi \cdot x} \mathbb{E}_B\{e^{i(\varepsilon\xi \cdot B_{t/\varepsilon^2} + M_t^\varepsilon)} - e^{i\varepsilon\xi \cdot B_{t/\varepsilon^2} - \frac{1}{2}\sigma^2 t}\} d\xi,
\end{aligned} \tag{3.25}$$

where $\varepsilon\xi \cdot B_{t/\varepsilon^2} + M_t^\varepsilon = \varepsilon \int_0^{t/\varepsilon^2} \sum_{k=1}^d (\xi_k + D_k \Phi_\lambda(y_s)) dB_s^k$ is a continuous, square-integrable martingale for almost every $\omega \in \Omega$. The estimation of $\mathbb{E}_B\{e^{i(\varepsilon\xi \cdot B_{t/\varepsilon^2} + M_t^\varepsilon)} - e^{i\varepsilon\xi \cdot B_{t/\varepsilon^2} - \frac{1}{2}\sigma^2 t}\}$ reduces to a control of the Wasserstein distance between $\varepsilon\xi \cdot B_{t/\varepsilon^2} + M_t^\varepsilon$ and $\varepsilon\xi \cdot B_{t/\varepsilon^2} + \sigma W_t$, where W_t is an independent Brownian motion from B_t . This is given by the following result.

Proposition 3.3 (Theorem 3.2., equation (3.3) [27]). *If M_t is a continuous martingale and W_t is a standard Brownian motion, then*

$$d_{1,k}(M_1, W_1) \leq (1 \vee k) \mathbb{E}\{| \langle M \rangle_1 - 1 |\}, \quad (3.26)$$

with the distance $d_{1,k}$ defined as

$$d_{1,k}(X, Y) = \sup\{|\mathbb{E}\{f(X) - f(Y)\}| : f \in C_b^2(\mathbb{R}), \|f'\|_\infty \leq 1, \|f''\|_\infty \leq k\}. \quad (3.27)$$

In the continuous case, the proof is simplified and presented in the Appendix for the sake of convenience.

Since $\sigma_\lambda^2 = \sum_{k=1}^d \langle D_k \Phi_\lambda, D_k \Phi_\lambda \rangle$, by Proposition 3.3 we have for almost every $\omega \in \Omega$:

$$\begin{aligned} & |\mathbb{E}_B\{e^{i(\varepsilon\xi \cdot B_{t/\varepsilon^2} + M_t^\varepsilon)}\} - e^{-\frac{1}{2}(|\xi|^2 + \sigma_\lambda^2)t}| \\ & \leq \left(1 \vee \frac{1}{\sqrt{(|\xi|^2 + \sigma_\lambda^2)t}}\right) \mathbb{E}_B\{|\varepsilon^2 \int_0^{t/\varepsilon^2} \sum_{k=1}^d (\xi_k + D_k \Phi_\lambda(y_s))^2 ds - (|\xi|^2 + \sigma_\lambda^2)t|\}. \end{aligned} \quad (3.28)$$

Now we can write $|(ii)| \leq (I) + (II)$, where

$$\begin{aligned} (I) &= \frac{1}{(2\pi)^d} \int_{\mathbb{R}^d} |\hat{f}(\xi)| \left(1 \vee \frac{1}{\sqrt{(|\xi|^2 + \sigma_\lambda^2)t}}\right) \mathbb{E}_B\{|\varepsilon^2 \int_0^{t/\varepsilon^2} \sum_{k=1}^d (\xi_k + D_k \Phi_\lambda(y_s))^2 ds - (|\xi|^2 + \sigma_\lambda^2)t|\} d\xi, \\ (II) &= \frac{1}{(2\pi)^d} \int_{\mathbb{R}^d} |\hat{f}(\xi)| |e^{-\frac{1}{2}(|\xi|^2 + \sigma_\lambda^2)t} - e^{-\frac{1}{2}(|\xi|^2 + \sigma^2)t}| d\xi. \end{aligned}$$

First, we have

$$(II) \lesssim |\sigma_\lambda^2 - \sigma^2|t. \quad (3.29)$$

Secondly, for (I) we have

$$\begin{aligned} (I) &= \frac{1}{(2\pi)^d} \int_{\mathbb{R}^d} |\hat{f}(\xi)| \left(1 \vee \frac{1}{\sqrt{(|\xi|^2 + \sigma_\lambda^2)t}}\right) \mathbb{E}_B\{|\varepsilon^2 \int_0^{t/\varepsilon^2} \sum_{k=1}^d (\xi_k + D_k \Phi_\lambda(y_s))^2 ds - (|\xi|^2 + \sigma_\lambda^2)t|\} d\xi \\ &= \frac{1}{(2\pi)^d} \int_{\mathbb{R}^d} |\hat{f}(\xi)| \left(1 \vee \frac{1}{\sqrt{(|\xi|^2 + \sigma_\lambda^2)t}}\right) \mathbb{E}_B\{|\varepsilon^2 \int_0^{t/\varepsilon^2} Z_{\lambda,\xi}(B_s) ds|\} d\xi, \end{aligned} \quad (3.30)$$

where

$$Z_{\lambda,\xi}(x) := \sum_{k=1}^d (\xi_k + \int_{\mathbb{R}^d} \partial_{x_k} G_\lambda(x-y) V(y) dy)^2 - |\xi|^2 - \sigma_\lambda^2,$$

with G_λ the Green's function of $\lambda - \frac{1}{2}\Delta$. Note that we have used the fact that

$$D_k \Phi_\lambda(\tau_x \omega) = \int_{\mathbb{R}^d} \partial_{x_k} G_\lambda(x-y) V(y) dy.$$

Clearly $Z_{\lambda,\xi}$ has zero mean; and by the ergodic theorem, we expect $\varepsilon^2 \int_0^{t/\varepsilon^2} Z_{\lambda,\xi}(B_s) ds$ to be small. This is quantified by the following control of the variance of Brownian motion in random scenery.

Lemma 3.4. *If V is a mean zero, stationary random field with covariance function $R(x)$, and B_s is Brownian motion independent from V , then*

$$\mathbb{E}\mathbb{E}_B\left\{\left(\varepsilon \int_0^{t/\varepsilon^2} V(B_s) ds\right)^2\right\} \lesssim t \int_{\mathbb{R}^d} \frac{|R(x)|}{|x|^{d-2}} dx. \quad (3.31)$$

Proof. By direct calculation, we have

$$\begin{aligned} \mathbb{E}\mathbb{E}_B\left\{\left(\varepsilon \int_0^{t/\varepsilon^2} V(B_s) ds\right)^2\right\} &= 2\varepsilon^2 \int_0^{t/\varepsilon^2} \int_0^s \int_{\mathbb{R}^d} R(x) \frac{1}{(2\pi u)^{\frac{d}{2}}} e^{-\frac{|x|^2}{2u}} dx du ds \\ &= 2\varepsilon^2 \int_0^\infty du \left(\frac{t}{\varepsilon^2} - u\right) 1_{u < \frac{t}{\varepsilon^2}} \int_{\mathbb{R}^d} R(x) \frac{1}{(2\pi u)^{\frac{d}{2}}} e^{-\frac{|x|^2}{2u}} dx \\ &= \varepsilon^2 \int_0^\infty d\lambda \left(\frac{t}{\varepsilon^2} - \frac{|x|^2}{2\lambda}\right) 1_{\frac{|x|^2}{2\lambda} < \frac{t}{\varepsilon^2}} \lambda^{\frac{d}{2}-2} e^{-\lambda} \int_{\mathbb{R}^d} \frac{1}{\pi^{\frac{d}{2}}} R(x) \frac{1}{|x|^{d-2}} dx \\ &\lesssim t \int_{\mathbb{R}^d} \frac{|R(x)|}{|x|^{d-2}} dx. \end{aligned} \quad (3.32)$$

□

Now we write $Z_{\lambda,\xi}(x) = Z_{1,\lambda,\xi}(x) + Z_{2,\lambda,\xi}(x)$ with

$$Z_{1,\lambda,\xi}(x) = \sum_{k=1}^d \left(\int_{\mathbb{R}^d} \partial_{x_k} G_\lambda(x-y) V(y) dy \right)^2 - \sigma_\lambda^2, \quad (3.33)$$

$$Z_{2,\lambda,\xi}(x) = 2 \sum_{k=1}^d \xi_k \int_{\mathbb{R}^d} \partial_{x_k} G_\lambda(x-y) V(y) dy. \quad (3.34)$$

Since $\sigma_\lambda^2 = \sum_{k=1}^d \langle D_k \Phi_\lambda, D_k \Phi_\lambda \rangle$, we have $\mathbb{E}\{Z_{i,\lambda,\xi}(x)\} = 0, i = 1, 2$. Therefore, Lemma 3.4 implies

$$\mathbb{E}\{(I)\} \lesssim \frac{\varepsilon}{(2\pi)^d} \int_{\mathbb{R}^d} |\hat{f}(\xi)| \left(1 \vee \frac{1}{\sqrt{(|\xi|^2 + \sigma_\lambda^2)t}} \right) \sqrt{t \int_{\mathbb{R}^d} \frac{|\mathcal{R}_{1,\lambda,\xi}(x)| + |\mathcal{R}_{2,\lambda,\xi}(x)|}{|x|^{d-2}} dx d\xi} \quad (3.35)$$

where $\mathcal{R}_{i,\lambda,\xi}(x) := \mathbb{E}\{Z_{i,\lambda,\xi}(0)Z_{i,\lambda,\xi}(x)\}, i = 1, 2$. By recalling (3.19) and (3.29), we have

$$\begin{aligned} &\mathbb{E}\{|u_\varepsilon(t, x) - u_0(t, x)|\} \\ &\lesssim \left(\sqrt{\lambda \langle \Phi_\lambda, \Phi_\lambda \rangle} + |\sigma_\lambda^2 - \sigma^2| + \varepsilon \int_{\mathbb{R}^d} \hat{f}(\xi) \sqrt{\int_{\mathbb{R}^d} \frac{|\mathcal{R}_{1,\lambda,\xi}(x)| + |\mathcal{R}_{2,\lambda,\xi}(x)|}{|x|^{d-2}} dx d\xi} \right) (1+t). \end{aligned} \quad (3.36)$$

The estimation of $\mathcal{R}_{i,\lambda,\xi}$ is done for strongly mixing potentials and long-range-correlated Gaussian potentials respectively in the following sections.

3.3.1 Strongly mixing case: proof of Theorem 2.6

Proposition 3.5. *Under Assumption 2.4, there exist a constant $c > 0$ and a sufficiently large $\beta > 0$ such that*

$$|\mathcal{R}_{1,\lambda,\xi}(x)| + |\mathcal{R}_{2,\lambda,\xi}(x)| \lesssim (1 + |\xi|)^2 \left(\lambda^{\frac{d}{2}-1} e^{-c\sqrt{\lambda}|x|} + 1 \wedge \frac{e^{-c\sqrt{\lambda}|x|}}{|x|^{d-2}} + 1 \wedge \frac{1}{|x|^\beta} \right). \quad (3.37)$$

Proof. We assume a positive function $\Psi(x) \lesssim 1 \wedge |x|^{-\beta}$ for $\beta > 0$ sufficiently large.

We first consider $\mathcal{R}_{1,\lambda,\xi}(x)$. By denoting $\phi_\lambda(x) = \int_{\mathbb{R}^d} G_\lambda(x-y)V(y)dy$, for any $m, n = 1, \dots, d$, we have

$$\begin{aligned} & \mathbb{E}\{(\partial_{x_m} \phi_\lambda(0))^2 (\partial_{x_n} \phi_\lambda(x))^2\} \\ &= \int_{\mathbb{R}^{4d}} \partial_{x_m} G_\lambda(y_1) \partial_{x_m} G_\lambda(z_1) \partial_{x_n} G_\lambda(y_2) \partial_{x_n} G_\lambda(z_2) \mathbb{E}\{V(-y_1)V(-z_1)V(x-y_2)V(x-z_2)\} dy_1 dy_2 dz_1 dz_2 \\ &= \int_{\mathbb{R}^{4d}} \partial_{x_m} G_\lambda(y_1) \partial_{x_m} G_\lambda(z_1) \partial_{x_n} G_\lambda(y_2) \partial_{x_n} G_\lambda(z_2) R(y_1-z_1)R(y_2-z_2) dy_1 dy_2 dz_1 dz_2 + I_{mn} \\ &= \|D_m \Phi_\lambda\|^2 \|D_n \Phi_\lambda\|^2 + I_{mn}, \end{aligned} \quad (3.38)$$

where I_{mn} are remainders in the calculation of fourth moment. By Lemma A.5, we obtain

$$|I_{mn}| \leq 2 \int_{\mathbb{R}^{4d}} |\partial_m G_\lambda(y_1) \partial_m G_\lambda(z_1) \partial_n G_\lambda(y_2) \partial_n G_\lambda(z_2)| \Psi(x-y_1+y_2) \Psi(x-z_1+z_2) dy_1 dy_2 dz_1 dz_2. \quad (3.39)$$

Since G_λ is the Green's function of $\lambda - \frac{1}{2}\Delta$, by scaling property, $G_\lambda(x) = \lambda^{\frac{d}{2}-1} G_1(\sqrt{\lambda}x)$. The estimate $|\nabla G_1(x)| \lesssim e^{-\rho|x|}|x|^{1-d}$ holds for some $\rho > 0$ [33]. Therefore, by change of variables, we have

$$|I_{mn}| \lesssim \left(\frac{1}{\lambda} \int_{\mathbb{R}^{2d}} \frac{e^{-\rho|y|}}{|y|^{d-1}} \frac{e^{-\rho|z|}}{|z|^{d-1}} \Psi\left(x - \frac{y-z}{\sqrt{\lambda}}\right) dy dz \right)^2. \quad (3.40)$$

Since $\sigma_\lambda^4 = \sum_{m,n=1}^d \|D_m \Phi_\lambda\|^2 \|D_n \Phi_\lambda\|^2$, we derive the following estimate

$$|\mathcal{R}_{1,\lambda,\xi}(x)| \lesssim \left(\frac{1}{\lambda} \int_{\mathbb{R}^{2d}} \frac{e^{-\rho|y|}}{|y|^{d-1}} \frac{e^{-\rho|z|}}{|z|^{d-1}} \Psi\left(x - \frac{y-z}{\sqrt{\lambda}}\right) dy dz \right)^2. \quad (3.41)$$

Now we consider $\mathcal{R}_{2,\lambda,\xi}(x)$. Similarly, we obtain that

$$\begin{aligned} |\mathcal{R}_{2,\lambda,\xi}(x)| &= \left| 4 \sum_{m,n=1}^d \xi_m \xi_n \int_{\mathbb{R}^{2d}} \partial_m G_\lambda(y) \partial_n G_\lambda(z) R(x-y+z) dy dz \right| \\ &\lesssim |\xi|^2 \frac{1}{\lambda} \int_{\mathbb{R}^{2d}} \frac{e^{-\rho|y|}}{|y|^{d-1}} \frac{e^{-\rho|z|}}{|z|^{d-1}} |R|\left(x - \frac{y-z}{\sqrt{\lambda}}\right) dy dz. \end{aligned} \quad (3.42)$$

Since $\Psi(x) \lesssim 1 \wedge |x|^{-\beta}$ for $\beta > 0$ sufficiently large, by Lemma A.3, we obtain

$$|\mathcal{R}_{1,\lambda,\xi}(x)| + |\mathcal{R}_{2,\lambda,\xi}(x)| \lesssim (1 + |\xi|)^2 \left(\lambda^{\frac{d}{2}-1} e^{-c\sqrt{\lambda}|x|} + 1 \wedge \frac{e^{-c\sqrt{\lambda}|x|}}{|x|^{d-2}} + 1 \wedge \frac{1}{|x|^\beta} \right) \quad (3.43)$$

for some constant $c > 0$, and $\beta > 0$ sufficiently large. The proof is complete. \square

By defining $F_\lambda(x) := \lambda^{\frac{d}{2}-1} e^{-c\sqrt{\lambda}|x|} + 1 \wedge \frac{e^{-c\sqrt{\lambda}|x|}}{|x|^{d-2}} + 1 \wedge \frac{1}{|x|^\beta}$, Proposition 3.5 and (3.36) lead to

$$\begin{aligned} & \mathbb{E}\{|u_\varepsilon(t, x) - u_0(t, x)|\} \\ & \lesssim \left(\sqrt{\lambda \langle \Phi_\lambda, \Phi_\lambda \rangle} + |\sigma_\lambda^2 - \sigma^2| + \varepsilon \sqrt{\int_{\mathbb{R}^d} \frac{F_\lambda(x)}{|x|^{d-2}} dx} \right) (1+t). \end{aligned} \quad (3.44)$$

We also see that for the initial condition f , the only requirement is $|\hat{f}(\xi)|(1+|\xi|)$ being integrable.

Now we only need the following lemma to complete the proof.

Lemma 3.6.

$$\int_{\mathbb{R}^d} \frac{F_\lambda(x)}{|x|^{d-2}} dx \lesssim \begin{cases} \lambda^{-\frac{1}{2}} & d = 3, \\ |\log \lambda| & d = 4, \\ 1 & d > 4. \end{cases} \quad (3.45)$$

Proof. Note that $1 \wedge \frac{1}{|x|^\beta}$ gives a term of order 1 since β could be sufficiently large. We first look at

$$\int_{\mathbb{R}^d} \frac{1}{|x|^{d-2}} \lambda^{\frac{d}{2}-1} e^{-c\sqrt{\lambda}|x|} dx = \lambda^{\frac{d}{2}-2} \int_{\mathbb{R}^d} \frac{e^{-c|y|}}{|y|^{d-2}} dy \lesssim \lambda^{\frac{d}{2}-2}. \quad (3.46)$$

Now we only have to deal with $1 \wedge \frac{e^{-c\sqrt{\lambda}|x|}}{|x|^{d-2}}$.

$$\int_{\mathbb{R}^d} \frac{1}{|x|^{d-2}} 1 \wedge \frac{e^{-c\sqrt{\lambda}|x|}}{|x|^{d-2}} dx \leq \int_{|x|<1} \frac{1}{|x|^{d-2}} dx + \int_{|x|>1} \frac{e^{-c\sqrt{\lambda}|x|}}{|x|^{2d-4}} dx. \quad (3.47)$$

When $d > 4$, RHS is bounded. When $d \leq 4$,

$$\int_{|x|>1} \frac{e^{-c\sqrt{\lambda}|x|}}{|x|^{2d-4}} dx = \lambda^{\frac{d-4}{2}} \int_{\sqrt{\lambda}}^{\infty} \frac{e^{-cr}}{r^{d-3}} dr, \quad (3.48)$$

which concludes the proof. \square

By Proposition 3.1 and 3.2 and the fact that $\lambda = \varepsilon^2$, we have under Assumption 2.4

$$\sqrt{\lambda \langle \Phi_\lambda, \Phi_\lambda \rangle} + |\sigma_\lambda^2 - \sigma^2| \lesssim \begin{cases} \sqrt{\varepsilon} & d = 3, \\ \varepsilon \sqrt{|\log \varepsilon|} & d = 4, \\ \varepsilon & d > 4. \end{cases} \quad (3.49)$$

By combining Lemma 3.6 and (3.44), the proof of Theorem 2.6 is complete.

3.3.2 Long-range-correlated Gaussian case: proof of Theorem 2.9

If we follow the proof of Proposition 3.5, it is straightforward to check that when V is Gaussian, we have

$$|\mathcal{R}_{1,\lambda,\xi}(x)| + |\mathcal{R}_{2,\lambda,\xi}(x)| \lesssim (1+|\xi|)^2 (F_\lambda(x) + F_\lambda^2(x)), \quad (3.50)$$

with

$$F_\lambda(x) := \frac{1}{\lambda} \int_{\mathbb{R}^{2d}} \frac{e^{-\rho|y|}}{|y|^{d-1}} \frac{e^{-\rho|z|}}{|z|^{d-1}} |R|(x - \frac{y-z}{\sqrt{\lambda}}) dy dz.$$

From (3.36), we have

$$\begin{aligned} & \mathbb{E}\{|u_\varepsilon(t, x) - u_0(t, x)|\} \\ & \lesssim \left(\sqrt{\lambda \langle \Phi_\lambda, \Phi_\lambda \rangle} + |\sigma_\lambda^2 - \sigma^2| + \varepsilon \sqrt{\int_{\mathbb{R}^d} \frac{F_\lambda(x) + F_\lambda^2(x)}{|x|^{d-2}} dx} \right) (1+t), \end{aligned} \quad (3.51)$$

then Theorem 2.9 comes from Lemma A.4 and Proposition 3.1, 3.2.

4 Proof of convergence to SPDE

From the proof of Theorem 2.2, we see that the key assumption for homogenization to occur besides stationarity and ergodicity is the integrability of $\hat{R}(\xi)|\xi|^{-2}$. In other words, $R(x)$ has to decay faster than $|x|^{-2}$ at infinity. In this section, we go beyond Assumption 2.1 by assuming $R(x)$ decays sufficiently slowly, and prove the transition to stochasticity from homogenization.

First, we recall that the n -th order Hermite polynomial is defined as

$$H_n(x) = (-1)^n \exp\left(\frac{x^2}{2}\right) \frac{d^n}{dx^n} \exp\left(-\frac{x^2}{2}\right), \quad (4.1)$$

and it has the property that

$$\mathbb{E}\{H_m(X)H_n(Y)\} = \begin{cases} n!(\mathbb{E}\{XY\})^n & m = n, \\ 0 & m \neq n, \end{cases} \quad (4.2)$$

if $X, Y \sim N(0, 1)$ and are jointly Gaussian.

Under Assumption 2.10, we can expand V in Hermite polynomials

$$V(x) = \Phi(g(x)) = \sum_{n=0}^{\infty} \frac{V_n}{n!} H_n(g(x)), \quad (4.3)$$

with $V_n = \mathbb{E}\{H_n(g(x))\Phi(g(x))\}$. By the assumption $V_0 = 0, V_1 \neq 0$, we have

$$\begin{aligned} R(x) &= \mathbb{E}\{V(0)V(x)\} = \mathbb{E}\{\Phi(g(0))\Phi(g(x))\} = \sum_{n=0}^{\infty} \frac{V_n^2}{(n!)^2} \mathbb{E}\{H_n(g(0))H_n(g(x))\} \\ &= \sum_{n=0}^{\infty} \frac{V_n^2}{n!} R_g(x)^n = V_1^2 R_g(x) + \sum_{n=2}^{\infty} \frac{V_n^2}{n!} R_g(x)^n. \end{aligned} \quad (4.4)$$

Since $\sum_{n=0}^{\infty} \frac{V_n^2}{n!} < \infty$, $R(x) \sim V_1^2 R_g(x)$ as $|x| \rightarrow \infty$. Since $R_g(x) \sim c_d \prod_{i=1}^d |x_i|^{-\alpha_i}$, we have $R(x) \sim V_1^2 c_d \prod_{i=1}^d |x_i|^{-\alpha_i}$ as $\min_{i=1, \dots, d} |x_i| \rightarrow \infty$.

The assumption of $V_1 \neq 0$ is crucial for the appearance of Gaussian noise in the limiting equation, and it turns out that by this assumption we can reduce the possibly non-Gaussian case to Gaussian case, namely $V(x) = g(x)$, so conditioning on B , $X_\varepsilon(t) := \frac{1}{\varepsilon^{\alpha/2}} \int_0^t V(\frac{B_s}{\varepsilon}) ds$ is Gaussian, and we can prove its weak convergence by proving convergence of the conditional mean and variance. Before that, following [19] we define the solution to the limiting SPDE (2.14).

4.1 Limiting SPDE

We first define the formally-written random variable $\int_0^t \dot{W}(B_s)ds = \int_0^t \int_{\mathbb{R}^d} \delta(x - B_s)W(dx)ds$, where $W(dx)$ is the generalized Gaussian random field independent from Brownian motion B_t . We use \mathbb{E} to denote the expectation with respect to $W(dx)$, and assume that the covariance function $\mathbb{E}\{W(dx)W(dy)\} = \frac{1}{\prod_{i=1}^d |x_i - y_i|^{\alpha_i}} dx dy$.

Proposition 4.1. *Assume $\sum_{i=1}^d \alpha_i < 2$ and define $Y_\varepsilon(t) = \int_0^t \int_{\mathbb{R}^d} q_\varepsilon(x - B_s)W(dx)ds$. Then $Y_\varepsilon(t)$ converges in L^2 as $\varepsilon \rightarrow 0$ to some random variable $Y(t)$, denoted as*

$$Y(t) = \int_0^t \dot{W}(B_s)ds = \int_0^t \int_{\mathbb{R}^d} \delta(x - B_s)W(dx)ds.$$

When conditioning on B , then Y_t is a Gaussian random variable with zero mean and variance

$$\mathbb{E}\{Y(t)^2\} = \int_0^t \int_0^t \frac{1}{\prod_{i=1}^d |B_i(s) - B_i(u)|^{\alpha_i}} ds du, \quad (4.5)$$

where $B_i(s)$ denotes the i -th component of B_s .

Proof. We first point out that the RHS of (4.5) is almost surely finite, and this comes from the fact that $\sum_{i=1}^d \alpha_i < 2$ and

$$\mathbb{E}_B \left\{ \int_0^t \int_0^t \frac{1}{\prod_{i=1}^d |B_i(s) - B_i(u)|^{\alpha_i}} ds du \right\} = \int_0^t \int_0^t \frac{1}{|s - u|^{\sum_{i=1}^d \alpha_i / 2}} ds du \prod_{i=1}^d \int_{\mathbb{R}^d} |x|^{-\alpha_i} q_1(x) dx, \quad (4.6)$$

Secondly, we calculate

$$\mathbb{E}\mathbb{E}_B\{Y_\varepsilon^2(t)\} = \int_0^t \int_0^t \int_{\mathbb{R}^{2d}} \mathbb{E}_B\{q_\varepsilon(x - B_s)q_\varepsilon(y - B_u)\} \frac{1}{\prod_{i=1}^d |x_i - y_i|^{\alpha_i}} dx dy ds du. \quad (4.7)$$

By Lemma A.6, $\int_{\mathbb{R}^{2d}} q_\varepsilon(x - B_s)q_\varepsilon(y - B_u) \frac{1}{\prod_{i=1}^d |x_i - y_i|^{\alpha_i}} dx dy \rightarrow \frac{1}{\prod_{i=1}^d |B_i(s) - B_i(u)|^{\alpha_i}}$ as $\varepsilon \rightarrow 0$. By Lemma A.7 and the dominated convergence theorem, we have the convergence

$$\mathbb{E}\mathbb{E}_B\{Y_\varepsilon^2(t)\} \rightarrow \int_0^t \int_0^t \mathbb{E}_B\left\{ \frac{1}{\prod_{i=1}^d |B_i(s) - B_i(u)|^{\alpha_i}} \right\} ds du. \quad (4.8)$$

Similarly, we can show $\mathbb{E}\mathbb{E}_B\{Y_{\varepsilon_1}(t)Y_{\varepsilon_2}(t)\} \rightarrow \int_0^t \int_0^t \mathbb{E}_B\left\{ \frac{1}{\prod_{i=1}^d |B_i(s) - B_i(u)|^{\alpha_i}} \right\} ds du$ as $\varepsilon_1, \varepsilon_2 \rightarrow 0$. Thus, we have shown that $\{Y_\varepsilon(t)\}$ is a Cauchy sequence in L^2 , since

$$\lim_{\varepsilon_1, \varepsilon_2 \rightarrow 0} \mathbb{E}\mathbb{E}_B\{(Y_{\varepsilon_1}(t) - Y_{\varepsilon_2}(t))^2\} = 0.$$

The limit is then denoted as $Y(t) = \int_0^t \dot{W}(B_s)ds = \int_0^t \int_{\mathbb{R}^d} \delta(x - B_s)W(dx)ds$.

Next, we consider the conditional distribution. Since $Y_\varepsilon(t) \rightarrow Y(t)$ in L^2 , there exists a subsequence ε_k such that $Y_{\varepsilon_k}(t) \rightarrow Y(t)$ almost surely. Note that $W(dx)$ and B_t are independent, so the

probability space is the product space. Then we know that conditioning on the Brownian motion, $Y_{\varepsilon_k}(t) \rightarrow Y(t)$ almost surely as $k \rightarrow \infty$, and this leads to convergence in distribution. Given B , $Y_\varepsilon(t)$ is Gaussian with variance

$$\begin{aligned} \mathbb{E}\{Y_\varepsilon^2(t)\} &= \int_0^t \int_0^t \int_{\mathbb{R}^{2d}} q_\varepsilon(x - B_s) q_\varepsilon(y - B_u) \frac{1}{\prod_{i=1}^d |x_i - y_i|^{\alpha_i}} dx dy ds du \\ &\rightarrow \int_0^t \int_0^t \frac{1}{\prod_{i=1}^d |B_i(s) - B_i(u)|^{\alpha_i}} ds du. \end{aligned} \quad (4.9)$$

The proof is complete. \square

Remark 4.2. If we define $Y^i(t) = \int_0^t \int_{\mathbb{R}^d} \delta(x - B_s^i) W(dx) ds$ for independent Brownian motions B^1, B^2 , the same proof implies that $Y^1(t), Y^2(t)$ are jointly Gaussian with covariance function given by $\mathbb{E}\{Y^1(t)Y^2(t)\} = \int_0^t \int_0^t \frac{1}{\prod_{i=1}^d |B_i^1(s) - B_i^2(u)|^{\alpha_i}} ds du$ when conditioning on B^1, B^2 .

Remark 4.3. From the proof of Proposition 4.1, we see that the distribution of $\int_0^t \int_{\mathbb{R}^d} \delta(x - B_s) W(dx) ds$ does not depend on the starting point of Brownian motion.

With random variable $\int_0^t \int_{\mathbb{R}^d} \delta(x - B_s) W(dx) ds$, we can formally write the solution to the SPDE

$$\partial_t u = \frac{1}{2} \Delta u + i \dot{W} u \quad (4.10)$$

with initial condition $u(0, x) = f(x)$ by Feynman-Kac formula as

$$u(t, x) = \mathbb{E}_B \left\{ f(x + B_t) \exp\left(i \int_0^t \int_{\mathbb{R}^d} \delta(y - x - B_s) W(dy) ds\right) \right\}. \quad (4.11)$$

We point that the $u(t, x)$ defined as above coincides with the usual definition of weak solution to SPDE (4.10):

Definition 4.4. A random field $u(t, x)$ is a weak solution to (4.10) if for any C^∞ function ϕ with compact support we have

$$\int_{\mathbb{R}^d} u(t, x) \phi(x) dx = \int_{\mathbb{R}^d} f(x) \phi(x) dx + \frac{1}{2} \int_0^t \int_{\mathbb{R}^d} u(s, x) \Delta \phi(x) dx ds + i \int_{\mathbb{R}^d} \int_0^t u(s, x) \phi(x) ds W(dx). \quad (4.12)$$

Proposition 4.5. If $\sum_{i=1}^d \alpha_i < 2$, $u(t, x)$ is a weak solution to (4.10).

The proof is a direct adaption of Theorem 4.3 in [19], and we do not present it here.

4.2 Convergence to a stochastic equation: proof of Theorem 2.11

First we reduce $V(x) = \Phi(g(x))$ to the Gaussian case by the following lemma:

Lemma 4.6. In the annealed sense, $Y_\varepsilon(t) := \frac{1}{\varepsilon^{\alpha/2}} \int_0^t (\Phi(g(\frac{B_s}{\varepsilon})) - V_1 g(\frac{B_s}{\varepsilon})) ds \rightarrow 0$ in probability as $\varepsilon \rightarrow 0$.

Proof. Since $\Phi(g) - V_1g = \sum_{n=2}^{\infty} \frac{V_n}{n!} H_n(g)$ and $\sum_{n=0}^{\infty} \frac{V_n^2}{n!} < \infty$, we have conditioning on B that

$$\begin{aligned} \mathbb{E}\{Y_\varepsilon(t)^2\} &= \frac{1}{\varepsilon^\alpha} \int_0^t \int_0^t \sum_{n=2}^{\infty} \frac{V_n^2}{n!} R_g\left(\frac{B_s - B_u}{\varepsilon}\right)^n dsdu \\ &\leq \frac{C}{\varepsilon^\alpha} \int_0^t \int_0^t R_g\left(\frac{B_s - B_u}{\varepsilon}\right)^2 dsdu \end{aligned} \quad (4.13)$$

for some constant C . Since R_g is bounded and satisfies $|R_g(x)| \lesssim \prod_{i=1}^d |x_i|^{-\alpha_i}$, we have

$$\begin{aligned} \mathbb{E}\{Y_\varepsilon(t)^2\} &\leq C \sup_{|x| \geq M} |R_g(x)| \int_0^t \int_0^t \frac{1}{\prod_{i=1}^d |B_i(s) - B_i(u)|^{\alpha_i}} 1_{|B_s - B_u| > M\varepsilon} dsdu \\ &\quad + \frac{C}{\varepsilon^\alpha} \int_0^t \int_0^t 1_{|B_s - B_u| \leq M\varepsilon} dsdu, \end{aligned} \quad (4.14)$$

which leads to

$$\mathbb{E}\mathbb{E}_B\{Y_\varepsilon(t)^2\} \leq C \sup_{|x| \geq M} |R_g(x)| + \frac{C}{\varepsilon^\alpha} \int_0^t \int_0^t \mathbb{E}_B\{1_{|B_s - B_u| \leq M\varepsilon}\} dsdu. \quad (4.15)$$

By Lemma A.8, first let $\varepsilon \rightarrow 0$, then $M \rightarrow \infty$, the proof is complete. \square

Now we can prove the weak convergence of $X_\varepsilon(t)$.

Proposition 4.7. *For fixed $t > 0$, in the annealed sense $X_\varepsilon(t) \Rightarrow V_1 \sqrt{c_d} \int_0^t \int_{\mathbb{R}^d} \delta(x - B_s) W(dx) ds$ as $\varepsilon \rightarrow 0$.*

Proof. By writing $X_\varepsilon(t) = \frac{1}{\varepsilon^{\alpha/2}} \int_0^t (\Phi(g(\frac{B_s}{\varepsilon})) - V_1g(\frac{B_s}{\varepsilon})) ds + \frac{1}{\varepsilon^{\alpha/2}} \int_0^t V_1g(\frac{B_s}{\varepsilon}) ds$ and Lemma 4.6, we only need to show the weak convergence of $\frac{1}{\varepsilon^{\alpha/2}} \int_0^t V_1g(\frac{B_s}{\varepsilon}) ds$.

By conditioning on B , we calculate the characteristic function

$$\mathbb{E}\left\{\exp\left(i\theta \frac{1}{\varepsilon^{\alpha/2}} \int_0^t V_1g\left(\frac{B_s}{\varepsilon}\right) ds\right)\right\} = \exp\left(-\frac{V_1^2 \theta^2}{2\varepsilon^\alpha} \int_0^t \int_0^t R_g\left(\frac{B_s - B_u}{\varepsilon}\right) dsdu\right), \quad (4.16)$$

and since $\frac{1}{\varepsilon^\alpha} \int_0^t \int_0^t R_g\left(\frac{B_s - B_u}{\varepsilon}\right) dsdu \rightarrow c_d \int_0^t \int_0^t \frac{1}{\prod_{i=1}^d |B_i(s) - B_i(u)|^{\alpha_i}} dsdu$ almost surely, we only need to apply the dominated convergence theorem to derive

$$\begin{aligned} \mathbb{E}\mathbb{E}_B\left\{\exp\left(i\theta \frac{1}{\varepsilon^{\alpha/2}} \int_0^t V_1g\left(\frac{B_s}{\varepsilon}\right) ds\right)\right\} &\rightarrow \mathbb{E}_B\left\{\exp\left(-\frac{1}{2} \theta^2 V_1^2 c_d \int_0^t \int_0^t \frac{1}{\prod_{i=1}^d |B_i(s) - B_i(u)|^{\alpha_i}} dsdu\right)\right\} \\ &= \mathbb{E}\mathbb{E}_B\left\{\exp\left(i\theta V_1 \sqrt{c_d} \int_0^t \int_{\mathbb{R}^d} \delta(x - B_s) W(dx) ds\right)\right\} \end{aligned} \quad (4.17)$$

as $\varepsilon \rightarrow 0$. \square

Now we are ready to prove the main theorem.

Proof of theorem 2.11. For fixed (t, x) , we let

$$Z_\varepsilon := u_\varepsilon(t, x) = \mathbb{E}_B \left\{ f(x + B_t) \exp\left(i \frac{1}{\varepsilon^{\alpha/2}} \int_0^t V\left(\frac{x + B_s}{\varepsilon}\right) ds\right) \right\}, \quad (4.18)$$

$$Z_0 := u_0(t, x) = \mathbb{E}_B \left\{ f(x + B_t) \exp\left(i V_1 \sqrt{c_d} \int_0^t \int_{\mathbb{R}^d} \delta(y - x - B_s) W(dy) ds\right) \right\}, \quad (4.19)$$

and claim that $\forall m, n \in \mathbb{N}$, $\mathbb{E}\{Z_\varepsilon^m \overline{Z_\varepsilon^n}\} \rightarrow \mathbb{E}\{Z_0^m \overline{Z_0^n}\}$.

Actually, we have

$$\mathbb{E}\{Z_\varepsilon^m \overline{Z_\varepsilon^n}\} = \mathbb{E} \mathbb{E}_B \left\{ \prod_{j=1}^m f(x + B_t^j) \overline{\prod_{j=m+1}^{m+n} f(x + B_t^j)} \exp\left(\frac{i}{\varepsilon^{\alpha/2}} \int_0^t \left(\sum_{j=1}^m V\left(\frac{x + B_s^j}{\varepsilon}\right) - \sum_{j=m+1}^{m+n} V\left(\frac{x + B_s^j}{\varepsilon}\right)\right) ds\right) \right\}, \quad (4.20)$$

where $B_t^j, j = 1, \dots, N = m + n$ are independent Brownian motions. Since $V(x)$ is stationary and all relevant functions are bounded and continuous, to prove the convergence of $\mathbb{E}\{Z_\varepsilon^m \overline{Z_\varepsilon^n}\}$, we only need to prove the annealed weak convergence of

$$W_\varepsilon := \sum_{j=1}^N \alpha_j B_t^j + \sum_{j=1}^N \beta_j \frac{1}{\varepsilon^{\alpha/2}} \int_0^t V\left(\frac{B_s^j}{\varepsilon}\right) ds \quad (4.21)$$

for $\alpha_j, \beta_j \in \mathbb{R}$. We write $W_\varepsilon = (i) + (ii) + (iii)$ with

$$(i) = \sum_{j=1}^N \alpha_j B_t^j, \quad (4.22)$$

$$(ii) = \sum_{j=1}^N \beta_j \frac{1}{\varepsilon^{\alpha/2}} \int_0^t V_1 g\left(\frac{B_s^j}{\varepsilon}\right) ds, \quad (4.23)$$

$$(iii) = \sum_{j=1}^N \beta_j \frac{1}{\varepsilon^{\alpha/2}} \int_0^t \left(\Phi\left(g\left(\frac{B_s^j}{\varepsilon}\right)\right) - V_1 g\left(\frac{B_s^j}{\varepsilon}\right)\right) ds, \quad (4.24)$$

$(iii) \rightarrow 0$ in probability by Lemma 4.6, and for $(i) + (ii)$, we calculate

$$\begin{aligned} & \mathbb{E} \mathbb{E}_B \left\{ \exp(i\theta_1(i) + i\theta_2(ii)) \right\} \\ &= \mathbb{E}_B \left\{ \exp\left(i\theta_1 \sum_{j=1}^N \alpha_j B_t^j\right) \exp\left(-\frac{1}{2} V_1^2 \theta_2^2 \sum_{i,j=1}^N \beta_i \beta_j \frac{1}{\varepsilon^\alpha} \int_0^t \int_0^t R_g\left(\frac{B_s^i - B_u^j}{\varepsilon}\right) ds du\right) \right\}, \end{aligned} \quad (4.25)$$

and by the same proof as in Proposition 4.7, we have

$$\frac{1}{\varepsilon^\alpha} \int_0^t \int_0^t R_g\left(\frac{B_s^i - B_u^j}{\varepsilon}\right) ds du \rightarrow \int_0^t \int_0^t \frac{c_d}{\prod_{k=1}^d |B_k^i(s) - B_k^j(u)|^{\alpha_k}} ds du \quad (4.26)$$

almost surely. Therefore, we see that

$$(i) + (ii) \Rightarrow \sum_{j=1}^N \alpha_j B_t^j + V_1 \sqrt{c_d} \sum_{j=1}^N \beta_j \int_0^t \int_{\mathbb{R}^d} \delta(y - x - B_s^j) W(dy) ds \quad (4.27)$$

in distribution in light of Remark 4.2, so

$$W_\varepsilon \Rightarrow \sum_{j=1}^N \alpha_j B_t^j + V_1 \sqrt{c_d} \sum_{j=1}^N \beta_j \int_0^t \int_{\mathbb{R}^d} \delta(y - x - B_s^j) W(dy) ds$$

in distribution. Thus the claim is proved.

Note that $|Z_\varepsilon|, |Z_0|$ are uniformly bounded, if we let $Z_\varepsilon = Z_{\varepsilon,1} + iZ_{\varepsilon,2}, Z_0 = Z_{0,1} + iZ_{0,2}$, the corresponding real and imaginary parts are uniformly bounded as well. From the fact that $\mathbb{E}\{Z_\varepsilon^m \overline{Z_\varepsilon^n}\} \rightarrow \mathbb{E}\{Z_0^m \overline{Z_0^n}\}$, we know $\forall m, n \in \mathbb{N}, \mathbb{E}\{Z_{\varepsilon,1}^m Z_{\varepsilon,2}^n\} \rightarrow \mathbb{E}\{Z_{0,1}^m Z_{0,2}^n\}$. So

$$\begin{aligned} \mathbb{E}\{\exp(i\theta_1 Z_{\varepsilon,1} + i\theta_2 Z_{\varepsilon,2})\} &= \sum_{k=0}^{\infty} \frac{1}{k!} \mathbb{E}\{(i\theta_1 Z_{\varepsilon,1} + i\theta_2 Z_{\varepsilon,2})^k\} \\ &\rightarrow \sum_{k=0}^{\infty} \frac{1}{k!} \mathbb{E}\{(i\theta_1 Z_{0,1} + i\theta_2 Z_{0,2})^k\} = \mathbb{E}\{\exp(i\theta_1 Z_{0,1} + i\theta_2 Z_{0,2})\}, \end{aligned} \quad (4.28)$$

which completes the proof. \square

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A Technical lemmas

Proposition A.1. *Consider the equation $\partial_t u = \frac{1}{2}\Delta u + iV(x)u$ with initial condition $u(0, x) = f(x) \in \mathcal{C}_b(\mathbb{R}^d)$. Let us define $u(t, x) = \mathbb{E}_B\{f(x + B_t) \exp(i \int_0^t V(x + B_s) ds)\}$. If V has locally bounded sample path almost surely, we have for any $\varphi \in \mathcal{C}_c^\infty(\mathbb{R}^d)$,*

$$\int_{\mathbb{R}^d} u(t, x) \varphi(x) dx = \int_{\mathbb{R}^d} f(x) \varphi(x) dx + \int_0^t \int_{\mathbb{R}^d} u(s, x) \frac{1}{2} \Delta \varphi(x) dx ds + i \int_0^t \int_{\mathbb{R}^d} u(s, x) V(x) \varphi(x) dx ds, \quad (A.1)$$

i.e., the Feynman-Kac solution $u(t, x)$ is a weak solution almost surely.

Proof. Fixing any $\delta, M > 0$, define

$$V_{\delta, M}(x) = \int_{\mathbb{R}^d} \phi_\delta(x - y) V(y) 1_{|y| < M} dy, \quad (A.2)$$

where ϕ_δ is a family of compactly supported mollifier. Fixing the realization, since $V(y) 1_{|y| < M}$ is bounded, $V_{\delta, M}$ is bounded, and we have $V_{\delta, M}(x) \rightarrow V(x) 1_{|x| < M}$ almost everywhere as $\delta \rightarrow 0$. In addition, $V_{\delta, M}$ is smooth, so for the equation $\partial_t u_{\delta, M} = \frac{1}{2}\Delta u_{\delta, M} + iV_{\delta, M}u_{\delta, M}$ with initial condition $u_{\delta, M}(0, x) = f(x)$, we have its classical solution given by the Feynman-Kac formula

$$u_{\delta, M}(t, x) = \mathbb{E}_B\{f(x + B_t) \exp(i \int_0^t V_{\delta, M}(x + B_s) ds)\}, \quad (A.3)$$

and if we first let $\delta \rightarrow 0$, then $M \rightarrow \infty$, $u_{\delta,M}(t, x) \rightarrow u(t, x)$ by the dominated convergence theorem. Since $u_{\delta,M}$ is also a weak solution, we have

$$\begin{aligned} \int_{\mathbb{R}^d} u_{\delta,M}(t, x) \varphi(x) dx &= \int_{\mathbb{R}^d} f(x) \varphi(x) dx + \int_0^t \int_{\mathbb{R}^d} u_{\delta,M}(s, x) \frac{1}{2} \Delta \varphi(x) dx ds \\ &\quad + i \int_0^t \int_{\mathbb{R}^d} u_{\delta,M}(s, x) V_{\delta,M}(x) \varphi(x) dx ds. \end{aligned} \quad (\text{A.4})$$

Let $\delta \rightarrow 0$, $M \rightarrow \infty$, we complete the proof. \square

Proof of Proposition 3.3.

Since M_t is continuous, the quadratic variation process $\langle M \rangle_t$ is continuous as well. We define

$$\tau = \sup\{t \in [0, 1] : \langle M \rangle_t \leq 1\}, \quad (\text{A.5})$$

and it is clear that τ is a stopping time. We construct \tilde{M}_t on $[0, 2]$ as

$$\tilde{M}_t = \begin{cases} M_t & t \in [0, \tau], \\ M_\tau & t \in (\tau, 1], \\ M_\tau + b_{t-1} & t \in (1, 2 - \langle M \rangle_\tau], \\ M_\tau + b_{1 - \langle M \rangle_\tau} & t \in (2 - \langle M \rangle_\tau, 2], \end{cases} \quad (\text{A.6})$$

where b is an independent Brownian motion.

Clearly \tilde{M}_t is a continuous martingale and $\langle \tilde{M} \rangle_2 = 1$, so $\tilde{M}_2 \sim N(0, 1)$. Therefore, $d_{1,k}(M_1, W_1) = d_{1,k}(M_1, \tilde{M}_2)$ and we have

$$d_{1,k}(M_1, \tilde{M}_2) \leq d_{1,k}(M_1, M_\tau) + d_{1,k}(M_\tau, \tilde{M}_2). \quad (\text{A.7})$$

For the first term, if $\|f''\|_\infty \leq k$,

$$|\mathbb{E}\{f(M_1)\} - \mathbb{E}\{f(M_\tau)\} - \mathbb{E}\{(M_1 - M_\tau)f'(M_\tau)\}| \leq \frac{k}{2} \mathbb{E}\{(M_1 - M_\tau)^2\}. \quad (\text{A.8})$$

Note $LHS = |\mathbb{E}\{f(M_1)\} - \mathbb{E}\{f(M_\tau)\}|$ because $\mathbb{E}\{\mathbb{E}\{(M_1 - M_\tau)f'(M_\tau)|\mathcal{F}_\tau\}\} = 0$, and $\mathbb{E}\{(M_1 - M_\tau)^2\} = \mathbb{E}\{\langle M \rangle_1 - \langle M \rangle_\tau\} \leq \mathbb{E}\{|\langle M \rangle_1 - 1|\}$.

For the second term, we have $\tilde{M}_2 = M_\tau + b_{1 - \langle M \rangle_\tau}$. So similarly

$$|\mathbb{E}\{f(\tilde{M}_2)\} - \mathbb{E}\{f(M_\tau)\} - \mathbb{E}\{b_{1 - \langle M \rangle_\tau} f'(M_\tau)\}| \leq \frac{k}{2} \mathbb{E}\{b_{1 - \langle M \rangle_\tau}^2\}. \quad (\text{A.9})$$

$LHS = |\mathbb{E}\{f(\tilde{M}_2)\} - \mathbb{E}\{f(M_\tau)\}|$ since b is independent from M , and

$$RHS = \frac{k}{2} \mathbb{E}\{1 - \langle M \rangle_\tau\} \leq \frac{k}{2} \mathbb{E}\{|1 - \langle M \rangle_1|\}.$$

To summarize, we have $d_{1,k}(M_1, W_1) \leq k \mathbb{E}\{|1 - \langle M \rangle_1|\}$. \square

Lemma A.2.

$$\int_{\mathbb{R}^d} \frac{e^{-\rho|x-y|}}{|x-y|^{d-1}} \frac{e^{-\rho|y|}}{|y|^{d-1}} dy \lesssim e^{-\rho|x|} \left(1 + \frac{1}{|x|^{d-2}}\right). \quad (\text{A.10})$$

Proof. See [8] Lemma A.1. \square

The result in Lemma A.3 is of convolution type. We prove it by the domain decomposition method. Here are some notations appearing in the proof. If we denote $B(z, r) = \{y : |y - z| \leq r\}$, then $\forall x \in \mathbb{R}^d$, let $\rho = |x| > 0$, $A_1 = \{z : |z| < |z - x|\}$, $A_2 = \{z : |z| \geq |z - x|\}$, and define $(I) = B(0, \rho) \cap A_1$, $(II) = B(x, \rho) \cap A_2$, $(III) = \mathbb{R}^d \setminus ((I) \cup (II))$.

(I) , (II) , (III) appears in the proof of Lemma A.3, and we will estimate the integral in each of them respectively. Ψ is assumed to be some positive function such that $\Psi(x) \lesssim 1 \wedge |x|^{-\alpha}$ for any $\alpha > 0$.

Lemma A.3.

$$\frac{1}{\lambda} \int_{\mathbb{R}^{2d}} \frac{e^{-\rho|y|}}{|y|^{d-1}} \frac{e^{-\rho|z|}}{|z|^{d-1}} \Psi\left(x - \frac{y-z}{\sqrt{\lambda}}\right) dy dz \lesssim \lambda^{\frac{d}{2}-1} e^{-c\sqrt{\lambda}|x|} + 1 \wedge \frac{e^{-c\sqrt{\lambda}|x|}}{|x|^{d-2}} + 1 \wedge \frac{1}{|x|^\beta} \quad (\text{A.11})$$

for some $c > 0$ and sufficiently large $\beta > 0$.

Proof. By Lemma A.2, we have

$$\frac{1}{\lambda} \int_{\mathbb{R}^{2d}} \frac{e^{-\rho|y|}}{|y|^{d-1}} \frac{e^{-\rho|z|}}{|z|^{d-1}} \Psi\left(x - \frac{y-z}{\sqrt{\lambda}}\right) dy dz \lesssim (i) + (ii), \quad (\text{A.12})$$

where

$$(i) = \lambda^{\frac{d}{2}-1} \int_{\mathbb{R}^d} e^{-\rho\sqrt{\lambda}|y|} (1 \wedge \frac{1}{|x-y|^\alpha}) dy, \quad (\text{A.13})$$

$$(ii) = \int_{\mathbb{R}^d} e^{-\rho\sqrt{\lambda}|y|} \frac{1}{|y|^{d-2}} (1 \wedge \frac{1}{|x-y|^\alpha}) dy. \quad (\text{A.14})$$

We have used $\Psi(x) \lesssim 1 \wedge \frac{1}{|x|^\alpha}$ for α sufficiently large. (i) , (ii) will be estimated separately but in the same way.

First of all, we clearly have that $(i) \lesssim \lambda^{\frac{d}{2}-1}$ and $(ii) \lesssim 1$. Now we assume $|x| \gg 1$ and divide \mathbb{R}^d into three parts, (I) , (II) , (III) .

For (i) , we have that when $|y - x| \leq 1$, $\int_{|y-x| \leq 1} e^{-\rho\sqrt{\lambda}|y|} dy \lesssim e^{-\rho\sqrt{\lambda}|x|}$. In region (I) , we have $|y - x| \geq \frac{|x|}{2}$, so

$$\int_I e^{-\rho\sqrt{\lambda}|y|} \frac{1}{|x-y|^\alpha} dy \lesssim \frac{1}{|x|^{\alpha-d}}.$$

In region (II) , $|y| \geq \frac{|x|}{2}$, so

$$\int_{II} 1_{|x-y| > 1} e^{-\rho\sqrt{\lambda}|y|} \frac{1}{|x-y|^\alpha} dy \lesssim e^{-\rho\sqrt{\lambda}|x|/2}.$$

In region (III) , $|x - y| \geq |y|/2$, so

$$\int_{III} e^{-\rho\sqrt{\lambda}|y|} \frac{1}{|x-y|^\alpha} dy \lesssim \int_{\mathbb{R}^d} 1_{|y| > |x|} \frac{1}{|y|^\alpha} dy e^{-\rho\sqrt{\lambda}|x|} \lesssim e^{-\rho\sqrt{\lambda}|x|}.$$

Therefore, in summary, we have

$$\int_{\mathbb{R}^d} e^{-\rho\sqrt{\lambda}|y|} (1 \wedge \frac{1}{|x-y|^\alpha}) dy \lesssim 1 \wedge (e^{-c\sqrt{\lambda}|x|} + \frac{1}{|x|^\beta}) \quad (\text{A.15})$$

for $c = \rho/2 > 0$ and β sufficiently large.

For (ii), when $|y-x| \leq 1$,

$$\int_{|y-x| \leq 1} e^{-\rho\sqrt{\lambda}|y|} \frac{1}{|y|^{d-2}} \lesssim e^{-\rho\sqrt{\lambda}|x|} \frac{1}{|x|^{d-2}}.$$

In region (I), by a similar discussion, we have

$$\int_{(I)} e^{-\rho\sqrt{\lambda}|y|} \frac{1}{|y|^{d-2}} dy \frac{1}{|x|^\alpha} \lesssim \frac{1}{|x|^{\alpha-2}}.$$

In region (II), $e^{-\rho\sqrt{\lambda}|y|} \frac{1}{|y|^{d-2}} \lesssim e^{-\rho\sqrt{\lambda}|x|/2} \frac{1}{|x|^{d-2}}$, so

$$\int_{(II)} e^{-\rho\sqrt{\lambda}|y|} \frac{1}{|y|^{d-2}} \frac{1}{|x-y|^\alpha} 1_{|x-y|>1} dy \lesssim e^{-\rho\sqrt{\lambda}|x|/2} \frac{1}{|x|^{d-2}}.$$

In region (III), we have

$$\int_{(III)} e^{-\rho\sqrt{\lambda}|y|} \frac{1}{|y|^{d-2}} \frac{1}{|x-y|^\alpha} dy \lesssim e^{-\rho\sqrt{\lambda}|x|} \frac{1}{|x|^{d-2}}.$$

The proof is complete. \square

Lemma A.4. For

$$F_\lambda(x) = \frac{1}{\lambda} \int_{\mathbb{R}^{2d}} \frac{e^{-\rho|y|}}{|y|^{d-1}} \frac{e^{-\rho|z|}}{|z|^{d-1}} |R|(x - \frac{y-z}{\sqrt{\lambda}}) dy dz,$$

and $|R(x)| \lesssim 1 \wedge |x|^{-\beta}$ with $\beta \in (2, d)$, we have the following estimates for some $c > 0$:

$$\begin{aligned} F_\lambda(x) &\lesssim \lambda^{\frac{\beta}{2}-1} e^{-c\sqrt{\lambda}|x|} + \frac{1}{\lambda|x|^\beta} \int_0^{\sqrt{\lambda}|x|} e^{-cr} r^{d-1} dr 1_{|x| \geq \frac{1}{2}} + \lambda^{\frac{d}{2}-1} e^{-c\sqrt{\lambda}|x|} |x|^{d-\beta} 1_{|x| \geq 1} \\ &+ 1 \wedge \left(\frac{1}{|x|^{\beta-2}} e^{-c\sqrt{\lambda}|x|} + \frac{1}{\lambda|x|^\beta} \int_0^{\sqrt{\lambda}|x|} e^{-cr} r dr + \lambda^{\frac{\beta}{2}-1} \int_{\sqrt{\lambda}|x|}^\infty e^{-cr} r^{1-\beta} dr \right), \end{aligned} \quad (\text{A.16})$$

and we have

$$\int_{\mathbb{R}^d} \frac{F_\lambda(x) + F_\lambda^2(x)}{|x|^{d-2}} dx \lesssim \begin{cases} \lambda^{\frac{\beta}{2}-2} & \beta < 4, \\ \log |\lambda| & \beta = 4, \\ 1 & \beta > 4. \end{cases} \quad (\text{A.17})$$

Proof. The proof is similar to that of Lemma A.3 and 3.6. The details are not presented here. \square

Lemma A.5. Let $x_i \in \mathbb{R}^d, i = 1, \dots, 4$, then under Assumption 2.4

$$\begin{aligned} & |\mathbb{E}\{V(x_1)V(x_2)V(x_3)V(x_4)\} - R(x_1 - x_2)R(x_3 - x_4)| \\ & \leq \Psi(|x_1 - x_3|)\Psi(|x_2 - x_4|) + \Psi(|x_1 - x_4|)\Psi(|x_2 - x_3|), \end{aligned} \quad (\text{A.18})$$

where $\Psi(r) \lesssim 1 \wedge r^{-\beta}$ for any $\beta > 0$.

Proof. The proof could be found in Lemma 2.3. [18], where $\mathbb{E}\{V^6(x)\} < \infty$ is used. \square

Lemma A.6. When $\alpha \in (0, 1)$, $\int_{\mathbb{R}^2} q_\varepsilon(x)q_\varepsilon(y) \frac{1}{|z+x-y|^\alpha} dx dy \rightarrow \frac{1}{|z|^\alpha}$ as $\varepsilon \rightarrow 0$ for $z \neq 0$.

Proof. By change of variables, we write

$$\begin{aligned} \int_{\mathbb{R}^2} q_\varepsilon(x)q_\varepsilon(y) \frac{1}{|z+x-y|^\alpha} dx dy &= \int_{\mathbb{R}^2} q_\varepsilon(w+y-z)q_\varepsilon(y) \frac{1}{|w|^\alpha} dy dw \\ &= \left(\int_{|w| < \frac{|z|}{2}} + \int_{|w| > \frac{|z|}{2}} \right) q_\varepsilon(w+y-z)q_\varepsilon(y) \frac{1}{|w|^\alpha} dy dw \\ &= (i) + (ii), \end{aligned} \quad (\text{A.19})$$

and since

$$(ii) = \int_{|\sqrt{\varepsilon}w+z| > \frac{|z|}{2}} q(w+y)q(y) \frac{1}{|\sqrt{\varepsilon}w+z|^\alpha} dy dw, \quad (\text{A.20})$$

by the dominated convergence theorem, we have $(ii) \rightarrow \frac{1}{|z|^\alpha}$ as $\varepsilon \rightarrow 0$. For (i) , we write

$$(i) = \left(\int_{|w| < \frac{|z|}{2}, |y| > \frac{|z|}{4}} + \int_{|w| < \frac{|z|}{2}, |y| < \frac{|z|}{4}} \right) q_\varepsilon(w+y-z)q_\varepsilon(y) \frac{1}{|w|^\alpha} dy dw. \quad (\text{A.21})$$

For the first term, use $q_\varepsilon(|z|/4)$ to bound $q_\varepsilon(y)$, then integrate in y, w ; for the second term, use $q_\varepsilon(|z|/4)$ to bound $q_\varepsilon(w+y-z)$, then integrate in y, w . Since $q_\varepsilon(|z|/4) \rightarrow 0$ as $\varepsilon \rightarrow 0$, we have $(i) \rightarrow 0$. The proof is complete. \square

Lemma A.7. Assume $\alpha \in (0, 1)$, then $\int_{\mathbb{R}^2} q_{\varepsilon_1}(x_1+y_1)q_{\varepsilon_2}(x_2+y_2)|y_1-y_2|^{-\alpha} dy_1 dy_2 \leq C|x_1-x_2|^{-\alpha}$ for some uniform constant C .

Proof. See Lemma A.2. in [19]. \square

Lemma A.8. When $d \geq 3$ and $\alpha \in (0, 2)$,

$$\lim_{\varepsilon \rightarrow 0} \frac{1}{\varepsilon^\alpha} \int_0^t \int_0^t \mathbb{P}(|B_s - B_u| \leq \varepsilon) ds du = 0. \quad (\text{A.22})$$

Proof. By explicit calculation, we have

$$\begin{aligned}
& \frac{1}{\varepsilon^\alpha} \int_0^t \int_0^t \mathbb{P}(|B_s - B_u| < \varepsilon) ds du \\
&= \frac{1}{(\pi)^{\frac{d}{2}} \varepsilon^\alpha} \int_0^t \int_{|x| < \varepsilon} \int_{\frac{|x|^2}{2s}}^\infty \lambda^{\frac{d}{2}-2} e^{-\lambda} \frac{1}{|x|^{d-2}} d\lambda dx ds \\
&= \frac{1}{(\pi)^{\frac{d}{2}} \varepsilon^\alpha} \int_0^\infty \int_{\mathbb{R}^d} \int_0^\infty 1_{|x| < \varepsilon} 1_{|x|^2 < 2\lambda s} 1_{s < t} \lambda^{\frac{d}{2}-2} e^{-\lambda} \frac{1}{|x|^{d-2}} d\lambda dx ds \tag{A.23} \\
&= \frac{1}{(\pi)^{\frac{d}{2}} \varepsilon^\alpha} \int_0^\infty d\lambda \int \lambda^{\frac{d}{2}-2} e^{-\lambda} \left(\lambda s 1_{\lambda < \frac{\varepsilon^2}{2s}} + \frac{1}{2} \varepsilon^2 1_{\lambda > \frac{\varepsilon^2}{2s}} \right) 1_{s < t} ds \\
&= \frac{1}{(\pi)^{\frac{d}{2}} \varepsilon^\alpha} \int_0^\infty d\lambda \lambda^{\frac{d}{2}-2} e^{-\lambda} \left(\frac{\lambda t^2}{2} 1_{\frac{\varepsilon^2}{2\lambda} > t} + \frac{\varepsilon^2 t}{2} 1_{\frac{\varepsilon^2}{2\lambda} < t} - \frac{\varepsilon^4}{8\lambda} 1_{\frac{\varepsilon^2}{2\lambda} < t} \right) = (i) + (ii) + (iii).
\end{aligned}$$

We check that $(i) \sim \varepsilon^{d-\alpha}$, and $(ii) \sim \varepsilon^{2-\alpha}$, $(iii) \sim \varepsilon^{4-\alpha} + \varepsilon^{d-\alpha}$, so the proof is complete. \square

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