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CENTRAL LIMIT THEOREMS AND QUADRATIC VARIATIONS IN TERMS OF SPECTRAL DENSITY

HERMINE BIERMÉ, ALINE BONAMI, AND JOSÉ R. LEÓN

ABSTRACT. We give a new proof and provide new bounds for the speed of convergence in the Central Limit Theorems of Breuer Major on stationary Gaussian time series, which generalizes to particular triangular arrays. Our assumptions are given in terms of the spectral density of the time series. We then consider generalized quadratic variations of Gaussian fields with stationary increments under the assumption that their spectral density is asymptotically self-similar and prove Central Limit Theorems in this context.

1. INTRODUCTION

In this paper we essentially develop Central Limit Theorems that are well adapted to obtain asymptotic properties of quadratic variations of Gaussian fields with stationary increments. Moreover, we give bounds for the speed of convergence, which partially improve the bounds given by Nourdin and Peccati in [21]. We rely heavily on their methods but adopt a spectral point of view, which is particularly adapted to applications in signal processing.

Before describing our theoretical results, let us describe the scope of applications that we have in mind. The finite distributional properties of a real valued Gaussian field $\{Y(t); t \in \mathbb{R}^\nu\}$, indexed by \mathbb{R}^ν ($\nu \geq 1$), with stationary increments, may be described from its variogram, that is, the function

$$(1) \quad v_Y(t) := \mathbb{E}(((Y(s+t) - Y(s))^2)$$

or from its spectral measure τ , which is such that

$$(2) \quad v_Y(t) = 2 \int_{\mathbb{R}^d} |e^{-it \cdot x} - 1|^2 d\tau(x), \quad \forall t \in \mathbb{R}^\nu.$$

Here $t \cdot x$ stands for the scalar product of the two vectors in \mathbb{R}^ν and $|x|$ denotes the Euclidean norm of the vector x . The spectral measure τ is a non negative even measure on \mathbb{R}^ν . We will only consider absolutely continuous spectral measures, that is, measures that can be written as $d\tau(x) := F(x)d\mu^\nu(x)$. Here μ^ν denotes the Lebesgue measure on \mathbb{R}^ν (we skip the exponent for $\nu = 1$). The function F , called the *spectral density* of Y , is assumed to be a non-negative even function of $L^1(\mathbb{R}^\nu, \min(1, |x|^2) d\mu^\nu(x))$. A typical example of such random fields is given by

$$(3) \quad Y(t) = \int_{\mathbb{R}^\nu} (e^{-it \cdot x} - 1) F(x)^{1/2} d\widetilde{W}^\nu(x), t \in \mathbb{R}^\nu,$$

where \widetilde{W}^ν is a complex centered Gaussian measure on \mathbb{R}^ν with Lebesgue control measure μ^ν , such that $\widetilde{W}^\nu(-A) = \overline{\widetilde{W}^\nu(A)}$ a.s. for any Borel set A of \mathbb{R}^ν . In fact, if we are only interested by finite distributions of the random field Y , we can always assume that Y is given by such a spectral representation (3).

Centered Gaussian fields with stationary increments are widely used as models for real data, for example to describe rough surfaces or porous media that possess some homogeneity properties. In particular the fractional Brownian field (fBf), first defined in Dimension $\nu = 1$ through a stochastic

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integral of moving-average type by Mandelbrot and Van Ness [20], admits such a representation with spectral density given by

$$F_H(x) = \frac{c}{|x|^{2H+\nu}}, \text{ with } c > 0 \text{ and } H \in (0, 1) \text{ called the Hurst parameter.}$$

The homogeneity of F_H implies a self-similarity property of the corresponding random field Y_H , namely

$$\forall \lambda > 0, \{Y_H(\lambda t); t \in \mathbb{R}^\nu\} \stackrel{fdd}{=} \lambda^H \{Y_H(t); t \in \mathbb{R}^\nu\}.$$

The choice of this power of the Euclidean norm for the spectral density is equivalent to the fact that the variogram is $v_{Y_H}(t) = c_H |t|^{2H}$, for some positive constant c_H . When $\nu \geq 2$, it induces the isotropy of the field Y_H (its law is invariant under vectorial rotations). Such a model is not adapted when anisotropic features are observed. Anisotropic but still self-similar generalizations are simply obtained by considering a spectral density given by $F(x) = \Omega(x)F_H(x)$ with Ω an homogeneous function of degree 0 satisfying $\Omega(x) = \Omega(x/|x|)$. Then the corresponding variogram is given in a similar form

$$v(t) = \omega(t/|t|)|t|^{2H}, \text{ with } \omega(t) = c_{H,\nu} \int_{|x|=1} |t \cdot x|^{2H} \Omega(x) dx,$$

where dx denotes the Lebesgue measure on $S^{\nu-1} := \{x \in \mathbb{R}^\nu; |x| = 1\}$. When using such a model, a typical question is the identification of the Hurst parameter H from real data. Many estimators for the Hurst parameter of a one-dimensional fBf (called fractional Brownian motion) have been proposed, based for example on time domain methods or spectral methods (see [10] and [3] and references therein). Quadratic variations are relevant estimators when considering H as the critical index of Hölder regularity for the sample paths. Moreover in [18] the authors give precise bounds of the bias of the variance and show that minimax rates are achieved for this kind of estimators. Generalized quadratic variations also apply to more general Gaussian processes and fields with stationary increments with the same Hölder regularity (see [16, 17] or [8, 9] for instance), for which the variogram satisfies

$$v(t) = \omega(t/|t|)|t|^{2H} + O_{|t \rightarrow 0}(|t|^{2H+s})$$

for $H \in (0, 1)$ and $s \in (0, 2 - 2H)$ with ω a positive function on the sphere $S^{\nu-1}$ (and additional assumptions of regularity). This kind of assumption can be replaced by an assumption on the spectral density F (which is a priori stronger but does not require any extra assumption of regularity). More precisely, we will be interested in random fields for which

$$(4) \quad F(x) = \frac{\Omega(x)}{|x|^{2H+\nu}} + O_{|x| \rightarrow +\infty} \left(\frac{1}{|x|^{2H+\nu+\gamma}} \right),$$

with Ω an even function on the sphere $S^{\nu-1}$ (or a constant when $\nu = 1$), $H > 0$ and $\gamma > 0$. Our particular interest in this situation, where the self-similar spectral density is perturbed by a rest that decreases more rapidly at infinity, may be understood from previous work [7, 5]. This arises in particular when one considers a weighted projection of a self-similar random field. We develop here methods that reveal to be stable when adding such a perturbation to the spectral density. A source of inspiration for us has also been the paper of Chan and Wood [8], which deals with stationary random Gaussian fields with asymptotic self-similar properties.

The estimation of Ω or H goes through the consideration of quadratic variations of Y , observed on finer and finer grids. Typically, we assume to have observed values of the random field on a grid with uniform mesh, that is, $\{Y(k/n); k = (k_1, \dots, k_\nu) \in \mathbb{Z}^\nu \text{ with } 0 \leq k_1, \dots, k_\nu \leq n - 1\}$. We want to have Central Limit Theorems for the quadratic variation of this sequence when n tends to ∞ . For fixed n , this quadratic variation is related to the means of a discrete time series, whose spectral density is obtained by periodization of F . Moreover, a central idea used in this paper consists in a change of scale, so that we can as well consider a fixed mesh, but for a different discrete time series at each scale. Because of the fact that F is asymptotically homogeneous. The rest does not appear in the limit, and acts only on the speed of convergence, which is in $n^{-\alpha}$, for some $\alpha > 0$ depending in particular on γ . Once we have Central Limit Theorems for finite distributions through this scaling

argument, we can also recover asymptotic properties for continuous time quadratic variations, which may be used when dealing with increments of non linear functionals of Y instead of increments of Y .

Let us come back to the theoretical part of this paper, which constitutes its core. We revisit Breuer Major's Theorem, which is our main tool to obtain Central Limit Theorems, and use the powerful theory developed by Nourdin, Nualart, Ortiz-Latorre, Peccati, Tudor and others to do so. This is described in the next section and we refer to it for more details. We would like to attract attention to a remark, which has its own interest: under appropriate additional assumptions, the Malliavin derivative of $\frac{1}{\sqrt{n}} \sum_{k=0}^{n-1} H(X)(k)$, where $(X(k))_{k \in \mathbb{Z}}$ is a stationary Gaussian time series and where the Hermite expansion of H starts with terms of order 2, can be written in terms of the integrated periodogram of the sequence $H'(X)(k)$. Recall that the periodogram of this time series is defined as

$$\frac{1}{n} \left| \sum_{k=0}^{n-1} H'(X)(k) e^{ikx} \right|^2.$$

Up to our knowledge, this link between two different theories had not been given before. As a consequence, the techniques that we use for having the speed of convergence in Central Limit Theorems may be used for consistency of estimators given in terms of integrated periodograms.

Section 2 is devoted to the theoretical aspects (Central Limit Theorems, integrated periodograms, speed of convergence) in Dimension one. We chose to give the proofs in this context, so that the reader can easily follow them. Once this done, we hope that it is not difficult to see how to adapt them in higher dimension, which we do more rapidly in Section 3. We then apply this to generalized quadratic variations in Section 4.

Acknowledgement. This work was mostly done independently of the paper of Nourdin, Peccati and Podolskij [22], which has been posted on the web while we were finishing to write this one. Compared to the results of [22], we deliberately restricted to simple cases, but have found better bounds for the speeds of convergence. It would certainly be helpful to make a synthesis between the two papers. We chose not to do it here, but to stick to our initial project and to the applications we had in view, with assumptions given on spectral densities and not on variograms.

2. BREUER-MAJOR THEOREM REVISITED

In this section we will be interested in stationary centered Gaussian time series $X = (X(k))_{k \in \mathbb{Z}}$ as well as approximate ones. We will start from Breuer-Major Theorem and give a proof of it which is based on the Malliavin Calculus, as exploited by Nourdin, Nualart, Ortiz-Latorre, Peccati, among others, to develop Central Limit Theorems in the context of Wiener Chaos (see [26, 21] for instance). This kind of proof is implicit in the work of these authors, and explicit in the last paper of Nourdin, Peccati and Podolskij [22], where speeds of convergence are given in a very general context. Our interest, here, is to see that assumptions are particularly simple and meaningful when they are given on the spectral density of the time series. Meanwhile, we improve the estimates for the speed of convergence to the best possible through this method under the assumption that the spectral density is in some Sobolev space. Also, this study will lead us to asymptotic estimates on integrated periodograms, which have their own interest and are particularly relevant when one interests to spectral densities.

Let us first state the theorem of Breuer Major in the simplest one dimensional case. For $l \geq 1$, we consider the stationary centered time series $H_l(X) = (H_l(X)(k))_{k \in \mathbb{Z}}$ where $H_l(X)(k) = H_l(X(k))$ with H_l the l -th Hermite polynomial.

Theorem 2.1 (Breuer-Major). *Let $(X(k))_{k \in \mathbb{Z}}$ be a centered stationary Gaussian time series. Assume that for $l \geq 1$, the sequence $r(k) = \mathbb{E}(X(j)X(j+k))$ satisfies the condition*

$$(5) \quad \sum_{k \in \mathbb{Z}} |r(k)|^l < \infty.$$

Then we have the following asymptotic properties for n tending to infinity:

(i)

$$\text{Var} \left(\frac{1}{\sqrt{n}} \sum_{k=0}^{n-1} H_l(X)(k) \right) \longrightarrow \sigma_l^2,$$

(ii)

$$\frac{1}{\sqrt{n}} \sum_{k=0}^{n-1} H_l(X)(k) \xrightarrow{d} \mathcal{N}(0, \sigma_l^2),$$

with

$$(6) \quad \sigma_l^2 = l! \sum_{k \in \mathbb{Z}} r(k)^l.$$

For $p \geq 1$, we introduce the Banach space $\ell^p(\mathbb{Z})$ of p -summable sequences equipped with the norm

$$\|u\|_{\ell^p(\mathbb{Z})} = \left(\sum_{k \in \mathbb{Z}} |u(k)|^p \right)^{1/p} \quad \text{for } u = (u(k))_{k \in \mathbb{Z}} \in \ell^p(\mathbb{Z}).$$

Then, Assumption (5) can be written as $r = (r(k))_{k \in \mathbb{Z}} \in \ell^l(\mathbb{Z})$. We recall that the sequence $r(k)$ can be seen as the Fourier coefficients of a positive even periodic finite measure, called the spectral measure of the time series (see [12] or [28] for instance). We will restrict to time series for which the spectral measure is absolutely continuous with respect to the Lebesgue measure μ .

We identify 2π -periodic functions both with functions on the torus $\mathbb{T} := \mathbb{R}/2\pi\mathbb{Z}$ and functions on $[-\pi, +\pi)$. The spaces $L^p(\mathbb{T})$ are spaces of measurable functions f on $[-\pi, +\pi)$ such that

$$(7) \quad \|f\|_p^p := \|f\|_{L^p(\mathbb{T})}^p := \frac{1}{2\pi} \int_{\mathbb{T}} |g(x)|^p d\mu(x) = \frac{1}{2\pi} \int_{-\pi}^{+\pi} |f(x)|^p d\mu(x).$$

Let us come back to our assumption on the spectral measure. We call f_X its density with respect to the measure μ , and speak of *spectral density of the time series* as it is classical. Moreover we pose $f_X = |g|^2$. We could of course choose g non negative, but have some flexibility.

So, in the following we assume that there exists some function $g \in L^2(\mathbb{T})$ which satisfies the assumption $\overline{g(x)} = g(-x)$, such that

$$(8) \quad r(k) := \frac{1}{2\pi} \int_{\mathbb{T}} e^{-ikx} |g(x)|^2 d\mu(x) = \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{-ikx} |g(x)|^2 d\mu(x).$$

Remark that the absolute continuity is only an additional property under (5) when $l > 2$. Actually, when the sequence $r(k)$ is square summable, one can find $f_X = |g|^2 \in L^2(\mathbb{T})$ by Plancherel's Theorem.

Remark 2.2. Recall that, for U and V two centered Gaussian variables such that $\mathbb{E}(UV) = \rho$, we have $\mathbb{E}(H_l(U)H_l(V)) = l! \rho^l$. So, whenever the time series X has the spectral density f_X , the time series $H_l(X)$ has the density $f_{H_l(X)} = l! f_X^{*l}$, where the notation f_X^{*l} stands for l times the convolution of f_X by itself on the torus. Assumption (5) implies the absolute convergence of the Fourier series of the spectral density of $H_l(X)$. It also means that f_X^{*l} is continuous on \mathbb{T} and that $\sigma_l^2 = l! f_X^{*l}(0)$. For all $l \geq 2$, Assumption (5) is in particular implied by the stronger assumption

$$(9) \quad f_X \in L^{\frac{l}{l-1}}(\mathbb{T}),$$

since $\|r\|_{\ell^l(\mathbb{Z})} \leq \|f_X\|_{L^{\frac{l}{l-1}}(\mathbb{T})}$ by Hausdorff-Young Inequality (see [19] for instance).

Remark 2.3. Note also that the assumption that the Gaussian time series X has a spectral density f_X implies in particular that the time series $H_l(X)$ is a strictly stationary ergodic one, for any $l \geq 1$, (see [11] for instance).

We will give a new proof of the theorem of Breuer Major under Assumption (8). We will use for instance Theorem 4 in [26], which asserts that the Central Limit Theorem is a consequence of the convergence of the variance given in (i) on one side, then of a quantity related to the Malliavin derivative on another side, so that one does not need to consider all moments as in the original proof of Breuer and Major. In a first subsection we recall the main tools in our framework in the classical

context of stochastic integrals of a Brownian Motion. Note however that we adopt here a spectral point view and use harmonizable representation (see [12] for instance). This could be generalized to isonormal Gaussian processes, as it is developed in the first chapter of [25] and used in [22], but we preferred to restrict to the classical case for simplification, even if the general context is necessary in the vectorial case.

2.1. Complex Wiener chaos and Malliavin calculus. Let W be a complex centered Gaussian measure on $[-\pi, +\pi)$ with Lebesgue control measure $\frac{1}{2\pi}\mu$ such that, for any Borel set A of $[-\pi, \pi)$ $W(-A) = \overline{W(A)}$ almost surely. We consider complex-valued functions ψ defined on $[-\pi, +\pi)$, considered as periodic functions of the torus that satisfy, for almost every $x \in \mathbb{T}$,

$$\overline{\psi(x)} = \psi(-x).$$

We write $L_e^2(\mathbb{T})$ for the real vector space of such functions that are square integrable with respect to the Lebesgue measure on \mathbb{T} . Endowed with the scalar product of $L^2(\mathbb{T})$, which we also note

$$\langle \psi, \varphi \rangle_\mu = \frac{1}{2\pi} \int_{\mathbb{T}} \psi(x) \overline{\varphi(x)} d\mu(x),$$

$L_e^2(\mathbb{T})$ is a real separable Hilbert space. Moreover, for any $\psi \in L_e^2(\mathbb{T})$, one can define its stochastic integral with respect to W as

$$I_1(\psi) = \int_{-\pi}^{+\pi} \psi(x) dW(x).$$

Then $I_1(\psi)$ is a real centered Gaussian variable with variance given by $\|\psi\|_2^2$, where $\|\cdot\|_2$ is the norm induced by the scalar product $\langle \cdot, \cdot \rangle_\mu$. To introduce the k -th Itô-Wiener integral, with $k \geq 1$, we consider the complex functions belonging to

$$L_e^2(\mathbb{T}^k) = \{\psi \in L^2(\mathbb{T}^k) : \psi(-x) = \overline{\psi(x)}\}.$$

The inner product in the real Hilbert space of complex functions of $L_e^2(\mathbb{T}^k)$ is given by

$$\langle \psi, \varphi \rangle_{\mu^k} = \frac{1}{(2\pi)^k} \int_{\mathbb{T}^k} \psi(x) \overline{\varphi(x)} d\mu^k(x).$$

The space $L_s^2(\mathbb{T}^k)$ denotes the subspace of functions of $L_e^2(\mathbb{T}^k)$ a.e. invariant under permutations of their arguments. By convention $L_s^2(\mathbb{T}^0) = \mathbb{R}$ for $k = 0$. Let us define $H(W)$ the subspace of random variables in $L^2(\Omega, \mathbb{P})$ measurable with respect to W . The k -Itô-Wiener integral I_k is defined in such a way that $(k!)^{-1/2}I_k$ is an isometry between $L_s^2(\mathbb{T}^k)$ and its range $\mathcal{H}_k \subset H(W)$, so that we have the orthogonal decomposition

$$H(W) = \bigoplus_{k=0}^{\infty} \mathcal{H}_k,$$

where \mathcal{H}_0 is the space of real constants. Each $Y \in H(W)$ has an $L^2(\Omega, \mathbb{P})$ convergent decomposition

$$Y = \sum_{k=0}^{\infty} I_k(\psi_k), \quad \psi_k \in L_s^2(\mathbb{T}^k).$$

When moreover $\sum_{k=1}^{+\infty} (k+1)! \|\psi_k\|_2^2 < +\infty$, with $\|\psi_k\|_2^2 = \langle \psi_k, \psi_k \rangle_{\mu^k}$, the Malliavin derivative of Y , denoted by DY , is defined as the complex valued random process given on \mathbb{T} by

$$D_t Y = \sum_{k=1}^{+\infty} k I_{k-1}(\psi_k(\cdot, t)), \quad t \in \mathbb{T}.$$

Furthermore if H_k is the k -th Hermite polynomial for the standard Gaussian measure and denoting by $\psi^{\odot k}$ the k -tensor product of the function $\psi \in L_e^2(\mathbb{T})$ we have

$$(10) \quad H_k(I_1(\psi)) = I_k(\psi^{\odot k}) := \int_{[-\pi, +\pi)^k} \psi(x_1) \dots \psi(x_k) dW(x_1) \dots dW(x_k),$$

so that its Malliavin derivative is given by $DH_k(I_1(\psi)) = kH_{k-1}(I_1(\psi))\psi$.

2.2. Proof of Breuer Major Theorem under Assumption (8). As far as finite distributions are concerned, when the time series X admits a covariance function given by (8) for some function $g \in L_e^2(\mathbb{T})$, we can assume, without loss of generality, that

$$(11) \quad X(k) := \int_{-\pi}^{+\pi} e^{-ikx} g(x) dW(x).$$

Up to normalization, we can also assume that $r(0) = 1$, or equivalently that $\|g\|_2^2 = \frac{1}{2\pi} \int_{\mathbb{T}} |g(x)|^2 d\mu(x) = 1$. For any $k \in \mathbb{Z}$, we write $g_k(x) = e^{-ikx} g(x) \in L_e^2(\mathbb{T})$ so that $X(k)$ may be written as the Itô-Wiener integral $I_1(g_k)$. Moreover $H_l(X)$ is in the Wiener chaos of order l with

$$H_l(X)(k) = I_l(g_k^{\odot l}), \quad k \in \mathbb{Z}.$$

Let us now proceed to the proof. The computation of the variance in (i) is direct. Let us write

$$Y_n = \frac{1}{\sqrt{n}} \sum_{k=0}^{n-1} H_l(X)(k).$$

Then,

$$(12) \quad \begin{aligned} \text{Var}(Y_n) &= \frac{1}{n} \sum_{k=0}^{n-1} \sum_{k'=0}^{n-1} \text{Cov}(H_l(X)(k), H_l(X)(k')) \\ &= \frac{l!}{n} \sum_{k=0}^{n-1} \sum_{k'=0}^{n-1} r(k-k')^l \\ &= l! \sum_{k=-(n-1)}^{n-1} \left(1 - \frac{|k|}{n}\right) r(k)^l, \end{aligned}$$

which tends to $l! \sum_{k \in \mathbb{Z}} r(k)^l = l! \sigma_l^2$. Recall that this last sum is absolutely convergent because of the assumption on r . This concludes the proof when $l = 1$ since Y_n is a Gaussian variable in this case.

When $l \geq 2$ we write $Y_n = I_l(F_n)$, with $F_n = \frac{1}{\sqrt{n}} \sum_{k=0}^{n-1} g_k^{\odot l}$. By Theorem 4 of [26], to prove Part (ii) it is sufficient to prove that

$$\|DY_n\|_2^2 \xrightarrow{n \rightarrow +\infty} l\sigma_l^2 \text{ in } L^2(\Omega, \mathbb{P}),$$

with DY_n the Malliavin's Derivative of Y_n , which is given by

$$DY_n = \frac{1}{\sqrt{n}} \sum_{k=0}^{n-1} lH_{l-1}(I_1(g_k))g_k.$$

We first remark that

$$\begin{aligned} \|DY_n\|_2^2 &= \frac{l^2}{n} \sum_{k,k'=0}^{n-1} H_{l-1}(I_1(g_k))H_{l-1}(I_1(g_{k'}))\langle g_k, g_{k'} \rangle_{\mu} \\ &= \frac{l^2}{n} \sum_{k,k'=0}^{n-1} H_{l-1}(X)(k)H_{l-1}(X)(k')r(k-k') \\ &= \frac{l^2}{2\pi} \int_{-\pi}^{\pi} I_n^{(l-1)}(x) f_X(x) d\mu(x), \end{aligned}$$

where

$$I_n^{(l-1)}(x) = \frac{1}{n} \sum_{k,k'=0}^{n-1} H_{l-1}(X)(k)H_{l-1}(X)(k')e^{i(k'-k)x} = \frac{1}{n} \left| \sum_{k=0}^{n-1} H_{l-1}(X)(k)e^{ikx} \right|^2,$$

is the periodogram of order n of the stationary sequence $(H_{l-1}(X)(k))_{k \in \mathbb{Z}}$ (see [14] for instance). The end of the proof is a direct consequence of the next subsection, which is devoted to the limit of integrated periodograms. The fact that the Malliavin derivative may be written in terms of the periodogram is an unexpected phenomenon.

Remark 2.4. *The additional assumption is not necessary to be able to use the method above. Indeed, there is always an isonormal Gaussian process $\{W(u) : u \in \mathfrak{H}\}$, where \mathfrak{H} is a separable Hilbert space, such that $X(k)$ may be seen as $W(u_k)$, with u_k a sequence in \mathfrak{H} such that $\langle u_k, u_{k'} \rangle_{\mathfrak{H}} = r(k - k')$. This is in particular used in [22] and is sufficient to develop the same formulas as in the next subsection in order to deal with the Malliavin derivative. We will refer to isonormal Gaussian processes for random vectors, since the analogue of the representation (11) is not available in general in the vectorial case.*

2.3. Integrated periodograms. We keep the notations of the last subsection, so that for $l \geq 1$,

$$(13) \quad I_n^{(l)}(x) := \frac{1}{n} \left| \sum_{k=0}^{n-1} H_l(X)(k)e^{ikx} \right|^2.$$

The periodogram $I_n^{(l)}$ is used as an estimator of the spectral density of the stationary sequence $(H_l(X)(k))_{k \in \mathbb{Z}}$, that is lf_X^{*l} since its Fourier coefficients are equal to $l!r(k)^l$. It is well known that $I_n^{(l)}(x)$ is not a consistent estimate of $lf_X^{*l}(x)$, even when well defined because of continuity (see [14] for instance). However we can hope consistency results for

$$(14) \quad I_{\phi,n}^{(l)} := \frac{1}{2\pi} \int_{-\pi}^{+\pi} I_n^{(l)}(x)\phi(x)d\mu(x).$$

Here ϕ is a test function, which is real, even, integrable and has some smoothness properties to be stated later on. Such quantities $I_{\phi,n}^{(l)}$ are called *integrated periodograms*.

We have the following proposition, which gives in particular the asymptotic properties that are required for the proof of Breuer Major Theorem. We introduce $c_k(\phi) = \frac{1}{2\pi} \int_{\mathbb{T}} \phi(x)e^{-ikx}d\mu(x)$ the k -th Fourier coefficient of ϕ .

Proposition 2.5. *Assume that $(r(k))_{k \in \mathbb{Z}} \in \ell^{\ell+1}(\mathbb{Z})$ and $\sum_{k \in \mathbb{Z}} |c_k(\phi)|^{\ell+1} < \infty$. Then, as n tends to ∞ ,*

- (i) $\mathbb{E}(I_{\phi,n}^{(l)})$ tends to $\frac{l!}{2\pi} \int_{\mathbb{T}} f_X^{*l}(x)\phi(x)d\mu(x)$.
- (ii) $I_{\phi,n}^{(l)} - \mathbb{E}(I_{\phi,n}^{(l)})$ tends to 0 in $L^2(\Omega, \mathbb{P})$.

Remark that conditions on r and ϕ imply that the integral $\frac{1}{2\pi} \int f_X^{*l}(x)\phi(x)d\mu(x)$ may be given meaning as $\sum_{k \in \mathbb{Z}} r(k)^l c_k(\phi)$, using the absolute convergence of the series. When $\phi = f_X$, as in the proof of Breuer Major Theorem, the limit of the expectation is $l! \sum_{k \in \mathbb{Z}} r(k)^{\ell+1} = \sigma_{\ell+1}^2 / (\ell + 1)$.

Proof. The first assertion follows from the fact that

$$\mathbb{E}(I_{\phi,n}^{(l)}) = l! \sum_{k=-n+1}^{n-1} \left(1 - \frac{|k|}{n}\right) r(k)^l c_k(\phi).$$

Next, in view of the second assertion, we consider the components of $\|DY_n\|_2^2$ in the Wiener chaos and use for this the multiplication formula (see [15] for instance), which we recall now:

$$H_l(X)(k)H_l(X)(k') = \sum_{p=0}^l p!(2(l-p))! \binom{l}{p}^2 I_{2l-2p}(g_k^{\odot l} \otimes_p g_{k'}^{\odot l}),$$

with

$$g_k^{\odot l} \otimes_p g_{k'}^{\odot l} = \langle g_k, g_{k'} \rangle_\mu^p \left(g_k^{\odot l-p} \otimes g_{k'}^{\odot l-p} \right)_s.$$

Here, as usual, if $\psi \in L_e^2(\mathbb{T}^k)$, we note $(\psi)_s$ its symmetrization in $L_s^2(\mathbb{T}^k)$, for $k \geq 2$. For simplification, we note $s(k) := c_k(\phi)$. Then we have

$$I_{\phi,n} - \mathbb{E}(I_{\phi,n}) = \sum_{p=0}^{l-1} p!(2(l-p))! \binom{l}{p}^2 U_{p,n},$$

with

$$\begin{aligned} U_{p,n} &= \frac{1}{n} \sum_{k,k'=0}^{n-1} s(k-k') I_{2l-2p}(g_k^{\odot l} \otimes_p g_{k'}^{\odot l}) \\ &= \frac{1}{n} \sum_{k,k'=0}^{n-1} s(k-k') r(k-k')^p I_{2l-2p}((g_k^{\odot l-p} \otimes g_{k'}^{\odot l-p})_s). \end{aligned}$$

Using orthogonality between components, it is sufficient to consider each of them separately. The next lemma gives the convergence in $L^2(\Omega, \mathbb{P})$ of each term.

Lemma 2.6. *Assume that $\sum_{k \in \mathbb{Z}} |r(k)|^{l+1} < \infty$ and $\sum_{k \in \mathbb{Z}} |s(k)|^{l+1} < \infty$. Let $p < l$. Then $\mathbb{E}(|U_{p,n}|^2)$ tends to 0 for n tending to ∞ .*

Proof. We can write $U_{p,n}$ as $I_{2(l-p)}(F_{p,n})$, with

$$F_{p,n} := \frac{1}{n} \sum_{k,k'=0}^{n-1} s(k-k') r(k-k')^p (g_k^{\odot l-p} \otimes g_{k'}^{\odot l-p})_s.$$

By isometry, the $L^2(\Omega, \mathbb{P})$ norm of $U_{p,n}$ is equal, up to the constant $(2(l-p))!^{1/2}$, to the $L_s^2(\mathbb{T}^{2(l-p)})$ norm of $F_{p,n}$. Now $F_{p,n}$ may be written as the mean of $(2(l-p))!$ terms, corresponding to permutations of the $2(l-p)$ variables. It is easy to see that all terms have the same norm, so that the $L_s^2(\mathbb{T}^{2(l-p)})$ norm of $F_{p,n}$ is bounded by the $L_e^2(\mathbb{T}^{2(l-p)})$ norm of one of the terms, that is

$$\left\| \frac{1}{n} \sum_{k,k'=0}^{n-1} s(k-k') r(k-k')^p g_k^{\odot l-p} \otimes g_{k'}^{\odot l-p} \right\|_2.$$

Finally, $\mathbb{E}(|U_{p,n}|^2)$ is bounded by

$$\frac{(2(l-p))!}{(2\pi)^{2l-2p}} \int_{(-\pi, +\pi)^{l-p} \times (-\pi, +\pi)^{l-p}} K_{p,n}(x, y) f_X(x_1) \cdots f_X(x_{l-p}) f_X(y_1) \cdots f_X(y_{l-p}) d\mu^{l-p}(x) d\mu^{l-p}(y),$$

with

$$\begin{aligned} K_{p,n}(x, y) &:= \left| \frac{1}{n} \sum_{k,k'=0}^{n-1} r(k-k')^p s(k-k') e^{-ik(x_1 + \cdots + x_{l-p})} e^{ik'(y_1 + \cdots + y_{l-p})} \right|^2 \\ &= \frac{1}{n^2} \sum_{j,j',k,k'=0}^{n-1} r(k-k')^p s(k-k') r(j-j')^p s(j-j') e^{-i(k-j)(x_1 + \cdots + x_{l-p})} e^{i(k'-j')(y_1 + \cdots + y_{l-p})}. \end{aligned}$$

We pose $\rho_1(k) := |r(k)|^p |s(k)|$ and $\rho_2(k) = |r(k)|^{l-p}$, for $k \in \mathbb{Z}$ and denote by $\rho_{1,n}(k)$, (resp. $\rho_{2,n}(k)$) the truncated sequence $\rho_{1,n}(k) = \rho_1(k)$ (resp. $\rho_{2,n}(k) = \rho_2(k)$) when $|k| \leq n-1$ and 0 otherwise.

Assumption on r implies that $\rho_2 \in \ell^{\frac{l+1}{l-p}}(\mathbb{Z})$ and, together with Assumption on s and Hölder Inequality, that $\rho_1 \in \ell^{\frac{l+1}{p+1}}(\mathbb{Z})$, with $\|\rho_1\|_{\ell^{\frac{l+1}{p+1}}(\mathbb{Z})} \leq \|r\|_{\ell^{l+1}(\mathbb{Z})}^p \|s\|_{\ell^{l+1}(\mathbb{Z})}$. Therefore the convolution product of ρ_1 and ρ_2 is well defined and is uniformly bounded:

$$\rho_1 * \rho_2(k) = \sum_{k' \in \mathbb{Z}} \rho_1(k - k') \rho_2(k') \leq \|\rho_1\|_{\ell^{\frac{l+1}{p+1}}(\mathbb{Z})} \|\rho_2\|_{\ell^{\frac{l+1}{l-p}}(\mathbb{Z})}.$$

Then, the same bound holds for $\rho_{1,n} * \rho_{2,n}(k)$ and

$$\begin{aligned} \mathbb{E}(|U_{p,n}|^2) &\leq \frac{(2(l-p))!}{n^2} \sum_{j, j', k, k'=0}^{n-1} \rho_{1,n}(k - k') \rho_{1,n}(j - j') \rho_{2,n}(k - j) \rho_{2,n}(j' - k') \\ &\leq \frac{(2(l-p))!}{n^2} \sum_{k, j'=0}^{n-1} (\rho_{1,n} * \rho_{2,n}(k - j'))^2. \end{aligned}$$

It follows that

$$\mathbb{E}(|U_{p,n}|^2) \leq \frac{(2(l-p))!}{n} \sum_{|j| \leq n-1} \left(1 - \frac{|j|}{n}\right) (\rho_{1,n} * \rho_{2,n}(j))^2,$$

so that $\mathbb{E}(|U_{p,n}|^2)$ is uniformly bounded with

$$\mathbb{E}(|U_{p,n}|^2) \leq (2(l-p))! \|r\|_{\ell^{l+1}(\mathbb{Z})}^{2l} \|s\|_{\ell^{l+1}(\mathbb{Z})}^2.$$

Let us now prove that $\mathbb{E}(|U_{p,n}|^2)$ tends to 0. We will use a density argument. For \tilde{s} a sequence with finite support, the quantity

$$\frac{1}{n^2} \mathbb{E} \left| \sum_{k, k'=0}^{n-1} \tilde{s}(k - k') I_{2l-2p}(g_k^{\odot l-1} \otimes_p g_{k'}^{\odot l-1})(k') \right|^2$$

tends to 0. To prove the same with s in place of \tilde{s} , for a given $\varepsilon > 0$ we write s as the sum of some \tilde{s} with finite support such that $\sum_{k \in \mathbb{Z}} |\tilde{s}(k) - s(k)|^l < \varepsilon$. We conclude by a standard argument. \square

We have completed the proof of Proposition 2.5, and in the same time the proof of Breuer Major Theorem under the assumption that the spectral measure has a density. \square

In the present context, this proposition on periodograms seems new. Actually Part (i) proves the asymptotic unbiasedness of the estimator $I_{\phi,n}^{(l)}$, while Part (ii) implies its consistency.

Remark 2.7. *If we are only interested in asymptotic unbiasedness, continuity of the function $f^{*l} * \phi$ at 0 is sufficient, see [13]. Remark that the assumptions given here imply that its Fourier series is absolutely convergent. Note also that consistency is proved through asymptotic normality under stronger assumptions of integrability in [13]. This proposition may also be compared with [2], where Central Limit Theorems are developed for integrated periodograms when the test functions are in the Sobolev space \mathcal{H}^α for $\alpha > 1/2$.*

Recall that $\mathcal{H}^\alpha := \mathcal{H}^\alpha(\mathbb{T})$ is the space of functions $\psi \in L^2(\mathbb{T})$ such that

$$\sum_{k \in \mathbb{Z}} |c_k(\psi)|^2 (1 + |k|)^{2\alpha} < \infty.$$

We now give a bound for the speed of convergence in Proposition 2.5 when ϕ is a test function that satisfies a condition of Sobolev type. More precisely, we have the following proposition.

Proposition 2.8. *Assume that $r \in \ell^{l+1}(\mathbb{Z})$ and $\sum_{k \in \mathbb{Z}} |c_k(\phi)|^{l+1} (1 + |k|)^{\alpha(l+1)} < \infty$, for some $\alpha > 0$.*

Then, for some constant C_α and for all $n \geq 1$, we have

$$\text{Var} \left(I_{\phi,n}^{(l)} \right) \leq C_\alpha \begin{cases} \max(n^{-1}, n^{-2\alpha}) & \text{if } \alpha \neq \frac{1}{2} \\ n^{-1} \log(n) & \text{if } \alpha = \frac{1}{2} \end{cases}$$

Proof. Going back to the last proof and its notations, it is sufficient to prove that

$$\sum_{|j| \leq n-1} (\rho_{1,n} * \rho_{2,n}(j))^2 \leq C_\alpha \begin{cases} \max(1, n^{1-2\alpha}) & \text{if } \alpha \neq \frac{1}{2} \\ \log(n) & \text{if } \alpha = \frac{1}{2} \end{cases}$$

We will only consider the case $p = 0$ and leave the reader see that the proof is the same for the other terms. In this case, $\rho_{2,n}$ is uniformly in $\ell^{\frac{l+1}{l}}(\mathbb{Z})$. By Hausdorff-Young Inequality, one has the inclusion $\ell^{\frac{l+1}{l}}(\mathbb{Z}) * \ell^q(\mathbb{Z}) \subset \ell^2(\mathbb{Z})$ when $\frac{1}{q} = \frac{1}{2} + \frac{1}{l+1}$, with the corresponding norm inequality. So it is sufficient to compute the norm of $\rho_{1,n}$ in $\ell^q(\mathbb{Z})$, which is elementary by Hölder Inequality. For this, we use the fact that

$$\sum_{|k| \leq n} (1 + |k|)^{-2\alpha} \leq C_\alpha \max(n^{1-2\alpha}, 1) \text{ when } \alpha \neq \frac{1}{2} \text{ and } \sum_{|k| \leq n} (1 + |k|)^{-1} \leq C_{\frac{1}{2}} \log(n).$$

□

This kind of proof can be generalized to other assumptions on data. We give now one computation that leads to a bound for the speed of convergence in Breuer major Theorem.

Proposition 2.9. *Assume that $\sum_{k \in \mathbb{Z}} |r(k)|^{l+1} (1 + |k|)^{\alpha(l+1)} < \infty$ for some $\alpha > 0$. Then, when $l = 1$, for some $C_\alpha > 0$ and for all $n \geq 1$ we have the uniform estimate*

$$\text{Var} \left(I_{f_X, n}^{(1)} \right) \leq C_\alpha \max(n^{-1}, n^{-4\alpha}).$$

For $l \geq 2$, for some $C_\alpha > 0$ and for all $n \geq 1$ we have

$$\text{Var} \left(I_{f_X, n}^{(l)} \right) \leq C_\alpha \begin{cases} n^{-2\alpha(l+1)} & : \quad \alpha < \frac{1}{l(l+1)} \\ n^{-2\alpha - \frac{2}{l+1}} & : \quad \frac{1}{l(l+1)} < \alpha < \frac{1}{2} - \frac{1}{l+1} \\ n^{-1} & : \quad \alpha > \frac{1}{2} - \frac{1}{l+1} \end{cases}.$$

Proof. Again, we go back to the previous notations and estimate $\sum_{|j| \leq n-1} (\rho_{1,n} * \rho_{2,n}(j))^2$. Let us first consider $l = 1$. The only case to consider is $p = 0$, and we want to prove the estimate

$$\sum_{|j| \leq n-1} (\rho_{1,n} * \rho_{2,n}(j))^2 \leq C \max(1, n^{1-4\alpha}).$$

Here $\rho_{1,n} = \rho_{2,n}$ coincides with $|r|$ for $|k| \leq n-1$. Assume first that $\alpha < 1/4$. It follows from Hölder inequality that $\|\rho_{1,n}\|_{\ell^{4/3}(\mathbb{Z})} \leq C_\alpha n^{1/4-\alpha}$. Now the convolution of two sequences in $\ell^{4/3}(\mathbb{Z})$ is in $\ell^2(\mathbb{Z})$, which allows to conclude in this case. For $\alpha > 1/4$, the sequence ρ_1 is in $\ell^{4/3}(\mathbb{Z})$ and we conclude in the same way.

It remains to conclude for $\alpha = 1/4$. We want to prove that $\sum_{|j| \leq n-1} (\rho_{1,n} * \rho_{2,n}(j))^2$ is uniformly bounded

under the assumption that $\sum_{k \in \mathbb{Z}} |r(k)|^2 (1 + |k|)^{1/2} < \infty$. Let h_n be the trigonometric polynomial with $\rho_{1,n}$ as Fourier coefficients. Then $\rho_{1,n} * \rho_{2,n} = \rho_{1,n} * \rho_{1,n}$ are the Fourier coefficients of the function h_n^2 . The function h_n is uniformly in the Sobolev space $\mathcal{H}^{1/4}$. Now it follows from Sobolev Theorem (see [19] for instance) that such functions are uniformly in $L^4(\mathbb{T})$. By Plancherel Identity,

$$(15) \quad \sum_{j \in \mathbb{Z}} (\rho_{1,n} * \rho_{1,n}(j))^2 = \frac{1}{2\pi} \int_{\mathbb{T}} |h_n(x)|^4 d\mu(x) \leq C.$$

Let us now consider $l \geq 2$ and estimate again the norm of $\rho_{1,n} * \rho_{2,n}$ in $\ell^2(\mathbb{Z})$. The worst case is obtained for $p = 0$. Then $\rho_{1,n}$ coincides with $|r|$ while ρ_2 is equal to $|r|^l$. Then

$$\|\rho_{1,n} * \rho_{2,n}\|_{\ell^2(\mathbb{Z})} \leq \|\rho_{1,n}\|_{\ell^2(\mathbb{Z})} \|\rho_{2,n}\|_{\ell^1(\mathbb{Z})}.$$

The first estimate is obtained by taking the norm of $\rho_{1,n}$ in $\ell^2(\mathbb{Z})$ and the norm of $\rho_{2,n}$ in $\ell^1(\mathbb{Z})$, as long as this last one is not uniformly bounded. For larger values of α , ρ_2 is in $\ell^1(\mathbb{Z})$ and the bound is given by the the norm of $\rho_{1,n}$ in $\ell^2(\mathbb{Z})$, as long as this last one is not uniformly bounded. \square

2.4. Variable spectral densities. In practice, the spectral density may change at each step of computation of the mean. This is what happens for instance when we look at increments of a Gaussian process at different scales. It is important to have still Central Limit Theorems in this context, as well as methods to compute the speed of convergence. Let us first state a CLT in this framework, which may also be seen as a CLT for particular triangular arrays.

Theorem 2.10. *Let $X_n = (X_n(k))_{k \in \mathbb{Z}}$ be centered stationary Gaussian time series with spectral densities f_{X_n} . Let $l \geq 2$. We assume that the functions f_{X_n} belong uniformly to the space $L^{\frac{l}{l-1}}(\mathbb{T})$ and converge in this space to a function f_X . We call $r(k) := \frac{1}{2\pi} \int_{\mathbb{T}} e^{-ikx} f_X(x) d\mu(x)$ and assume, without loss of generality, that $r(0) = 1$. Then we have the following asymptotic properties for n tending to infinity:*

(i)

$$\text{Var} \left(\frac{1}{\sqrt{n}} \sum_{k=0}^{n-1} H_l(X_n)(k) \right) \rightarrow \sigma_l^2,$$

(ii)

$$\frac{1}{\sqrt{n}} \sum_{k=0}^{n-1} H_l(X_n)(k) \xrightarrow{d} \mathcal{N}(0, \sigma_l^2),$$

with

$$(16) \quad \sigma_l^2 = l! \sum_{k \in \mathbb{Z}} r(k)^l.$$

Proof. Let X be a centered stationary Gaussian time series with spectral density f_X . We define Y_n as before. Let us define

$$Z_n := \frac{1}{\sqrt{n}} \sum_{k=0}^{n-1} H_l(X_n)(k).$$

Similar computations as for Y_n imply that

$$\text{Var}(Z_n) = l! \sum_{k=-(n-1)}^{n-1} \left(1 - \frac{|k|}{n}\right) r_n(k)^l.$$

It follows from the assumption and Hausdorff-Young Inequality that the sequence r_n tends to r in $\ell^l(\mathbb{Z})$. This implies that $\text{Var}(Y_n)$ and $\text{Var}(Z_n)$ have the same limit.

We then have to prove that $\text{Var}(\|DZ_n\|_2^2)$ tends to 0 in place of $\text{Var}(\|DY_n\|_2^2)$, with a variable spectral density in place of a fixed one. For this, it is sufficient to revisit the proof of Lemma 2.6, where we consider r_n in place of r and s , and so, later on, $\tilde{\rho}_{1,n}$ and $\tilde{\rho}_{2,n}$ instead of $\rho_{1,n}$ and $\rho_{2,n}$, which are obtained when replacing r by r_n . We write $r_n = r + r - r_n$ and develop the corresponding formulas by multi-linearity. When all r_n 's are replaced by r , we have the limit 0 by Lemma 2.6. Now, when one r_n is replaced by $r - r_n$ somewhere, the proof goes the same way, except for the fact that $r - r_n$ has an arbitrarily small norm in $\ell^l(\mathbb{Z})$. So the limit is 0. \square

Remark that one has the inequalities

$$(17) \quad \begin{aligned} |\text{Var}(Y_n) - \text{Var}(Z_n)| &= l! \left| \sum_{k=-(n-1)}^{n-1} \left(1 - \frac{|k|}{n}\right) (r(k)^l - r_n(k)^l) \right| \\ &\leq C_l \|r - r_n\|_{\ell^l(\mathbb{Z})} \\ &\leq C_l \|f_X - f_{X_n}\|_{\frac{l}{l-1}}, \end{aligned}$$

according to Hausdorff-Young Inequality.

Remark 2.11. *The conclusion of Theorem 2.10 holds true under the weaker assumption that r_n tends to r in $\ell^l(\mathbb{Z})$. Moreover, one does not need to have spectral densities, according to Remark 2.4.*

2.5. Speed of convergence in Breuer Major Central Limit Theorem. We are now able to bound the speed of convergence in Theorem 2.1 under the assumption that $\sum |r(k)|^l(1+|k|)^{l\alpha}$ is finite for some $\alpha > 0$, as well as in Theorem 2.10. We recall that the distance of Kolmogorov between the random variables Y and Z is defined as

$$(18) \quad d_{Kol}(Y, Z) = \sup_{z \in \mathbb{R}} |P(Y < z) - P(Z < z)|.$$

We will be particularly interested by the distance of Kolmogorov to some normal random variable σN , where $N \sim \mathcal{N}(0, 1)$. We recall that (see [21] for instance), for Z a centered random variable with variance 1 in the l -th Wiener chaos,

$$(19) \quad d_{Kol}(Z, N) \leq \sqrt{\left(\text{Var} \left(\frac{1}{l} \|DZ\|_2^2 \right) \right)}.$$

The following lemma will be used to compute the required Kolmogorov distances.

Lemma 2.12. *For Y a centered random variable in the l -th Wiener chaos we have the inequality*

$$d_{Kol}(Y, \sigma N) \leq \frac{2}{\sigma^2} |\text{Var}(Y) - \sigma^2| + \sqrt{\left(\text{Var} \left(\frac{1}{l\sigma^2} \|DY\|_2^2 \right) \right)}.$$

Proof. When $\frac{|\text{Var}(Y) - \sigma^2|}{\sigma^2} > \frac{1}{2}$ there is nothing to prove. Otherwise we write

$$d_{Kol}(Y, \sigma N) \leq d_{Kol}(Y, \sqrt{\text{Var}(Y)}N) + d_{Kol}(\sqrt{\text{Var}(Y)}N, \sigma N).$$

We use the Malliavin derivative for the first distance, then a direct computation of the distance between N and a multiple of N . More precisely, for example for $z > 0$ and $\sigma > 1$, one has the inequality $P(z \leq N \leq \sigma z) \leq (\sigma - 1)ze^{-z^2/2} \leq \sigma - 1$. \square

We can now state the first theorem of this subsection, which gives the speed of convergence in Breuer Major Theorem.

Theorem 2.13. *Let $(X(k))_{k \in \mathbb{Z}}$ be a centered stationary Gaussian time series with an absolutely continuous spectral measure. Assume that r satisfies $r(0) = 1$ and the assumption*

$$(20) \quad \sum_{k \in \mathbb{Z}} |r(k)|^l (1 + |k|)^{l\alpha} < \infty$$

for some $\alpha > 0$. Then, for $l = 2$, for some constant $C_\alpha > 0$ and for all $n \geq 1$,

$$(21) \quad d_{Kol} \left(\frac{1}{\sqrt{n}} \sum_{k=0}^{n-1} H_2(X)(k), \sigma_2 N \right) \leq C_\alpha \max(n^{-2\alpha}, n^{-1/2}),$$

while, for $l \geq 3$, for some constant $C_\alpha > 0$ and for all $n \geq 1$,

$$(22) \quad d_{Kol} \left(\frac{1}{\sqrt{n}} \sum_{k=0}^{n-1} H_l(X)(k), \sigma_l N \right) \leq C_\alpha \begin{cases} n^{-\alpha l} & : \quad \alpha < \frac{1}{l(l-1)} \\ n^{-\alpha - \frac{1}{l}} & : \quad \frac{1}{l(l-1)} < \alpha < \frac{1}{2} - \frac{1}{l} \\ n^{-\frac{1}{2}} & : \quad \alpha > \frac{1}{2} - \frac{1}{l} \end{cases} .$$

with $\sigma_l^2 = l! \sum_{k \in \mathbb{Z}} r(k)^l$.

Proof. Let us first prove that

$$(23) \quad |\sigma_l^2 - \text{Var}(Y_n)| \leq C \max(n^{-\alpha l}, n^{-1}).$$

From the expression of $\text{Var}(Y_n)$ given in (12) we deduce that

$$l^{-1} |\sigma_l^2 - \text{Var}(Y_n)| \leq \frac{1}{n} \sum_{k=-(n-1)}^{n-1} |k| |r(k)|^l + \sum_{|k| \geq n} |r(k)|^l.$$

We conclude directly using the fact that $\sum_{k \in \mathbb{Z}} |r(k)|^l (1 + |k|)^{l\alpha} < \infty$. Now the required estimate for the Malliavin derivative is given by Proposition 2.9. \square

This bound for the speed of convergence can be compared to the ones given in [22], which it improves. In particular, the speed of convergence for the fractional Brownian Noise given in Example 2.7 in [22] can be improved by using the proof of Proposition 2.9. This is a particular case of the following example.

Remark 2.14. Assume that $r(k) = O(|k|^{-a})$. Then, for $a > \frac{1}{2}$, $l = 2$ and $a \neq \frac{3}{4}$,

$$(24) \quad d_{Kol} \left(\frac{1}{\sqrt{n}} \sum_{k=0}^{n-1} H_2(X)(k), \sigma_2 N \right) \leq C \max(n^{1-2a}, n^{-1/2}),$$

while, for $l \geq 2$ and $a > \frac{1}{l}$

$$(25) \quad d_{Kol} \left(\frac{1}{\sqrt{n}} \sum_{k=0}^{n-1} H_l(X)(k), \sigma_l N \right) \leq C \begin{cases} n^{-la+1} & : a < \frac{1}{l-1} \\ n^{-a} & : \frac{1}{l-1} < a < \frac{1}{2} \\ n^{-\frac{1}{2}} & : a > \frac{1}{2} \end{cases}.$$

These estimates seem the best possible that one can obtain by this use of the Malliavin derivative. Let us consider the case $l = 2$ and $a = 3/4$ and prove that one cannot then have the rate $n^{-1/2}$ in general. Indeed, assume that f_X is given by the Riesz potential, whose behavior at 0 is $\simeq |x|^{-1/4}$ and whose Fourier coefficients behave like $|k|^{-3/4}$. Then f_X is not square integrable, which proves that one cannot have a uniform bound in (15).

For $a = 1/2$, one can also improve the logarithmic rate given in [22].

Next we give the speed of convergence in Theorem 2.10, which depends on the speed of convergence of f_{X_n} to f_X .

Theorem 2.15. Let $X_n = (X_n(k))_{k \in \mathbb{Z}}$ be centered stationary Gaussian time series with spectral densities f_{X_n} which satisfy the assumptions of Theorem 2.10 with $r(k) := \frac{1}{2\pi} \int_{\mathbb{T}} e^{-ikx} f_X(x) d\mu(x)$. We assume moreover that the two following properties are satisfied.

$$(26) \quad \sum_{k \in \mathbb{Z}} |r(k)|^l (1 + |k|)^{\alpha l} < \infty.$$

$$(27) \quad \|f_{X_n} - f_X\|_{\frac{l}{l-1}} \leq C n^{-\beta}.$$

Then, for $l = 2$, for some constant $C_{\alpha, \beta}$ and for all $n \geq 1$, we have

$$(28) \quad d_{Kol} \left(\frac{1}{\sqrt{n}} \sum_{k=0}^{n-1} H_2(X_n)(k), \sigma_2 N \right) \leq C_{\alpha, \beta} \max(n^{-\beta}, n^{-2\alpha}, n^{-1/2}),$$

while, for $l \geq 3$, for some constant $C_{\alpha, \beta}$ and for all $n \geq 1$, we have

$$(29) \quad d_{Kol} \left(\frac{1}{\sqrt{n}} \sum_{k=0}^{n-1} H_l(X_n)(k), \sigma_l N \right) \leq C_{\alpha, \beta} \begin{cases} \max(n^{-\beta}, n^{-\alpha l}) & : \alpha < \frac{1}{l(l-1)} \\ \max(n^{-\beta}, n^{-\alpha - \frac{1}{l}}) & : \frac{1}{l(l-1)} < \alpha < \frac{1}{2} - \frac{1}{l} \\ \max(n^{-\beta}, n^{-\frac{1}{2}}) & : \alpha > \frac{1}{2} - \frac{1}{l} \end{cases}.$$

Proof. We go back to the notations used in the proof of Theorem 2.10. We will use Lemma 2.12 with Z_n in place of Y . We first want to have the speed of convergence of $\text{Var}(Z_n) - \sigma_l^2$ to 0. This is given by (17) and (23). We then have to bound $\text{Var}(\|DZ_n\|_2^2)$ in place of $\text{Var}(\|DY_n\|_2^2)$, with a variable spectral density in place of a fixed one. So we have to consider $\tilde{\rho}_{1,n}$ and $\tilde{\rho}_{2,n}$ instead of $\rho_{1,n}$ and $\rho_{2,n}$,

with r replaced by r_n .

When $l = 2$ we use the fact that $\|\tilde{\rho}_{1,n}\|_{\ell^{4/3}(\mathbb{Z})} \leq \|\tilde{\rho}_{1,n} - \rho_{1,n}\|_{\ell^{4/3}(\mathbb{Z})} + \|\rho_{1,n}\|_{\ell^{4/3}(\mathbb{Z})}$, with

$$\|\tilde{\rho}_{1,n} - \rho_{1,n}\|_{\ell^{4/3}(\mathbb{Z})}^4 \leq n \|r_n - r\|_{\ell^2(\mathbb{Z})}^4 \leq Cn^{1-4\beta}.$$

So $\|\tilde{\rho}_{1,n}\|_{\ell^{4/3}(\mathbb{Z})} \leq Cn^{1/4-\alpha\wedge\beta}$. When $l \geq 3$, similarly we use the fact that

$$\|\tilde{\rho}_{1,n}\|_{\ell^2(\mathbb{Z})}^2 \leq C \left(n^{\frac{l-2}{l}} \|r_n - r\|_{\ell^l(\mathbb{Z})}^2 + \|\rho_{1,n}\|_{\ell^2(\mathbb{Z})}^2 \right), \text{ and } \|\tilde{\rho}_{2,n}\|_{\ell^1(\mathbb{Z})}^2 \leq C \left(n^{\frac{2}{l}} \|r_n - r\|_{\ell^l(\mathbb{Z})}^2 + \|\rho_{2,n}\|_{\ell^1(\mathbb{Z})}^2 \right).$$

□

3. VECTOR-VALUED CENTRAL LIMIT THEOREM AND GENERALIZATIONS

3.1. Vector-valued central limit theorem. We now describe a very useful extension of Theorem 2.10 to the vectorial case. Our main tool is [27] where it is proved that vectorial Central Limit Theorems follow from Central Limit Theorems for marginals and convergence of covariance matrix. For $d \geq 2$ we consider a vector-valued centered stationary Gaussian time series defined by $\vec{X}(k) = (X_1(k), X_2(k), \dots, X_d(k))$. We assume that the covariance matrix of \vec{X} is given by

$$r_{i,j}(k) = \text{Cov}(X_i(k'+k), X_j(k')) := \frac{1}{2\pi} \int_{-\pi}^{+\pi} e^{-ikx} \left(f_{\vec{X}} \right)_{i,j}(x) d\mu(x).$$

With a little abuse we say that the Hermitian d times d matrix $f_{\vec{X}}$ is the spectral density of \vec{X} . Then we can consider the stationary vector-valued processes

$$\overrightarrow{H_l(\vec{X})}(k) = (H_l(X_1)(k), \dots, H_l(X_d)(k)), \quad k \in \mathbb{Z}, \quad l \geq 1.$$

In fact we are interested in the more general case of variable spectral densities.

Theorem 3.1. *Let $(\vec{X}_n(k))_{k \in \mathbb{Z}}$ be centered stationary time series with values in \mathbb{R}^d . We call $f_{\vec{X}_n}$ the spectral density matrix of \vec{X}_n . Let $l \geq 2$. We assume that $f_{\vec{X}_n}$ belongs uniformly to the space $L^{\frac{l}{l-1}}(\mathbb{T})$ and converges in this space to a function $f_{\vec{X}}$ (in the sense that $\| (f_{\vec{X}_n})_{i,j} - (f_{\vec{X}})_{i,j} \|_{\frac{l}{l-1}}$ tends to 0 as n tends to infinity for all $1 \leq i, j \leq d$). We call $r_{i,j}(k) := \frac{1}{2\pi} \int_{\mathbb{T}} e^{-ikx} (f_{\vec{X}})_{i,j}(x) d\mu(x)$ and assume, without loss of generality, that $r_{i,i}(0) = 1$. Then we have the following vectorial CLT for n tending to infinity:*

$$\frac{1}{\sqrt{n}} \sum_{k=0}^{n-1} \overrightarrow{H_l(X_n)}(k) \xrightarrow{d} \mathcal{N}(0, \Sigma_l),$$

with $(\Sigma_l)_{i,j} = l! \sum_{k \in \mathbb{Z}} r_{i,j}(k)^l$.

Proof. It is no more possible in general to write \vec{X}_n as a Brownian stochastic integral, but we can still use an isonormal Gaussian process (see Remark 2.4 and [22]), which allows us to use the results of [27]. Let us introduce as before

$$\vec{Z}_n = \frac{1}{\sqrt{n}} \sum_{k=0}^{n-1} \overrightarrow{H_l(X_n)}(k).$$

Once we have a one dimensional CLT for each coordinate of \vec{Z}_n , then it is sufficient to prove that the covariance matrix of \vec{Z}_n tends to the matrix Σ_l (that is, Assumption 6 of Proposition 2 of [27]). First, let us remark that for any $1 \leq i \leq d$, $X_{n,i}$ admits $(f_{\vec{X}_n})_{i,i}$ for spectral density. Since

$\| (f_{\overline{X}_n})_{i,i} - (f_{\overline{X}})_{i,i} \|_{\frac{l}{l-1}}$ tends to 0 as n tends to infinity, we already know by Theorem 2.10 that the random variable $Z_{n,i}$ converges in distribution to $\mathcal{N}(0, (\Sigma_l)_{i,i})$. Now, for $1 \leq i, j \leq d$, we have

$$\begin{aligned}
 \text{Cov}(Z_{n,i}, Z_{n,j}) &= \frac{1}{n} \sum_{k=0}^{n-1} \sum_{k'=0}^{n-1} \mathbb{E}(H_l(X_{n,i})(k)H_l(X_{n,j})(k')) \\
 &= \frac{l!}{n} \sum_{k=0}^{n-1} \sum_{k'=0}^{n-1} r_{n,i,j}(k-k')^l \\
 &= l! \sum_{k=-(n-1)}^{n-1} \left(1 - \frac{|k|}{n}\right) r_{n,i,j}(k)^l.
 \end{aligned}$$

From this point, the proof that this quantity tends to $(\Sigma_l)_{i,j}$ is the same as for a scalar valued time series. \square

Remark 3.1. *One can also have a bound for the speed of convergence as in Section 2, based on results of [24, 23]. One considers now the distance of Wasserstein*

$$d_W(\overline{Y}, \overline{Z}) = \sup |\mathbb{E}(\Phi(\overline{Y})) - \mathbb{E}(\Phi(\overline{Z}))|,$$

where the supremum is taken on all Lipschitz functions with Lipschitz constant bounded by 1, under the assumption that the matrix Σ_l is positive definite. When it is not the case, the function Φ is taken of class \mathcal{C}^2 , with bounded second derivatives. Mutatis mutandis, the bounds obtained for the speed of convergence are the same as in the last section, see Theorem 2.15.

3.2. Extension to stationary centered Gaussian fields. Until now, we have chosen to restrict our study to stationary centered Gaussian processes, essentially for notational sake of simplicity. However, all previous results have their counterpart in the framework of Gaussian random fields that are indexed by \mathbb{Z}^ν for some integer $\nu \geq 2$ instead of \mathbb{Z} . Then Theorems 2.10 and 3.1 are generalized in the following setting.

Theorem 3.2. *Let $\nu, d \geq 1$ integers. Let $\overline{X}_n = (\overline{X}_n(k))_{k \in \mathbb{Z}^\nu}$ be centered stationary Gaussian fields with values in \mathbb{R}^d . Let $l \geq 2$. We call $f_{\overline{X}_n}$ the spectral density matrix of \overline{X}_n and assume that $f_{\overline{X}_n}$ belongs to the space $L^{\frac{l}{l-1}}(\mathbb{T}^\nu)$ and converges in this space to a function $f_{\overline{X}}$. We call $r_{i,j}(k) := \frac{1}{(2\pi)^\nu} \int_{\mathbb{T}^\nu} e^{-ik \cdot x} (f_{\overline{X}})_{i,j}(x) d\mu^\nu(x)$ and assume that $r_{i,i}(0) = 1$ for $1 \leq i \leq d$. Then, for n tending to infinity,*

(i)

$$\text{Var} \left(\frac{1}{n^{\nu/2}} \sum_{k_1, \dots, k_d=0}^{n-1} H_l(X_{n,i})(k) \right) \longrightarrow (\Sigma_l)_{i,i},$$

(ii)

$$\frac{1}{n^{\nu/2}} \sum_{k_1, \dots, k_d=0}^{n-1} H_l(\overline{X}_n)(k) \xrightarrow{d} \mathcal{N}(0, \Sigma_l),$$

with

$$(30) \quad (\Sigma_l)_{i,j} = l! \sum_{k \in \mathbb{Z}^\nu} r_{i,j}(k)^l.$$

In the case where $\overline{X}_n = \overline{X}$, this result is a particular consequence of Theorem 4 of Arcones [1].

Remark 3.3. *One can also have a bound for the speed of convergence (written in terms of the distance of Wasserstein if $d > 1$) as in the last subsection, but with different exponents coming from the generalization of Proposition 2.9. In this proposition, the new bound is $\max(n^{-\nu}, n^{-4\alpha})$ when*

$l = 1$, due to the fact that the Sobolev space \mathcal{H}^α is contained in $L^4(\mathbb{T}^\nu)$ for $\alpha = \nu/4$. When $l \geq 2$, the new bound is, up to a constant,

$$\max(n^{-2(l+1)\alpha}, n^{-2\alpha - \frac{2\nu}{l+1}}, n^{-\nu}).$$

In Theorem 3.2, whenever $\|f_{\overline{X}_n} - f_{\overline{X}_n}\|_{\frac{l}{l-1}} \leq Cn^{-\beta}$, the speed of convergence is $O(\max(n^{-\beta}, n^{-2\alpha}, n^{-1/2}))$ for $l = 2$. Whenever $l > 2$, it is bounded, up to a constant, by

$$\begin{cases} \max(n^{-\beta}, n^{-\alpha l}) & : & \frac{\alpha}{\nu} < \frac{1}{l(l-1)} \\ \max(n^{-\beta}, n^{-\alpha - \frac{\nu}{l}}) & : & \frac{1}{l(l-1)} < \frac{\alpha}{\nu} < \frac{1}{2} - \frac{1}{l} \\ \max(n^{-\beta}, n^{-\frac{\nu}{2}}) & : & \frac{\alpha}{\nu} > \frac{1}{2} - \frac{1}{l} \end{cases} .$$

4. APPLICATION TO GENERALIZED QUADRATIC VARIATIONS

In this section we consider a continuous time real-valued centered Gaussian field with stationary increments, defined through a spectral representation

$$(31) \quad Y(t) = \int_{\mathbb{R}^\nu} (e^{-it \cdot x} - 1) F(x)^{1/2} d\widetilde{W}^\nu(x), t \in \mathbb{R}^\nu,$$

where \widetilde{W}^ν is a complex centered Gaussian measure on \mathbb{R}^ν with Lebesgue control measure μ^ν , such that $\widetilde{W}^\nu(-A) = \overline{\widetilde{W}^\nu(A)}$ a.s. for any Borel set A of \mathbb{R}^ν . The function F satisfies the integrability condition

$$\int_{\mathbb{R}^\nu} \min(1, |x|^2) d\mu^\nu(x) < \infty.$$

Remark that this condition could be relaxed when only higher order increments are stationary (see [28]). We refer to the introduction for more notations and comments.

We assume that only $\{Y(k/n); k = (k_1, \dots, k_\nu) \in \mathbb{Z}^\nu \text{ with } 0 \leq k_1, \dots, k_\nu \leq n-1\}$ are known for some large n .

Let us first describe our method in the simplest possible example, that is, the Fractional Brownian Motion in one dimension. So, for a moment we assume that $\nu = 1$ and $F(x) := |x|^{-2H-1}$, with $0 < H < 1$. We are interested in first increments $X_n(k) := Y((k+1)/n) - Y(k/n)$ and want to have a CLT for the means

$$\frac{1}{n} \sum_{k=0}^{n-1} |X_n(k)|^2$$

which are also the quadratic variations of the sequence $Y(k/n)$. We remark that

$$\text{Cov}(X_n(k), X_n(k')) = \int_{\mathbb{R}} e^{-i\frac{(k-k')x}{n}} \left| e^{-i\frac{x}{n}} - 1 \right|^2 F(x) d\mu(x).$$

We use the homogeneity of F to write this covariance as

$$\text{Cov}(X_n(k), X_n(k')) = n^{-2H} \int_{\mathbb{R}} e^{-i(k-k')x} \left| e^{-ix} - 1 \right|^2 F(x) d\mu(x).$$

Then, by a standard argument (which may be seen as an elementary version of Poisson's Formula), the spectral density of this time series is given by a periodization of F , that is,

$$\text{Cov}(X_n(k), X_n(k')) = n^{-2H} \int_{-\pi}^{+\pi} e^{-i(k-k') \cdot x} \left| e^{-ix} - 1 \right|^2 \sum_j \frac{1}{|x + 2\pi j|^{2H+1}} d\mu(x).$$

So, if we consider asymptotic properties of normalized increments $n^H X_n(k)$, they are the same as the ones of a unique time series, whose spectral density is the periodic function

$$f_X(x) := \left| e^{-ix} - 1 \right|^2 \sum_j \frac{1}{|x + 2\pi j|^{2H+1}}.$$

In particular, one observes a Central Limit Theorem for the quadratic variations $\frac{1}{n} \sum_{k=0}^{n-1} |X(k)|^2$ (once centralized and reduced) if one has the same for the means of $H_2(X)$. This can be deduced

from Section 2 as soon as the function f_X is in $L^2(\mathbb{T})$, which is the case for $H < 3/4$ (we give the proof of this fact in the general case).

If F is only asymptotically homogeneous, we will still be able to use the same argument, but with a variable spectral density.

We now consider the general case $\nu \geq 1$ and define generalized quadratic variations (recall that one has to deal with higher increments for $H \geq 3/4$ in Dimension one). We first define generalized increments. More precisely, our first step is to consider a stationary field induced by these observations. This is obtained through a filtering of this sequence. In particular we consider the discrete time stationary field

$$Z_{n,\mathbf{a}}(k) = \sum_{m_1, \dots, m_\nu=0}^p a_1(m_1) \dots a_\nu(m_\nu) Y \left(\frac{k_1 + m_1}{n}, \dots, \frac{k_\nu + m_\nu}{n} \right), \quad \text{for } k = (k_1, \dots, k_\nu) \in \mathbb{Z}^\nu$$

and $\mathbf{a} = (\mathbf{a}_1, \dots, \mathbf{a}_\nu)$ with $\mathbf{a}_j = (a_j(0), \dots, a_j(p)) \in \mathbb{R}^{p+1}$ a discrete filter of length $p+1$ and of order K_j ($p, K_j \in \mathbb{N}$ with $p \geq K_j$), which means that $\sum_{m_j=0}^p a_j(m_j) \neq 0$ when $K_j = 0$ and otherwise

$$\sum_{m_j=0}^p a_j(m_j) m_j^r = 0 \quad \text{for } 0 \leq r \leq K_j - 1 \quad \text{and} \quad \sum_{m_j=0}^p a_j(m_j) m_j^{K_j} \neq 0.$$

For $\nu = 1$, examples are given

- the increments of Y : $Z_{n,\mathbf{a}}(k) = Y\left(\frac{k+1}{n}\right) - Y\left(\frac{k}{n}\right)$ for $\mathbf{a} = (-1, 1)$, which is a filter of order 1.
- the second order increments of Y : $Z_{n,\mathbf{a}}(k) = Y\left(\frac{k+2}{n}\right) - 2Y\left(\frac{k+1}{n}\right) + Y\left(\frac{k}{n}\right)$ for $\mathbf{a} = (1, -2, 1)$, which is a filter of order 2.

In Dimension $\nu = 2$, following the works of Chan & Wood [8] and Zu & Stein [29] we can also consider the following types of increments:

- Vertical $Z_{n,\mathbf{a}}(k) = Y\left(\frac{k_1}{n}, \frac{k_2+2}{n}\right) - 2Y\left(\frac{k_1}{n}, \frac{k_2+1}{n}\right) + Y\left(\frac{k_1}{n}, \frac{k_2}{n}\right)$ for $\mathbf{a}_1 = (1)$ filter of order 0 and $\mathbf{a}_2 = (1, -2, 1)$ filter of order 2.
- Horizontal $Z_{n,\mathbf{a}}(k) = Y\left(\frac{k_1+2}{n}, \frac{k_2}{n}\right) - 2Y\left(\frac{k_1+1}{n}, \frac{k_2}{n}\right) + Y\left(\frac{k_1}{n}, \frac{k_2}{n}\right)$ for $\mathbf{a}_1 = (1, -2, 1)$ filter of order 2 and $\mathbf{a}_2 = (1)$ filter of order 0.
- Superficial $Z_{n,\mathbf{a}}(k) := \square_{k_1, k_2}^n(Y) = Y\left(\frac{k_1+1}{n}, \frac{k_2+1}{n}\right) - Y\left(\frac{k_1+1}{n}, \frac{k_2}{n}\right) - Y\left(\frac{k_1}{n}, \frac{k_2+1}{n}\right) + Y\left(\frac{k_1}{n}, \frac{k_2}{n}\right)$ for $\mathbf{a}_1 = \mathbf{a}_2 = (-1, 1)$ filter of order 1.

Coming back to the general case, let us associate to the filter \mathbf{a}_j the real polynomial

$$P_{\mathbf{a}_j}(x_j) = \sum_{m_j=0}^p a_j(m_j) x_j^{m_j}, \quad \text{for } x_j \in \mathbb{R}.$$

Then \mathbf{a}_j is a filter of order $K_j \geq 1$ if and only if $P_{\mathbf{a}_j}^{(r)}(1) = 0$, for $0 \leq r \leq K_j - 1$ and $P_{\mathbf{a}_j}^{(K_j)}(1) \neq 0$. By Taylor formula, this implies that there exists $c_j > 0$ such that

$$(32) \quad |P_{\mathbf{a}_j}(e^{-ix_j})| \leq c_j \min(|x_j|^{K_j}, 1), \quad x_j \in \mathbb{R}.$$

Moreover using the spectral representation of Y , one has

$$Z_{n,\mathbf{a}}(k) = \int_{\mathbb{R}^\nu} e^{-i\frac{k \cdot x}{n}} \prod_{j=1}^\nu P_{\mathbf{a}_j} \left(e^{-i\frac{x_j}{n}} \right) F(x)^{1/2} d\widetilde{W}^\nu(x).$$

We will note $P_{\mathbf{a}}(x) := \prod_{j=1}^\nu P_{\mathbf{a}_j}(x_j)$. The only assumption that we will use is the fact that $P_{\mathbf{a}}$ has a zero of order $K := K_1 + K_2 + \dots + K_\nu$ at $(1, \dots, 1)$. We say that the filter \mathbf{a} has order K . Then we

have

$$\begin{aligned} \text{Cov}(Z_{n,\mathbf{a}}(k), Z_{n,\mathbf{a}}(k')) &= \int_{\mathbb{R}^\nu} e^{-i\frac{(k-k')\cdot x}{n}} \left| P_{\mathbf{a}} \left(e^{-i\frac{x_1}{n}}, \dots, e^{-i\frac{x_\nu}{n}} \right) \right|^2 F(x) d\mu^\nu(x) \\ &= \frac{1}{(2\pi)^\nu} \int_{[-\pi, \pi]^\nu} e^{-i(k-k')\cdot x} \left| P_{\mathbf{a}} \left(e^{-ix_1}, \dots, e^{-ix_\nu} \right) \right|^2 \sum_{k \in \mathbb{Z}^\nu} (2\pi n)^\nu F(nx + 2n\pi k) d\mu^\nu(x). \end{aligned}$$

So the spectral density of $Z_{n,\mathbf{a}}$ is given by

$$(33) \quad f_{n,\mathbf{a}}(x) = \left| P_{\mathbf{a}} \left(e^{-ix_1}, \dots, e^{-ix_\nu} \right) \right|^2 \sum_{k \in \mathbb{Z}^\nu} (2\pi n)^\nu F(nx + 2n\pi k), \quad x \in [-\pi, \pi]^\nu.$$

Because of the assumption on \mathbf{a} , one can find a positive constant $c > 0$ such that

$$(34) \quad \left| P_{\mathbf{a}} \left(e^{-ix_1}, \dots, e^{-ix_\nu} \right) \right| \leq c|x|^K, \quad x = (x_1, \dots, x_\nu) \in [-\pi, \pi]^\nu,$$

Then, the generalized quadratic variations of Y are defined as

$$(35) \quad V_{n,\mathbf{a}} = \frac{1}{(n-p+1)^\nu} \sum_{k_1, \dots, k_\nu=0}^{n-p} (Z_{n,\mathbf{a}}(k))^2.$$

Such quantities are very helpful to estimate the H parameter as explained below.

4.1. Central Limit Theorem for quadratic variations. We now consider random fields Y for which Assumption 4 is valid. More precisely, let Ω be a strictly positive homogeneous function of degree 0 that is continuous on the sphere $S^{\nu-1}$. We assume that

$$(36) \quad F(x) = \frac{\Omega(x)}{|x|^{2H+\nu}} + R(x),$$

where the rest R satisfies the estimate

$$(37) \quad |R(x)| \leq \frac{\kappa}{|x|^{2H+\nu+\gamma}} \quad \text{for } |x| > A.$$

We will prove a Central Limit Theorem for the generalized quadratic variations related to H . We will see that the limit does not depend on the rest. We use the notations given above.

Theorem 4.1. *Let us assume that F , the spectral density of Y satisfies (36) and (37) for some $H > 0$ and $\gamma > 0$. Let \mathbf{a} be a filter of order K . Moreover, we assume that $|x|^{4K} F(x)^2$ is integrable on compact sets. If $K > H + \frac{\nu}{4}$, then for n tending to infinity,*

- (i) $(n-p+1)^\nu \text{Var} \left(\frac{V_{n,\mathbf{a}}}{\mathbb{E}(V_{n,\mathbf{a}})} - 1 \right) \longrightarrow \sigma_{\mathbf{a}}^2(H)$
- (ii) $(n-p+1)^{\nu/2} \left(\frac{V_{n,\mathbf{a}}}{\mathbb{E}(V_{n,\mathbf{a}})} - 1 \right) \xrightarrow{d} \mathcal{N}(0, \sigma_{\mathbf{a}}^2(H)),$

with

$$(38) \quad \sigma_{\mathbf{a}}^2(H) = \frac{2(2\pi)^\nu}{C_{\mathbf{a}}(H)^2} \int_{[-\pi, \pi]^\nu} \left| P_{\mathbf{a}} \left(e^{-ix_1}, \dots, e^{-ix_\nu} \right) \right|^4 \left| \sum_{k \in \mathbb{Z}^\nu} \frac{\Omega(x + 2\pi k)}{|x + 2\pi k|^{2H+\nu}} \right|^2 d\mu^\nu(x),$$

where

$$(39) \quad C_{\mathbf{a}}(H) = \int_{\mathbb{R}^\nu} \left| P_{\mathbf{a}} \left(e^{-ix_1}, \dots, e^{-ix_\nu} \right) \right|^2 \frac{\Omega(x)}{|x|^{2H+\nu}} d\mu^\nu(x).$$

Proof. This will be a direct consequence of the previous sections. We can write

$$(n-p+1)^{\nu/2} \left(\frac{V_{n,\mathbf{a}}}{\mathbb{E}(V_{n,\mathbf{a}})} - 1 \right) = \frac{1}{(n-p+1)^{\nu/2}} \sum_{k_1, \dots, k_\nu=0}^{n-p} H_2(X_{n,\mathbf{a}}(k)),$$

with $\{X_{n,\mathbf{a}}(k), k \in \mathbb{Z}^\nu\}$ a stationary Gaussian time series, given by

$$X_{n,\mathbf{a}}(k) := \frac{Z_{n,\mathbf{a}}(k)}{\sqrt{\text{Var}(Z_{n,\mathbf{a}}(k))}}.$$

The spectral density of $X_{n,\mathbf{a}}$ is easily deduced from the one of $Z_{n,\mathbf{a}}$ given in (33), using the fact that

$$C_{n,\mathbf{a}} := \text{Var}(Z_{n,\mathbf{a}}(k)) = \int_{\mathbb{R}^\nu} |P_{\mathbf{a}}(e^{-ix_1}, \dots, e^{-ix_\nu})|^2 n^\nu F(nx) d\mu^\nu(x).$$

This means that $f_{X_{n,\mathbf{a}}}$ is given by

$$(40) \quad f_{X_{n,\mathbf{a}}}(x) := \frac{(2\pi n)^\nu}{C_{n,\mathbf{a}}} |P_{\mathbf{a}}(e^{-ix_1}, \dots, e^{-ix_\nu})|^2 \sum_{k \in \mathbb{Z}^\nu} F(nx + 2\pi k).$$

We are in position to apply Theorem 2.10 or Theorem 3.2 depending on the dimension. It is sufficient to prove that $f_{X_{n,\mathbf{a}}}$ is uniformly in $L^2(\mathbb{T})$ and converges to $f_{X_{\mathbf{a}}}$, with

$$(41) \quad f_{X_{\mathbf{a}}}(x) = \frac{(2\pi n)^\nu}{C_{\mathbf{a}}(H)} |P_{\mathbf{a}}(e^{-ix_1}, \dots, e^{-ix_\nu})|^2 \sum_{k \in \mathbb{Z}^\nu} \frac{\Omega(x + 2\pi k)}{|x + 2\pi k|^{2H+\nu}}$$

and $C_{\mathbf{a}}(H)$ given by (39). The required convergence properties are contained in the following lemma.

Lemma 4.2. *We have the following.*

$$n^{2H} \mathbb{E}(V_{n,\mathbf{a}}) - C_{\mathbf{a}}(H) = \begin{cases} O_{n \rightarrow +\infty}(n^{-2(K-H)}) & \text{if } K - H < \gamma/2 \\ O_{n \rightarrow +\infty}(n^{-\gamma} \log n) & \text{if } K - H = \gamma/2 \\ O_{n \rightarrow +\infty}(n^{-\gamma}) & \text{if } K - H > \gamma/2 \end{cases}.$$

Moreover $f_{X_{n,\mathbf{a}}}$ and $f_{X_{\mathbf{a}}}$ are in $L^2(\mathbb{T})$ and

$$\|f_{X_{n,\mathbf{a}}} - f_{X_{\mathbf{a}}}\|_2 = \begin{cases} O_{n \rightarrow +\infty}(n^{-(2K-2H-\nu/2)}) & \text{if } K - H < \gamma + \nu/4 \\ O_{n \rightarrow +\infty}(n^{-2\gamma} \log n) & \text{if } K - H = \gamma + \nu/4 \\ O_{n \rightarrow +\infty}(n^{-2\gamma}) & \text{if } K - H > \gamma + \nu/4 \end{cases}.$$

Proof. For the first estimates, we have to bound

$$\int_{\mathbb{R}^\nu} \min(|x|^{2K}, 1) n^{2H+\nu} |R(nx)| dx = \int_{|x| < A/n} + \int_{A/n < |x| < 1} + \int_{|x| > 1}.$$

For the first term, since we have no assumption on R except for the fact that it is the difference between F and $\frac{\Omega(x)}{|x|^{2H+\nu}}$, we consider each quantity separately. For the integral in F , we change of variable and use the assumption of integrability on F to conclude that it is a term in $n^{-2(K-H)}$. The other estimates are straightforward.

Next, let us prove that $f_{X_{\mathbf{a}}}$ is in $L^2(\mathbb{T})$. We write that

$$\begin{aligned} \int_{\mathbb{T}^\nu} (f_{X_{\mathbf{a}}}(x))^2 d\mu^\nu(x) &= c \int_{[-\pi, \pi]^\nu} |P_{\mathbf{a}}(e^{-ix_1}, \dots, e^{-ix_\nu})|^4 \left(\sum_{k \in \mathbb{Z}^\nu} \frac{\Omega(x + 2\pi k)}{|x + 2\pi k|^{2H+\nu}} \right)^2 d\mu^\nu(x) \\ &\leq c \int_{[-\pi, \pi]^\nu} |x|^{4K} \frac{\Omega(x)^2}{|x|^{4H+2\nu}} d\mu^\nu(x) + C \\ &< +\infty. \end{aligned}$$

We have used the fact that, for $|x| \leq \pi$, the sum $\sum_{k \neq 0} \frac{1}{|x + 2\pi k|^{2H+\nu}}$ is uniformly bounded since $K > H + \frac{\nu}{4}$. Next, in order to bound the norm of $f_{X_{n,\mathbf{a}}} - f_{X_{\mathbf{a}}}$, we have to consider the quantity

$$\Delta_n(x) := n^{\nu+2H} \sum_{k \in \mathbb{Z}^\nu} R(n(x + 2k\pi)).$$

From Assumptions (36) and (37) and from the fact that Ω is bounded below on the unit sphere, we deduce that, for $|x| > A/n$ (with some constant C that varies from line to line)

$$|R(x)| \leq \frac{C}{|x|^\gamma} \frac{\Omega(x)}{|x|^{2H+\nu}}.$$

It follows that, for $|x| > \frac{2C}{n}$, we have the inequality

$$\Delta_n(x) \leq \frac{C}{n^\gamma |x|^{2H+\nu+\gamma}}.$$

Using this inequality, we estimate easily

$$\int_{|x| > \frac{2C}{n}} (f_{X_{n,\mathbf{a}}}(x) - f_{X_{\mathbf{a}}}(x))^2 d\mu^\nu(x).$$

To conclude, it is sufficient, after a change of variables, to bound

$$n^{4H+\nu-4K} \int_{|x| \leq 2C} |x|^{4K} F(x)^2 d\mu^\nu(x),$$

which is direct upon the local integrability assumption on F . \square

This finishes the proof of the theorem. \square

4.2. Remark on the speed of convergence. We keep the notations of the last subsection and interest ourselves to the speed of convergence towards a Gaussian law. We want to give a bound for the Kolmogorov distance in one variable, or the distance of Wasserstein in general, between $\frac{V_{n,\mathbf{a}}}{\mathbb{E}(V_{n,\mathbf{a}})}$ and a Gaussian random variable of law $\mathcal{N}(0, \sigma_{\mathbf{a}}^2(H))$. By Lemma 4.2, we have a bound for the speed of convergence of $f_{X_{n,\mathbf{a}}}$ towards $f_{X_{\mathbf{a}}}$. So we can use Theorem 2.15 or Remark 3.3 as soon as $f_{X_{\mathbf{a}}}$ belongs to some Sobolev space \mathcal{H}^α . Or, if the Fourier coefficients of $f_{X_{\mathbf{a}}}$ behave like a power $|k|^{-a}$, then we can also use Remark 2.14 to have a bound for the speed of convergence. This is what we discuss now.

Let us start with Dimension one, where Ω is a constant. Then the Fourier coefficients of $f_{X_{\mathbf{a}}}$, which we note $r_{\mathbf{a}}$, are also, up to a constant, the values of the Fourier transform of the function

$$\frac{|P_{\mathbf{a}}(e^{-ix})|^2}{|x|^{2H+\nu}}.$$

It is classical that these last ones may be written as

$$r_{\mathbf{a}}(k) := \sum_{m=-p}^p b_m |k+m|^{2H},$$

where b_m are coefficients of the polynomial $Q := |P|^2$. Using the fact that Q vanishes at order $2K$ and Taylor's Formula, one sees that

$$(42) \quad r_{\mathbf{a}}(k) = O(|k|^{2H-2K}),$$

In higher dimension, we will show that we can conclude with some regularity assumption on Ω . Specifically, if we assume that Ω is of class \mathcal{C}^1 on the unit sphere, then the first partial derivatives of

$$h_{\mathbf{a}}(x) := \frac{|P_{\mathbf{a}}(e^{-ix})|^2 \Omega(x)}{|x|^{2H+\nu}}$$

satisfy the same kind of estimates as the function itself, apart from the loss of 1 in the power of $|x|$ in one term, and the fact that P or \bar{P} has been replaced by its derivative in another one. If again $r_{\mathbf{a}}(k) := \int_{\mathbb{R}^\nu} e^{-ik \cdot x} h_{\mathbf{a}}(x) d\mu^\nu(x)$, then $k_j r_{\mathbf{a}}(k)$ appears as the Fourier coefficients of the j th partial derivative of $h_{\mathbf{a}}$. Remark first that we have proved in Lemma 4.2 that the sequence $r_{\mathbf{a}}(k)$ is in $\ell^2(\mathbb{Z}^\nu)$ by proving that the periodization of $h_{\mathbf{a}}$ is in $L^2(\mathbb{T}^\nu)$, which is equivalent by Plancherel Theorem. For the same reason, to prove that $k_j r_{\mathbf{a}}(k)$ is a sequence in $\ell^2(\mathbb{Z}^\nu)$, it is equivalent to prove that the periodization of the j th derivative of $h_{\mathbf{a}}$ is in $L^2(\mathbb{T}^\nu)$. Under the assumption that Ω is of class \mathcal{C}^1 on the unit sphere, we do this by the same method, but on the stronger assumption that $K - 1 - H > \nu/4$. The necessity of a stronger assumption is linked to the loss of 1 in the power of $|x|$. Finally, under these two assumptions, we conclude that $\sum_{k \in \mathbb{Z}^\nu} |k|^2 |r_{\mathbf{a}}(k)|^2 < \infty$ and one can apply

Theorem 3.3.

One can weaken or strengthen these assumptions on Ω to obtain the full range of Sobolev spaces. In all cases we have a speed of convergence towards a Gaussian law in $|n|^{-\delta}$ with δ depending on γ , K , H , and the regularity of Ω .

4.3. Application to the identification of H . As we said before, a central question is the estimation of H from real data. As an application of generalized quadratic variations, we obtain Proposition 1.3 of [5] without additional assumption of regularity on the spectral density. Actually, let us fix the dimension $\nu = 1$ and, following [17], let us consider the filtered process of Y with a dilated filter. More precisely, let $U \geq 2$ an integer. For an integer $u \in \{1, \dots, U\}$, the dilation \mathbf{a}^u of \mathbf{a} is defined by, for $0 \leq m \leq pu$,

$$a_m^u = \begin{cases} a_{m'} & \text{if } m' = mu \\ 0 & \text{otherwise.} \end{cases}$$

Since $\sum_{m=0}^{pu} m^r a_m^u = u^r \sum_{m=0}^p m^r a_m$, the filter \mathbf{a}^u has the same order than \mathbf{a} but length pu . Then,

$$\{X_{n,\mathbf{a}^u}(k); k \in \mathbb{Z}^\nu, u \in \{1, \dots, U\}\} \stackrel{fdd}{=} \left\{ \frac{Z_{n,\mathbf{a}^u}(k)}{\sqrt{\text{Var}(Z_{n,\mathbf{a}^u}(k))}}; k \in \mathbb{Z}^\nu, u \in \{1, \dots, U\} \right\},$$

so that $\left(\frac{V_{n,\mathbf{a}^u}}{\mathbb{E}(V_{n,\mathbf{a}^u})}, \frac{V_{n,\mathbf{a}^v}}{\mathbb{E}(V_{n,\mathbf{a}^v})} \right) \xrightarrow{n \rightarrow +\infty} (1, 1)$ almost surely with asymptotic normality for $K > H + \frac{1}{4}$, according to Theorems 3.2 and 4.1, for any $u, v \in \{1, \dots, U\}$. According to Proposition 1.1 of [5] (see also Lemma 4.2 above), Assumption (4) implies that

$$n^{2H} \mathbb{E}(V_{n,\mathbf{a}^u}) = u^{2H} C_{\mathbf{a}}(H) + \begin{cases} O(n^{-2(K-H)}) & \text{if } K - H < \gamma/2 \\ O(n^{-\gamma} \log n) & \text{if } K - H = \gamma/2 \\ O(n^{-\gamma}) & \text{if } K - H > \gamma/2 \end{cases},$$

so that for $u, v \in \{1, \dots, U\}$,

$$\widehat{H}_{n,\mathbf{a}}(u, v) := \frac{1}{2 \log(u/v)} \log \left(\frac{V_{n,\mathbf{a}^u}}{V_{n,\mathbf{a}^v}} \right) \xrightarrow{n \rightarrow +\infty} H \text{ a.s.}$$

with asymptotic normality when $K > H + 1/4$ and $\gamma > 1/2$. We refer to [5] for details. The main difference here is the fact that we only need an assumption on the behavior of the rest, not on its derivatives, due to the use of Theorem 3.2.

4.4. Functional Central Limit Theorem for Quadratic variations of a stationary Gaussian random process. Up to now, we have only considered finite distributions. In this last subsection we want to prove that one can have convergence for continuous time processes as well. We will restrict our study to the case $\nu = 1$. So let us consider the random process Y given by (3) in Dimension one. Then Assumption (4) on the spectral density F of Y can be written as

$$(43) \quad F(x) = \frac{c}{|x|^{2H+1}} + \underset{|x| \rightarrow +\infty}{O} \left(\frac{1}{|x|^{2H+1+\gamma}} \right).$$

We keep the notations of the previous section and consider for a discrete filter \mathbf{a} of length $p+1$ and order $K \geq 1$ the filtered process of discrete observations of Y defined for $n \geq p$ by

$$Z_{n,\mathbf{a}}(k) = \sum_{m=0}^p a_m Y \left(\frac{k+m}{n} \right), \text{ for } k \in \mathbb{Z}.$$

Following Donsker's Theorem we consider a functional version of the Central Limit Theorem obtained in Theorem 4.1. For this purpose let us introduce the continuous time random process defined for $t \in [\frac{p}{n}, 1]$ by

$$S_{n,\mathbf{a}}(t) = \frac{1}{\sqrt{n-p+1}} \sum_{k=0}^{[nt]-p} \left(\frac{Z_{n,\mathbf{a}}(k)^2}{C_{n,\mathbf{a}}} - 1 \right),$$

and $S_{n,\mathbf{a}}(t) = 0$ for $0 \leq t < \frac{p}{n}$, where $C_{n,\mathbf{a}} = \mathbb{E}(Z_{n,\mathbf{a}}(k)^2)$. Then $S_{n,\mathbf{a}}(1) = \sqrt{n-p+1} \left(\frac{V_{n,\mathbf{a}}}{\mathbb{E}(V_{n,\mathbf{a}})} - 1 \right)$. Moreover, $S_{n,\mathbf{a}}$ is a.s. a càdlàg process on $[0, 1]$ and we denote as usual $\mathcal{D}([0, 1])$ the set of such processes. We also introduce the càdlàg random process defined on $[0, 1]$ by $Y_n(t) = Y \left(\frac{[nt]}{n} \right)$. Let us recall that according to (43) and Proposition 1 of [7] we can assume that Y is a.s. continuous on $[0, 1]$. It follows that Y_n converges in law to Y in the space $\mathcal{D}([0, 1])$ equipped with the Skorohod topology. Then, Theorem 6 of [4] has the following counterpart in our setting.

Theorem 4.3. *We keep notations introduced in the previous section. Let us assume that F , the spectral density of Y satisfies (43) for some $H > 0$ and $\gamma > 0$. Let \mathbf{a} be a filter of order K . Moreover, we assume that $|x|^{4K} F(x)^2$ is integrable on compact sets. If $K > H + \frac{1}{4}$, then for n tending to infinity, we obtain the weak convergence (in the space $\mathcal{D}([0, 1])^2$ equipped with the Skorohod topology)*

$$(Y_n(t), S_{n,\mathbf{a}}(t)) \longrightarrow (Y(t), \sigma_{\mathbf{a}}(H)B(t)),$$

where B is a standard Brownian motion on $[0, 1]$ that is defined on the same probability space than Y , independent of Y and

$$(44) \quad \sigma_{\mathbf{a}}^2(H) = \frac{4\pi}{C_{\mathbf{a}}(H)^2} \int_{[-\pi, \pi]} |P_{\mathbf{a}}(e^{-ix})|^4 \left| \sum_{k \in \mathbb{Z}} \frac{c}{|x + 2\pi k|^{2H+1}} \right|^2 d\mu(x),$$

where

$$(45) \quad C_{\mathbf{a}}(H) = \int_{\mathbb{R}} |P_{\mathbf{a}}(e^{-ix})|^2 \frac{c}{|x|^{2H+1}} d\mu(x).$$

Proof. Let us first consider the convergence of $S_{n,\mathbf{a}}(t)$. For fixed t , this is a small modification of the data of the previous section, and we immediately have

$$S_{n,\mathbf{a}}(t) \xrightarrow[n \rightarrow +\infty]{d} \mathcal{N}(0, t\sigma_{\mathbf{a}}^2(H)) = \sigma_{\mathbf{a}}(H)B(t).$$

Next, we want to deal with a finite vector $(S_{n,\mathbf{a}}(t_1), \dots, S_{n,\mathbf{a}}(t_d))$. We are not exactly in the same setting as in Theorem 3.2 since for the computation of each coordinate we use the same discrete time series, but modify the mean that we are taking depending on the coordinate. But it is easy to see that the same strategy is available, that is, it is sufficient to have the convergence of the covariance matrix according to Proposition 2 of [27]. Therefore, we are linked to prove, for any fixed $0 < t < s$, that

$$\text{Cov}(S_{n,\mathbf{a}}(t), S_{n,\mathbf{a}}(s)) \xrightarrow[n \rightarrow +\infty]{} \sigma_{\mathbf{a}}^2(H)t,$$

or, which is equivalent, to prove the convergence to 0 of $\text{Cov}(S_{n,\mathbf{a}}(t), S_{n,\mathbf{a}}(s) - S_{n,\mathbf{a}}(t))$. As previously we introduce the function

$$f_{\mathbf{a}}(x) = \frac{1}{C_{\mathbf{a}}(H)^2} |P_{\mathbf{a}}(e^{-ix})|^2 \sum_{k \in \mathbb{Z}} \frac{2\pi c}{|x + 2\pi k|^{2H+1}}$$

and denote by $r_{\mathbf{a}}$ the Fourier coefficients of $f_{\mathbf{a}}$. We consider the centered stationary discrete Gaussian time series $X_{\mathbf{a}}$ which admits $f_{\mathbf{a}}$ for spectral density, and therefore $r_{\mathbf{a}}$ as covariance sequence. Then, let us define the random process

$$\tilde{S}_{n,\mathbf{a}}(t) = \frac{1}{\sqrt{n-p+1}} \sum_{k=0}^{[nt]-p} H_2(X_{\mathbf{a}})(k),$$

for $t \in [\frac{p}{n}, 1]$ and $\tilde{S}_{n,\mathbf{a}}(t) = 0$ otherwise. It is easily seen, as in the proof of Theorem 2.10, that limits are the same for $\tilde{S}_{n,\mathbf{a}}$ or $S_{n,\mathbf{a}}$. So, let us compute

$$\begin{aligned} \text{Cov}\left(\tilde{S}_{n,\mathbf{a}}(t), \tilde{S}_{n,\mathbf{a}}(s) - \tilde{S}_{n,\mathbf{a}}(t)\right) &= \frac{2}{n-p+1} \sum_{k=0}^{[nt]-p} \sum_{l=[nt]-p+1}^{[ns]-p} r_{\mathbf{a}}^2(l-k) \\ &\leq \frac{2}{n-p+1} \sum_{j=1}^{[ns]} j r_{\mathbf{a}}^2(j) + \sum_{j=\min([nt]-p, [ns]-[nt]-1)}^{[ns]} r_{\mathbf{a}}^2(j). \end{aligned}$$

The second term tends to zero as a rest of a convergent series, since $t < s$. For the first term, recall that, by (42),

$$|r_{\mathbf{a}}(k)| \leq C(1+|k|)^{-2(K-H)},$$

so that for $\alpha \in (0, \min(2(K-H-1/4), 1/2))$

$$\frac{2}{n-p+1} \sum_{j=1}^{[ns]} j r_{\mathbf{a}}^2(j) \leq C n^{-2\alpha} s^{1-2\alpha},$$

which tends to zero as n tends to infinity. This ends the proof of the convergence in finite dimensional distributions of $\tilde{S}_{n,\mathbf{a}}$ and thus $S_{n,\mathbf{a}}$ to $\sigma_{\mathbf{a}}(H)B$.

Let us prove the tightness. We clearly have for $0 < t \leq s$

$$\begin{aligned} \mathbb{E}\left((S_{n,\mathbf{a}}(t) - S_{n,\mathbf{a}}(s))^2\right) &\leq C \|f_{X_{n,\mathbf{a}}}\|_2^2 \left(\frac{[ns] - [nt]}{n}\right) \\ &\leq C' \left(\frac{[ns] - [nt]}{n}\right). \end{aligned}$$

Finally for $t \leq s \leq r$, by Hölder inequality and using the equivalence of $L^p(\Omega, \mathbb{P})$ norms in the second chaos,

$$\begin{aligned} \mathbb{E}\left((S_{n,\mathbf{a}}(t) - S_{n,\mathbf{a}}(s))^2 (S_{n,\mathbf{a}}(r) - S_{n,\mathbf{a}}(s))^2\right) &\leq \mathbb{E}\left((S_{n,\mathbf{a}}(t) - S_{n,\mathbf{a}}(s))^4\right)^{1/2} \mathbb{E}\left((S_{n,\mathbf{a}}(r) - S_{n,\mathbf{a}}(s))^4\right)^{1/2} \\ &\leq C \mathbb{E}\left((S_{n,\mathbf{a}}(t) - S_{n,\mathbf{a}}(s))^2\right) \mathbb{E}\left((S_{n,\mathbf{a}}(r) - S_{n,\mathbf{a}}(s))^2\right) \\ &\leq C \left(\frac{[ns] - [nt]}{n}\right) \left(\frac{[nr] - [ns]}{n}\right). \end{aligned}$$

This quantity is bounded by $(r-t)^2$. Indeed, it is clearly the case when $r-t \geq 1/n$. When $r-t < 1/n$, either $[ns] = [nt]$ or $[nt] = [nr]$, so that it vanishes. The tightness of $S_{n,\mathbf{a}}$ follows from Theorem 13.5 of [6].

Now, let us consider the sequence of vectorial processes $(Y_n, S_{n,\mathbf{a}})$, which belong to $\mathcal{D}([0, 1])^2$. Each coordinate is tight, thus $(Y_n, S_{n,\mathbf{a}})$ is also tight. It remains to study the finite dimensional convergence. Any linear combination of the coordinates of the above vector belongs to the order one and order two Chaos respectively. Moreover they have both a Gaussian limit. Thus Theorem 1 (item (iv)) of [27] allows to conclude of the vector itself and that the two Gaussian limits are independent. Summarizing we have

$$(Y_n, S_{n,\mathbf{a}}) \xrightarrow{d} (Y, \sigma_{\mathbf{a}}B),$$

where the convergence is in distribution in the space $\mathcal{D}^2([0, 1])$ and the two processes coordinates are Gaussian and independent. This also implies that the convergence is stable in law. \square

Such a result is a fundamental tool when one deals with a non linear function of a Gaussian field, see [9] for instance. In applications to porous media for instance, it is natural to consider that the observed field is $U(t) = g(Y(t))$, $t \in \mathbb{R}$, where g is a non-linear function g with extra assumptions of smoothness and integrability. In this context we are interested in the asymptotic behavior of the quadratic variations of U instead of Y . A Central Limit Theorem can still be obtained, using a Taylor expansion of g and similar methods to the ones that have been developed in the proof of Theorem

7 in [4]. In this case the limit variable is no more Gaussian. It is given by the stochastic integral $\sigma_{\mathbf{a}}(H) \int_0^1 (g'(Y(t)))^2 dB(t)$. We intend to develop this, in connection with applications, in another work.

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