

How big are the l^∞ -valued random fields?*

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Abstract

In this paper we establish path properties and a generalized uniform law of the iterated logarithm (LIL) for strictly stationary and linearly positive quadrant dependent (LPQD) or linearly negative quadrant dependent (LNQD) random fields taking values in l^∞ -space.

Keywords: linearly positive quadrant dependence, linearly negative quadrant dependence, stationary random field, law of the iterated logarithm..

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1 Introduction and Results

In the last years there has been growing interest in concepts of positive/negative dependence for families of random variables. Such concepts are of considerable use in deriving inequalities in probability and statistics. Recently, Csörgő et al. [1] and Choi and Csörgő [2] studied path properties and asymptotic properties for l^∞ -valued Gaussian random fields, respectively. In this paper we are interested in path properties for any positive or negative dependent random fields with multidimensional indices taking values in l^∞ -space.

Newman [3] introduced and discussed the following concepts of positive or negative dependence. The random field $\{X_i(\mathbf{t}); \mathbf{t} := (t_1, \dots, t_N) \in [0, \infty)^N\}_{i=1}^\infty$ is said to be *linearly positive quadrant dependent* (LPQD) if, for any positive numbers λ_i and any disjoint finite subsets A, B of \mathbb{Z}_+ (set of positive integers), the inequality

$$P\left\{\sum_{i \in A} \lambda_i X_i(\mathbf{t}_i) \geq x, \sum_{j \in B} \lambda_j X_j(\mathbf{t}_j) \geq y\right\} \geq P\left\{\sum_{i \in A} \lambda_i X_i(\mathbf{t}_i) \geq x\right\} P\left\{\sum_{j \in B} \lambda_j X_j(\mathbf{t}_j) \geq y\right\} \quad (1.1)$$

holds for all $x, y \in \mathbb{R}$ (set of real numbers), where $\{\mathbf{t}_j\}_{j=1}^\infty \subset \{\mathbf{t}\}$, which is equivalent to the inequality (Lehmann [6], pp. 1137-1138)

$$P\left\{\sum_{i \in A} \lambda_i X_i(\mathbf{t}_i) \leq x, \sum_{j \in B} \lambda_j X_j(\mathbf{t}_j) \leq y\right\} \geq P\left\{\sum_{i \in A} \lambda_i X_i(\mathbf{t}_i) \leq x\right\} P\left\{\sum_{j \in B} \lambda_j X_j(\mathbf{t}_j) \leq y\right\}, \quad (1.2)$$

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while the random field $\{X_i(\mathbf{t})\}_{i=1}^\infty$ is said to be *linearly negative quadrant dependent* (LNQD) if the inequalities in (1.1) and (1.2) are reversed. For the results related to such dependence, one can refer to [3, 4, 5]. In general, two random variables X and Y have been called *positively* (resp. *negatively*) *quadrant dependent* (PQD) (resp. NQD) by Lehmann [6], if $P(X \geq x, Y \geq y) \geq$ (resp. \leq) $P(X \geq x)P(Y \geq y)$ for all $x, y \in \mathbb{R}$.

The objective of this paper is to establish a generalized uniform law of the iterated logarithm and investigate path properties for LPQD or LNQD random fields taking values in l^∞ -space, whose description now follows. For $\mathbf{s} := (s_1, \dots, s_N)$, $\mathbf{t} := (t_1, \dots, t_N) \in [0, \infty)^N$, denote

$$\begin{aligned} \mathbf{0} &= (0, \dots, 0), \quad \mathbf{1} = (1, \dots, 1), \quad \mathbf{s} \pm \mathbf{t} = (s_1 \pm t_1, \dots, s_N \pm t_N), \\ \mathbf{s} \leq \mathbf{t} &\text{ if } s_m \leq t_m \text{ for each } m = 1, 2, \dots, N, \\ a\mathbf{t} &= (at_1, \dots, at_N) \text{ for } a \in (-\infty, \infty), \quad (\mathbf{s}, \mathbf{t}) = (s_1, \dots, s_N, t_1, \dots, t_N) \in [0, \infty)^{2N}. \end{aligned}$$

Assume that $\{X_i(\mathbf{t}); \mathbf{t} \in [0, \infty)^N\}_{i=1}^\infty$ is a sequence of centered strictly stationary and LPQD (or LNQD) random fields with $X_i(\mathbf{0}) = 0$ and stationary increments

$$\sigma_i(\|\mathbf{t}\|) := \sqrt{E\{X_i(\mathbf{s} + \mathbf{t}) - X_i(\mathbf{s})\}^2}, \quad i \geq 1,$$

where $\sigma_i(t)$ are nondecreasing continuous functions of $t > 0$, and $\|\cdot\|$ denotes the Euclidean norm such that $\|\mathbf{t}\| = (\sum_{m=1}^N t_m^2)^{1/2}$. Put

$$\sigma_*(t) = \sup_{i \geq 1} \sigma_i(t)$$

and assume that $\sigma_*(\cdot)$ is a regularly varying function with exponent $\alpha > 0$ at ∞ . Recall that a positive function $\sigma(t)$ of $t > 0$ is said to be *regularly varying* with exponent $\alpha > 0$ at $b \geq 0$ if $\lim_{t \rightarrow b} \{\sigma(xt)/\sigma(t)\} = x^\alpha$ for $x > 0$.

Let $\{\mathbb{X}(\mathbf{t}) := (X_1(\mathbf{t}), X_2(\mathbf{t}), \dots); \mathbf{t} \in [0, \infty)^N\}$ be a centered strictly stationary and LPQD (LNQD) random field taking values in l^∞ -space (i.e. *l^∞ -valued random field*) with l^∞ -norm $\|\cdot\|_\infty$ defined by $\|\mathbb{X}(\mathbf{t})\|_\infty = \sup_{i \geq 1} |X_i(\mathbf{t})|$.

For each $m = 1, 2, \dots, N$, let $a_m(x)$ and $b_m(x)$ be positive nondecreasing functions of $x > 0$ such that $a_m(x) \leq b_m(x)$ and $\lim_{x \rightarrow \infty} b_m(x) = \infty$. Denote

$$\begin{aligned} \mathbf{a}_x &= (a_1(x), \dots, a_N(x)), \quad \mathbf{b}_x = (b_1(x), \dots, b_N(x)), \\ \gamma(x) &= \sqrt{2\{\log(\|\mathbf{b}_x\|/\|\mathbf{a}_x\|) + \log \log \|\mathbf{b}_x\|\}}, \end{aligned}$$

where $\log z = \log(\max\{z, e\})$.

The main results are as follows. Let $\{x_k; x_k > 0\}_{k=1}^\infty$ be an increasing sequence with $x_0 > 0$ and $\lim_{k \rightarrow \infty} x_k = \infty$, and let $u_k = O(v_k)$ denote $\limsup_{k \rightarrow \infty} u_k/v_k < \infty$.

Theorem 1.1. *Let $\{\mathbb{X}(\mathbf{t}); \mathbf{t} \in [0, \infty)^N\}$ be a centered strictly stationary and LPQD (LNQD) l^∞ -valued random field with l^∞ -norm $\|\cdot\|_\infty$ and $E|X_1(\mathbf{t})|^{2+\delta} < \infty$ for some $\delta \in (0, 1]$, which satisfies conditions*

- (i) $\sum_{j \geq k+1} |\text{Cov}(X_i(\mathbf{1}), X_i(\mathbf{b}_j))| = O(\|\mathbf{b}_k\|^{-\lambda})$ for each $i, k \geq 1$ and some $\lambda > 2$,
- (ii) $\inf_{x \geq 1} \sigma_*^2(x)/x > 0$.

For each $m = 1, 2, \dots, N$, let the functions $a_m(x)$ and $b_m(x)$ satisfy conditions

- (iii) $b_m(x)/a_m(x) (> 1)$ is increasing,
- (iv) there exists $c_0 > 1$ such that $b_m(x_k) \leq c_0 b_m(x_{k-1})$ for $k \geq 1$.

Then we have

$$\limsup_{x \rightarrow \infty} \sup_{\|\mathbf{s}\| \leq \|\mathbf{b}_x\|} \sup_{\|\mathbf{t}\| \leq \|\mathbf{b}_x\|} \frac{\|\mathbb{X}(\mathbf{s} + \mathbf{t}) - \mathbb{X}(\mathbf{s})\|_\infty}{\sigma_*(\|\mathbf{b}_x\|)\gamma(x)} = \limsup_{x \rightarrow \infty} \frac{\|\mathbb{X}(\mathbf{b}_x)\|_\infty}{\sigma_*(\|\mathbf{b}_x\|)\gamma(x)} = 1 \quad \text{a.s.} \quad (1.3)$$

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Theorem 1.1 presents a path property for l^∞ -valued random field, while we can obtain the following law of the iterated logarithm (LIL) without conditions (iii)-(iv) of Theorem 1.1.

Theorem 1.2. Let $\{\mathbb{X}(\mathbf{t}); \mathbf{t} \in [0, \infty)^N\}$ be as in Theorem 1.1 with conditions (i)-(ii). Then

$$\begin{aligned} \limsup_{x \rightarrow \infty} \sup_{\|\mathbf{s}\| \leq \|\mathbf{b}_x\|} \sup_{\|\mathbf{t}\| \leq \|\mathbf{b}_x\|} \frac{\|\mathbb{X}(\mathbf{s} + \mathbf{t}) - \mathbb{X}(\mathbf{s})\|_\infty}{\sigma_*(\|\mathbf{b}_x\|) \sqrt{2 \log \log \|\mathbf{b}_x\|}} \\ = \limsup_{x \rightarrow \infty} \frac{\|\mathbb{X}(\mathbf{b}_x)\|_\infty}{\sigma_*(\|\mathbf{b}_x\|) \sqrt{2 \log \log \|\mathbf{b}_x\|}} = 1 \quad \text{a.s.} \end{aligned} \quad (1.4)$$

Note that the first result in (1.4) implies a *generalized uniform law of the iterated logarithm* for LPQD or LNQD l^∞ -valued random fields, but the second one in (1.4) is a standard form of the ordinary LIL for any dependent (or independent) l^∞ -valued random fields, which is an extension of some theorems in [1, 2, 4, 8].

Returning to our present exposition of Theorem 1.2, we present the following examples.

Example 1.3. Let $\{X_i(\mathbf{t}); \mathbf{t} \in [0, \infty)^N\}_{i=1}^\infty$ be a sequence of centered stationary and independent l^∞ -valued Gaussian random fields with exponent $\alpha = 1/2$ (e.g. Wiener random field). For each $i = 1, 2, \dots, N$, let $b_i(x) = \sqrt{i}x$. Then

$$\mathbf{b}_x := (b_1(x), \dots, b_N(x)) = (1, \sqrt{2}, \dots, \sqrt{N})x, \quad \|\mathbf{b}_x\| = \sqrt{N(N+1)/2}x.$$

Hence, by Theorem 1.2, we have the *uniform law of the iterated logarithm*

$$\limsup_{x \rightarrow \infty} \sup_{\|\mathbf{s}\| \leq \|\mathbf{b}_x\|} \sup_{\|\mathbf{t}\| \leq \|\mathbf{b}_x\|} \frac{\|\mathbb{X}(\mathbf{s} + \mathbf{t}) - \mathbb{X}(\mathbf{s})\|_\infty}{\sqrt{\|\mathbf{b}_x\|} \sqrt{2 \log \log \|\mathbf{b}_x\|}} = 1 \quad \text{a.s.}$$

From the ordinary LIL in (1.4), one can obtain Theorem 1 in [4] for LPQD random sequence $\{\xi_n; n \geq 1\}$, as in Example 1.4 below. In (1.1) and Theorem 1.2, denote $X(n) = X_n(\mathbf{t}_n)$, $X(n) = S_n := \xi_1 + \dots + \xi_n$ and $\sigma(n) := \sqrt{E(S_n)^2}$, when indexed by a single time-parameter n in Theorems 1.1-1.2.

Example 1.4. Let $\{\xi_n; n \geq 1\}$ be a centered strictly stationary and LPQD (or LNQD) random sequence with $E\xi_1^2 > 0$, which satisfies conditions

- (i) $E|\xi_1|^p < \infty$ for each $p > 2$,
- (ii) $\sum_{j \geq k+1} |\text{Cov}(\xi_1, \xi_j)| = O(k^{-\lambda})$ for each $k \geq 1$ and some $\lambda > 2$,
- (iii) $\sigma^2 := E\xi_1^2 + 2 \sum_{j=2}^\infty |\text{Cov}(\xi_1, \xi_j)| < \infty$.

Then we have

$$\limsup_{n \rightarrow \infty} \frac{S_n}{\sigma(n) \sqrt{2 \log \log n}} = 1 \quad \text{a.s.},$$

where it is easy to prove that $\sigma(n) \approx \sigma\sqrt{n}$ for n large enough.

2 Proofs

In this section, let c denote a positive constant which may take different values whenever they appear in different lines. We need the following properties.

(P_1) Two random variables X and Y are PQD (resp. NQD) if and only if $\text{Cov}(f(X), g(Y)) \geq$ (resp. \leq) 0 for all real-valued nondecreasing functions f and g (such that $f(X)$ and $g(Y)$ have finite variances) (see Lehmann [6]);

(P_2) (*Hoeffding equality*): For any absolutely continuous functions f and g on the real line and for any random variables X and Y satisfying $Ef^2(X) + Eg^2(Y) < \infty$, we have

$$\begin{aligned} & \text{Cov}(f(X), g(Y)) \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f'(x)g'(y) \{P(X \geq x, Y \geq y) - P(X \geq x)P(Y \geq y)\} dx dy. \end{aligned}$$

The main ingredients of the proofs of Theorems 1.1-1.2 are Propositions 2.1-2.3 below. Note that conditions (i)-(ii) in Theorem 1.1 imply conditions (C2) and (I)-(II) in [4] and [5], respectively. Moreover, $\|\mathbb{X}(\mathbf{t})\|_\infty / \sigma_*(\|\mathbf{t}\|)$ is a standardized random variable. Thus Lemma 2 in [4] and Corollary 2.1 in [5] are easily changed to the following Berry-Esseen type theorem.

Proposition 2.1 (Berry-Esseen type theorem). *Let $\{\mathbb{X}(\mathbf{t}); \mathbf{t} \in [0, \infty)^N\}$ be as in Theorem 1.1 with conditions (i)-(ii). Then*

$$\sup_{z \in \mathbb{R}} \left| P \left\{ \frac{\|\mathbb{X}(\mathbf{b}_x)\|_\infty}{\sigma_*(\|\mathbf{b}_x\|)} \leq z \right\} - \Phi(z) \right| = O(\|\mathbf{b}_x\|^{-1/5}), \quad x \rightarrow \infty,$$

where $\Phi(\cdot)$ is a standard normal distribution function and $\|\mathbf{b}_x\| \rightarrow \infty$ as $x \rightarrow \infty$.

Denote $\mathbf{b}_k = \mathbf{b}_{x_k}$ for a positive increasing sequence $\{x_k\}_{k=1}^\infty$. Using Proposition 2.1 above, the following proposition is immediate from the proof of Lemma 9 in Petrov [7, p. 311].

Proposition 2.2. *Let $\{\mathbb{X}(\mathbf{t})\}$ be as in Proposition 2.1. Assume that $g(x)$ is a positive nondecreasing function of $x > 0$ and that $\{\|\mathbf{b}_k\|; k \geq 1\}$ is a positive nondecreasing sequence such that $\sum_{k=1}^\infty \|\mathbf{b}_k\|^{-1/5} < \infty$. Then the following statements are equivalent.*

- (A) $\sum_{k=1}^\infty P \left\{ \frac{\|\mathbb{X}(\mathbf{b}_k)\|_\infty}{\sigma_*(\|\mathbf{b}_k\|)} > g(\|\mathbf{b}_k\|) \right\} < \infty,$
- (B) $\sum_{k=1}^\infty \frac{1}{g(\|\mathbf{b}_k\|)} \exp \left(-\frac{1}{2} g^2(\|\mathbf{b}_k\|) \right) < \infty.$

The next proposition on the large deviation probability is essential to prove our theorems for any strictly stationary l^∞ -valued random field, which is proved in a way similar to those of Lemmas 2.2 and 2.3 in [8].

Proposition 2.3. *Let $\{\mathbb{X}(\mathbf{t}); \mathbf{t} \in [0, \infty)^N\}$ be a centered strictly stationary l^∞ -valued random field. Then, for any $\varepsilon > 0$ there exists a constant $c_\varepsilon > 0$ such that, for $v > 1$,*

$$\begin{aligned} & P \left\{ \sup_{\|\mathbf{s}\| \leq \|\mathbf{b}_x\|} \sup_{\|\mathbf{t}\| \leq \|\mathbf{b}_x\|} \frac{\|\mathbb{X}(\mathbf{s} + \mathbf{t}) - \mathbb{X}(\mathbf{s})\|_\infty}{\sigma_*(\|\mathbf{b}_x\|)} \geq v \right\} \\ & \leq c_\varepsilon \left(P \left\{ \frac{\|\mathbb{X}(\mathbf{b}_x)\|_\infty}{\sigma_*(\|\mathbf{b}_x\|)} \geq \frac{v}{1 + \varepsilon} \right\} + \sum_{n=1}^\infty 2^{2N2^n} P \left\{ \frac{\|\mathbb{X}(\mathbf{b}_x)\|_\infty}{\sigma_*(\|\mathbf{b}_x\|)} \geq \frac{v}{1 + \varepsilon} \sqrt{1 + 2N \log 3 \cdot 2^{n/2}} \right\} \right). \end{aligned}$$

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Proof of Theorem 1.1. Since $\gamma(x) \geq \sqrt{2 \log \log \|\mathbf{b}_x\|}$, we will first prove the sharper result

$$\limsup_{x \rightarrow \infty} \sup_{\|\mathbf{s}\| \leq \|\mathbf{b}_x\|} \sup_{\|\mathbf{t}\| \leq \|\mathbf{b}_x\|} \frac{\|\mathbb{X}(\mathbf{s} + \mathbf{t}) - \mathbb{X}(\mathbf{s})\|_\infty}{\sigma_*(\|\mathbf{b}_x\|) \sqrt{2 \log \log \|\mathbf{b}_x\|}} \leq 1 \quad \text{a.s.} \quad (2.1)$$

without conditions (iii)-(iv), whose result is used to prove (1.4). For $\theta > 1$ and $k \geq 1$, set $A_k = \{x; \theta^k \leq \|\mathbf{b}_x\| \leq \theta^{k+1}\}$. Note that $\sqrt{2 \log \log \theta^k} \geq \theta^{-1} \sqrt{2 \log \log \theta^{k+1}}$ since $(\log u)/u$ is decreasing for $u > e^e$. By the regularity of $\sigma_*(\cdot)$, we get $\sigma_*(\|\mathbf{b}_x\|)/\sigma_*(\theta^{k+1}) \geq \theta^{-2\alpha}$ and hence

$$\begin{aligned} & \limsup_{x \rightarrow \infty} \sup_{\|\mathbf{s}\| \leq \|\mathbf{b}_x\|} \sup_{\|\mathbf{t}\| \leq \|\mathbf{b}_x\|} \frac{\|\mathbb{X}(\mathbf{s} + \mathbf{t}) - \mathbb{X}(\mathbf{s})\|_\infty}{\sigma_*(\|\mathbf{b}_x\|) \sqrt{2 \log \log \|\mathbf{b}_x\|}} \\ & \leq \limsup_{k \rightarrow \infty} \sup_{x \in A_k} \sup_{\|\mathbf{s}\| \leq \|\mathbf{b}_x\|} \sup_{\|\mathbf{t}\| \leq \|\mathbf{b}_x\|} \frac{\|\mathbb{X}(\mathbf{s} + \mathbf{t}) - \mathbb{X}(\mathbf{s})\|_\infty}{\sigma_*(\|\mathbf{b}_x\|) \sqrt{2 \log \log \theta^k}} \\ & \leq \theta^{1+2\alpha} \limsup_{k \rightarrow \infty} \sup_{\|\mathbf{s}\| \leq \theta^{k+1}} \sup_{\|\mathbf{t}\| \leq \theta^{k+1}} \frac{\|\mathbb{X}(\mathbf{s} + \mathbf{t}) - \mathbb{X}(\mathbf{s})\|_\infty}{\sigma_*(\theta^{k+1}) \sqrt{2 \log \log \theta^{k+1}}}. \end{aligned} \quad (2.2)$$

For convenience, let $\|\mathbf{b}_k\| = \theta^k$, where $\mathbf{b}_k := \mathbf{b}_{x_k}$ for a positive increasing sequence $\{x_k\}_{k=1}^\infty$. Using Proposition 2.3, it follows that for any $\varepsilon > 0$ there exists a positive constant c_ε such that

$$\begin{aligned} & P \left\{ \sup_{\|\mathbf{s}\| \leq \theta^{k+1}} \sup_{\|\mathbf{t}\| \leq \theta^{k+1}} \frac{\|\mathbb{X}(\mathbf{s} + \mathbf{t}) - \mathbb{X}(\mathbf{s})\|_\infty}{\sigma_*(\theta^{k+1}) \sqrt{2 \log \log \theta^{k+1}}} > 1 + 2\varepsilon \right\} \\ & \leq c_\varepsilon \left(P \left\{ \frac{\|\mathbb{X}(\mathbf{b}_{k+1})\|_\infty}{\sigma_*(\theta^{k+1})} \geq \frac{(1 + 2\varepsilon) \sqrt{2 \log \log \theta^{k+1}}}{1 + \varepsilon} \right\} \right. \\ & \quad \left. + \sum_{n=1}^\infty 2^{2N2^n} P \left\{ \frac{\|\mathbb{X}(\mathbf{b}_{k+1})\|_\infty}{\sigma_*(\theta^{k+1})} \geq \frac{(1 + 2\varepsilon) \sqrt{2 \log \log \theta^{k+1}}}{1 + \varepsilon} \sqrt{1 + 2N \log 3} \cdot 2^{n/2} \right\} \right). \end{aligned} \quad (2.3)$$

Now let us apply Proposition 2.2 with $\|\mathbf{b}_k\| = \theta^k$ and $g(\theta^k) = g_1(\theta^k)$ (or $g_2(\theta^k)$), where

$$g_1(\theta^k) := \frac{(1 + 2\varepsilon) \sqrt{2 \log \log \theta^{k+1}}}{1 + \varepsilon}, \quad g_2(\theta^k) := \frac{(1 + 2\varepsilon) \sqrt{2 \log \log \theta^{k+1}}}{1 + \varepsilon} \sqrt{1 + 2N \log 3} \cdot 2^{n/2}$$

in (2.3). Considering the right hand side of (2.3) and equivalence of Proposition 2.2, we have

$$\begin{aligned} & \sum_{k=1}^\infty \frac{1}{g_1(\theta^k)} e^{-g_1^2(\theta^k)/2} \leq c \sum_{k=1}^\infty (\log \theta^{k+1})^{-1-\varepsilon'} < \infty \\ & \Rightarrow \sum_{k=1}^\infty P \left\{ \frac{\|\mathbb{X}(\mathbf{b}_{k+1})\|_\infty}{\sigma_*(\theta^{k+1})} \geq g_1(\theta^k) \right\} < \infty, \end{aligned}$$

where $\varepsilon' = \varepsilon/(1 + \varepsilon)$, by the strict stationarity of $\mathbb{X}(\mathbf{t})$, and also

$$\begin{aligned} & \frac{1}{g_2(\theta^k)} \exp \left(-\frac{1}{2} g_2^2(\theta^k) \right) \leq \exp \left(-\frac{1}{2} \left(\frac{1 + 2\varepsilon}{1 + \varepsilon} \right)^2 (2 \log \log \theta^{k+1}) (1 + 2N \log 3) 2^n \right) \\ & \leq ((k + 1) \log \theta)^{-(1+\varepsilon')(1+2N \log 3) 2^n} \leq c (k + 1)^{-(1+\varepsilon')(1+2N \log 3) 2^n} \end{aligned}$$

which implies

$$P \left\{ \frac{\|\mathbb{X}(\mathbf{b}_{k+1})\|_\infty}{\sigma_*(\theta^{k+1})} > g_2(\theta^k) \right\} \leq c (k + 1)^{-(1+\varepsilon')(1+2N \log 3) 2^n}$$

by Proposition 2.2. Thus

$$\begin{aligned} \sum_{k=1}^{\infty} \sum_{n=1}^{\infty} 2^{2N2^n} P\left\{ \frac{\|\mathbb{X}(\mathbf{b}_{k+1})\|_\infty}{\sigma_*(\theta^{k+1})} > g_2(\theta^k) \right\} &\leq c \sum_{k=1}^{\infty} \sum_{n=1}^{\infty} 2^{2N2^n} (k+1)^{-(1+\varepsilon')(1+2N \log 3)2^n} \\ &\leq c \sum_{k=1}^{\infty} \sum_{n=1}^{\infty} 2^{-N2^n \log_2(k+1)} \cdot 2^{-n} \leq c \sum_{k=1}^{\infty} \sum_{n=1}^{\infty} k^{-2} \cdot 2^{-n} < \infty. \end{aligned}$$

In conclusion, it follows from (2.3) that

$$\sum_{k=1}^{\infty} P\left\{ \sup_{\|\mathbf{s}\| \leq \theta^{k+1}} \sup_{\|\mathbf{t}\| \leq \theta^{k+1}} \frac{\|\mathbb{X}(\mathbf{s} + \mathbf{t}) - \mathbb{X}(\mathbf{s})\|_\infty}{\sigma_*(\theta^{k+1})\sqrt{2 \log \log \theta^{k+1}}} > 1 + 2\varepsilon \right\} < \infty$$

and the Borel-Cantelli lemma yields

$$\limsup_{k \rightarrow \infty} \sup_{\|\mathbf{s}\| \leq \theta^{k+1}} \sup_{\|\mathbf{t}\| \leq \theta^{k+1}} \frac{\|\mathbb{X}(\mathbf{s} + \mathbf{t}) - \mathbb{X}(\mathbf{s})\|_\infty}{\sigma_*(\theta^{k+1})\sqrt{2 \log \log \theta^{k+1}}} \leq 1 + 2\varepsilon \quad \text{a.s.}$$

Combining this with (2.2) implies (2.1) since ε and θ are arbitrary.

By virtue of (2.1), the proof of (1.3) is completed if we show that

$$\limsup_{x \rightarrow \infty} \frac{\|\mathbb{X}(\mathbf{b}_x)\|_\infty}{\sigma_*(\|\mathbf{b}_x\|)\gamma(x)} \geq 1 \quad \text{a.s.} \tag{2.4}$$

Let $\{x_k; x_k > 0\}_{k=1}^\infty$ be an increasing sequence such that $x_0 > 0$ and the $(k-1)$ st point x_{k-1} is placed by the relation $b_m(x_k) - a_m(x_k) = b_m(x_{k-1}), 1 \leq m \leq N$, with x_k defined by induction, since $b_m(x) - a_m(x)$ is increasing by (iii). For convenience, put $\mathbf{a}_k = \mathbf{a}_{x_k}$ and $\mathbf{b}_k = \mathbf{b}_{x_k}$, and let $i_0 \geq 1$ be an integer such that $\sigma_{i_0}(\|\mathbf{b}_k\|) = \sigma_*(\|\mathbf{b}_k\|)$, where $\|\mathbf{b}_k\| := \theta^k$ as above. Then,

$$\limsup_{k \rightarrow \infty} \frac{\|\mathbb{X}(\mathbf{b}_k)\|_\infty}{\sigma_*(\|\mathbf{b}_k\|)\gamma(x_k)} \geq \limsup_{k \rightarrow \infty} \frac{X_{i_0}(\mathbf{b}_k)}{\sigma_{i_0}(\|\mathbf{b}_k\|)\gamma(x_k)} \tag{2.5}$$

and the inequality (2.4) is immediate from (2.5) if we prove

$$\limsup_{k \rightarrow \infty} \frac{X_{i_0}(\mathbf{b}_k)}{\sigma_{i_0}(\|\mathbf{b}_k\|)\gamma(x_k)} > 1 - 4\varepsilon \quad \text{a.s.} \tag{2.6}$$

for any small $\varepsilon > 0$. For each $k \geq 1$, we see that

$$U_k := \frac{X_{i_0}(\mathbf{b}_k) - X_{i_0}(\mathbf{b}_{k/2})}{\sigma_{i_0}(\|\mathbf{b}_k - \mathbf{b}_{k/2}\|)}$$

is a standardized random variable. Let $B_k = \{U_k > (1 - 2\varepsilon)\gamma(x_k)\}$. If \mathcal{N} is a standard normal random variable, then it follows from Proposition 2.1 and the strict stationarity of $\mathbb{X}(\mathbf{t})$ that

$$\begin{aligned} P(B_k) &= \left(1 - P\{U_k \leq (1 - 2\varepsilon)\gamma(x_k)\} - 1 + P\{\mathcal{N} \leq (1 - 2\varepsilon)\gamma(x_k)\} \right) \\ &\quad + P\{\mathcal{N} > (1 - 2\varepsilon)\gamma(x_k)\} \\ &\geq -c_1 \|\mathbf{b}_k - \mathbf{b}_{k/2}\|^{-1/5} + \frac{1}{\sqrt{2\pi}(1 - 2\varepsilon)^2 \gamma^2(x_k)} \exp\left(-\frac{1 - 2\varepsilon}{2} \gamma^2(x_k)\right) \\ &\geq -c_1 \frac{1}{(\log \|\mathbf{b}_k\|)^{1-\varepsilon}} + c \left(\frac{\|\mathbf{a}_k\|}{\|\mathbf{b}_k\| \log \|\mathbf{b}_k\|} \right)^{1-\varepsilon} \geq c \frac{1}{(\log \|\mathbf{b}_k\|)^{1-\varepsilon}} \left(\varepsilon \frac{\|\mathbf{a}_k\|}{\|\mathbf{b}_k\|} \right) \end{aligned}$$

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for all large k by (iii), where c and c_1 are positive constants, and further

$$\sum_{k=k_0}^{\ell} P(B_k) \geq \varepsilon \frac{1}{(\log \|\mathbf{b}_\ell\|)^{1-\varepsilon}} \sum_{k=k_0}^{\ell} \frac{\|\mathbf{a}_k\|}{\|\mathbf{b}_k\|}$$

for some $k_0 \geq 1$ with $k_0 \leq k \leq \ell$. Also there exist constants $c_2, c_3 > 1$ such that

$$\log \|\mathbf{b}_\ell\| \leq c_2 \sum_{k=k_0}^{\ell} \log \frac{\|\mathbf{b}_k\|}{\|\mathbf{b}_{k-1}\|} \leq c_2 \sum_{k=k_0}^{\ell} \log \left(c_0 + \frac{\|\mathbf{a}_k\|}{\|\mathbf{b}_{k-1}\|} \right) \leq c_2 \sum_{k=k_0}^{\ell} \log \left(c_0 + \frac{c_3 \|\mathbf{a}_{k-1}\|}{\|\mathbf{b}_{k-1}\|} \right) \quad (2.7)$$

since $c_0 \|\mathbf{b}_{k-1}\| \geq \|\mathbf{b}_k\| - \|\mathbf{a}_k\|$ by (iv). The last inequality of (2.7) follows from the fact that

$$\frac{\|\mathbf{a}_k\|}{\|\mathbf{a}_{k-1}\|} \leq \frac{\|\mathbf{b}_k\|}{\|\mathbf{b}_{k-1}\|} \leq \frac{c_0 \|\mathbf{b}_k\|}{\|\mathbf{b}_k\| - \|\mathbf{a}_k\|} = \frac{c_0}{1 - (\|\mathbf{a}_k\|/\|\mathbf{b}_k\|)} \leq c_3$$

by (iii). Thus, by (2.7), there exists a constant $K > 1$ such that

$$\log \|\mathbf{b}_\ell\| \leq c_2 \sum_{k=k_0}^{\ell} \log \left(c_0 + \frac{c_3 \|\mathbf{a}_k\|}{\|\mathbf{b}_{k-1}\|} \right) \leq K \sum_{k=k_0}^{\ell} \frac{c_3^2 \|\mathbf{a}_k\|}{\|\mathbf{b}_k\|}.$$

Therefore, we have $\sum_{k=1}^{\ell} P(B_k) \geq \varepsilon (\log \|\mathbf{b}_\ell\|)^\varepsilon / (K c_3^2) \rightarrow \infty$ as $\ell \rightarrow \infty$; that is, we get $\sum_{k=1}^{\infty} P(B_k) = \infty$.

Next, let $B'_k = \{U_k > (1 - 3\varepsilon)\gamma(x_k)\}$. We will show that $P(B'_k, i.o.) = 1$. Choose a differential function $f(x)$ on \mathbb{R} such that $|f'(x)| \leq \kappa$ for some $0 < \kappa < \infty$ and

$$0 \leq I\{x > (1 - 2\varepsilon)\gamma(x_k)\} \leq f(x) \leq I\{x > (1 - 3\varepsilon)\gamma(x_k)\} \leq 1, \quad (2.8)$$

where $I\{\cdot\}$ is an indicator function. In order to prove $P(B'_k, i.o.) = 1$, it is enough to show that $\sum_{k=1}^{\infty} f(U_k) = \infty$ a.s. Since $\sum_{k=1}^{\infty} P(B_k) = \infty$ in the above statement, it follows from (2.8) that $\sum_{k=1}^{\infty} E f(U_k) \geq \sum_{k=1}^{\infty} P(B_k) = \infty$. By Markov inequality, we have

$$\begin{aligned} P \left\{ \sum_{k=1}^{\infty} f(U_k) < \frac{1}{2} \sum_{k=1}^n E f(U_k) \right\} &\leq P \left\{ \left| \sum_{k=1}^n f(U_k) - \sum_{k=1}^n E f(U_k) \right| > \frac{1}{2} \sum_{k=1}^n E f(U_k) \right\} \\ &\leq 4 \text{Var} \left(\sum_{k=1}^n f(U_k) \right) / \left(\sum_{k=1}^n E f(U_k) \right)^2 \\ &\leq \frac{4}{\sum_{k=1}^n E f(U_k)} + \frac{8 \sum_{k=1}^{\infty} \sum_{j=k+1}^{\infty} |\text{Cov}(f(U_k), f(U_j))|}{\left(\sum_{k=1}^n E f(U_k) \right)^2}. \end{aligned} \quad (2.9)$$

Noting that U_k and U_j are LPQD (resp. LNQD) from the definition of LPQD (resp.

LNQD), it follows from (P_1) , (P_2) , condition (i) and the regularity of $\sigma_*(\cdot)$ that

$$\begin{aligned} & \sum_{k=1}^{\infty} \sum_{j=k+1}^{\infty} |\text{Cov}(f(U_k), f(U_j))| \\ & \leq \kappa^2 \sum_{k=1}^{\infty} \sum_{j=k+1}^{\infty} \left| \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (P\{U_k \geq x, U_j \geq y\} - P\{U_k \geq x\}P\{U_j \geq y\}) dx dy \right| \\ & \leq c \sum_{k=1}^{\infty} \frac{\|\mathbf{b}_k - \mathbf{b}_{k/2}\|}{\sigma_{i_0}^2(\|\mathbf{b}_k - \mathbf{b}_{k/2}\|)} \sum_{j=k+1}^{\infty} \left| \text{Cov}(X_{i_0}(\mathbf{1}), X_{i_0}(\mathbf{b}_j) - X_{i_0}(\mathbf{b}_{j/2})) \right| \tag{2.10} \\ & \leq c \sum_{k=1}^{\infty} (\theta^k)^{1-2\alpha} \|\mathbf{b}_{(k+1)/2}\| \sum_{j \geq k+1} \left| \text{Cov}(X_{i_0}(\mathbf{1}), X_{i_0}(\mathbf{b}_j)) \right| \\ & \leq c \sum_{k=1}^{\infty} \theta^{-(\lambda-2+2\alpha)k} < \infty. \end{aligned}$$

Since $\sum_{k=1}^{\infty} E f(U_k) = \infty$ as above, letting $n \rightarrow \infty$ in (2.9) yields $P\{\sum_{k=1}^{\infty} f(U_k) < \infty\} = 0$ by (2.10). This proves $\sum_{k=1}^{\infty} f(U_k) = \infty$ a.s. and consequently $P(B'_k, i.o.) = 1$. Let

$$C_k = \left\{ \frac{X_{i_0}(\mathbf{b}_{k/2})}{\sigma_{i_0}(\|\mathbf{b}_{k/2}\|)} \geq -2\gamma(x_{k/2}) \right\}.$$

Since $P(B'_k, i.o.) = 1$, it follows from (2.1) that $P(B'_k \cap C_k, i.o.) = 1$. It is easy to see that

$$\begin{aligned} & P\left\{ \frac{X_{i_0}(\mathbf{b}_k)}{\sigma_{i_0}(\|\mathbf{b}_k\|)} > (1 - 4\varepsilon)\gamma(x_k), i.o. \right\} \\ & \geq P\left\{ \frac{X_{i_0}(\mathbf{b}_k)}{\sigma_{i_0}(\|\mathbf{b}_k\|)} > (1 - 3\varepsilon)\gamma(x_k) - 2\gamma(x_{k/2}), i.o. \right\} \\ & \geq P\{B'_k \cap C_k, i.o.\} = 1 \end{aligned}$$

for k large enough, by the stationarity of $\mathbb{X}(\mathbf{t})$. This implies (2.6) and hence (2.4) holds true.

Proof of Theorem 1.2. Since we have proved (2.1) without conditions (iii)-(iv) of Theorem 1.1, it is enough to show that

$$\limsup_{x \rightarrow \infty} \frac{\|\mathbb{X}(\mathbf{b}_x)\|_\infty}{\sigma_*(\|\mathbf{b}_x\|)\sqrt{2 \log \log \|\mathbf{b}_x\|}} \geq 1 \quad \text{a.s.} \tag{2.11}$$

Set $\mathbf{b}_k = \mathbf{b}_{x_k}$ for a positive increasing sequence $\{x_k\}_{k=1}^\infty$, and let $i_0 \geq 1$ be an integer such that $\sigma_{i_0}(\|\mathbf{b}_k\|) = \sigma_*(\|\mathbf{b}_k\|)$. Then

$$\limsup_{k \rightarrow \infty} \frac{\|\mathbb{X}(\mathbf{b}_k)\|_\infty}{\sigma_*(\|\mathbf{b}_k\|)\sqrt{2 \log \log \|\mathbf{b}_k\|}} \geq \limsup_{k \rightarrow \infty} \frac{X_{i_0}(\mathbf{b}_k)}{\sigma_{i_0}(\|\mathbf{b}_k\|)\sqrt{2 \log \log \|\mathbf{b}_k\|}} \tag{2.12}$$

and (2.11) is immediate from (2.12) if we prove

$$\limsup_{k \rightarrow \infty} \frac{X_{i_0}(\mathbf{b}_k)}{\sigma_{i_0}(\|\mathbf{b}_k\|)\sqrt{2 \log \log \|\mathbf{b}_k\|}} > 1 - 4\varepsilon \quad \text{a.s.}$$

for any small $\varepsilon > 0$. For $\theta > 1$, set $\|\mathbf{b}_k\| = \theta^k$ and $B_k^* = \{U_k > (1 - 2\varepsilon)\sqrt{2 \log \log \|\mathbf{b}_k - \mathbf{b}_{k/2}\|}\}$ as in the proof of (2.6). Then $\|\mathbf{b}_k - \mathbf{b}_{k/2}\| \approx \theta^k$ for sufficiently large k . If we apply Proposition 2.2 with $g(\|\mathbf{b}_k - \mathbf{b}_{k/2}\|) = (1 - 2\varepsilon)\sqrt{2 \log \log \|\mathbf{b}_k - \mathbf{b}_{k/2}\|}$, then

$$\sum_{k=1}^{\infty} \frac{1}{g(\|\mathbf{b}_k - \mathbf{b}_{k/2}\|)} \exp\left(-\frac{1}{2}g^2(\|\mathbf{b}_k - \mathbf{b}_{k/2}\|)\right) \geq c \sum_{k=1}^{\infty} k^{-1+\varepsilon} = \infty$$

and hence $\sum_{k=1}^{\infty} P(B_k^*) = \infty$ by the strict stationarity of $X_i(\mathbf{t})$ for $i \geq 1$. The remainder of the proof is the same as the corresponding proof in (2.8)-(2.10). The details are omitted. This completes the proof of Theorem 1.2.

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