

FOURIER TRANSFORMS OF STATIONARY PROCESSES

WEI BIAO WU

(Communicated by Richard C. Bradley)

ABSTRACT. We consider the asymptotic behavior of Fourier transforms of stationary and ergodic sequences. Under sufficiently mild conditions, central limit theorems are established for almost all frequencies as well as for a given frequency. Applications to the widely used linear processes and iterated random functions are discussed. Our results shed new light on the foundation of spectral analysis in that the asymptotic distribution of the periodogram, the fundamental quantity in the frequency-domain analysis, is obtained.

1. INTRODUCTION

Let $(X_n)_{n \in \mathbb{Z}}$ be a stationary and ergodic Markov chain on the state space \mathcal{X} ; let g be a real-valued function on \mathcal{X} such that $\mathbb{E}[g(X_0)] = 0$ and $\mathbb{E}[|g^2(X_0)|] < \infty$. Define the Fourier transform

$$(1) \quad S_n(\theta) = S_n(\theta; g) = \sum_{k=1}^n g(X_k) e^{ik\theta}, \quad \theta \in \mathbb{R},$$

where $i = \sqrt{-1}$ is the imaginary unit. The setup (1) is general enough to allow one to consider $S_n^Y(\theta) = \sum_{k=1}^n Y_k e^{ik\theta}$ for any stationary and ergodic process $(Y_n)_{n \in \mathbb{Z}}$ by constructing a Markov chain $X_n = (\dots, Y_{n-1}, Y_n)$ and $g(X_n) = Y_n$. The quantity (1) is of fundamental importance in the spectral analysis of stationary processes.

This paper considers the asymptotic normality of (1). This problem has a substantial history. Rosenblatt ([14], Theorem 5.3, p. 131) considers mixing processes; Brockwell and Davis ([3], Theorem 10.3.2., p. 347), Walker [18] and Terrin and Hurvich [16] discuss linear processes. Other contributions can be found in Olshen [11], Rootzén [12], Yajima [23] and Walker [19] among others.

Under surprisingly weak conditions (cf. (2)), we show that the real and imaginary parts of $S_n(\theta)/\sqrt{n}$ are asymptotically iid normal for almost all frequencies $\theta \in \mathbb{R}$. Thus the periodogram $n^{-1}|S_n(\theta)|^2$ is asymptotically distributed as a multiple of a $\chi^2(2)$ random variable. For a fixed θ , we present sufficient conditions for the asymptotic normality of $S_n(\theta)/\sqrt{n}$. Our general results go beyond earlier ones by providing mild and verifiable conditions. In our proof, we apply the

Received by the editors March 24, 2003 and, in revised form, June 27, 2003 and September 18, 2003.

2000 *Mathematics Subject Classification.* Primary 60F05, 60F17; Secondary 60G35.

Key words and phrases. Spectral analysis, linear process, martingale central limit theorem, periodogram, Fourier transformation, nonlinear time series.

©2004 American Mathematical Society

celebrated Carleson theorem in Fourier analysis to construct approximating martingales. Applications to special sequences such as linear processes and iterated random functions, which are widely used in time series modelling, are discussed.

2. MAIN RESULTS

Let $(\Omega, \mathcal{B}(\Omega), \mathbb{P})$ be the probability space on which the sequence X_n is defined, where $\mathcal{B}(\Omega)$ is a sigma algebra on Ω . For a random variable ξ on the space $(\Omega, \mathcal{B}(\Omega), \mathbb{P})$, we denote its $\mathcal{L}^2(\mathbb{P})$ norm by $\|\xi\| = \sqrt{\mathbb{E}(|\xi|^2)} \leq \infty$. Define the projection operator

$$\mathcal{P}_k \xi = \mathbb{E}(\xi | \dots, X_{k-1}, X_k) - \mathbb{E}(\xi | \dots, X_{k-1}).$$

Then by the Markovian property, $\mathcal{P}_1 g(X_n) = \mathbb{E}[g(X_n) | X_1] - \mathbb{E}[g(X_n) | X_0]$ for $n \in \mathbb{N}$. Let $\Re z$ and $\Im z$ be the real and the imaginary parts of the complex number z , namely $z = \Re z + i \Im z$, and let $|z| = \sqrt{(\Re z)^2 + (\Im z)^2}$. Denote by $N(\mu, \Sigma)$ the multivariate normal distribution with mean vector μ and covariance matrix Σ ; denote by Id_p the $p \times p$ identity matrix. Theorems 1 and 2 concern asymptotic normality for almost all θ and for a given θ , respectively.

Theorem 1. *Assume that*

$$(2) \quad \sum_{n=1}^{\infty} \frac{1}{n} \|\mathbb{E}[g(X_n) | X_0]\|^2 < \infty.$$

Then (i) for almost all $\theta \in \mathbb{R}$ (Lebesgue), there exists $0 \leq \sigma(\theta) < \infty$ such that

$$(3) \quad \begin{pmatrix} \Re \\ \Im \end{pmatrix} \frac{S_n(\theta)}{\sqrt{n}} \Rightarrow N[0, \sigma^2(\theta) \text{Id}_2].$$

(ii) Moreover, for almost all pairs (θ, φ) (Lebesgue), $S_n(\theta)/\sqrt{n}$ and $S_n(\varphi)/\sqrt{n}$ are asymptotically independent.

Theorem 2. *For a given $\theta \in [0, 2\pi)$, suppose there exists $\xi(\theta, X_0, X_1) \in \mathcal{L}^2(\mathbb{P})$ such that*

$$(4) \quad \sum_{n=1}^N e^{in\theta} \mathcal{P}_1 g(X_n) \rightarrow \xi(\theta, X_0, X_1) \quad (\mathcal{L}^2(\mathbb{P})),$$

as $N \rightarrow \infty$, and

$$(5) \quad \|\mathbb{E}[S_n(\theta) | X_0]\|^2 = o(n).$$

Then (i) if $\theta \neq 0, \pi$,

$$(6) \quad \begin{pmatrix} \Re \\ \Im \end{pmatrix} \frac{S_n(\theta)}{\sqrt{n}} \Rightarrow N[0, \sigma^2(\theta) \text{Id}_2],$$

where $\sigma^2(\theta) = \|\xi(\theta, X_0, X_1)\|^2/2$, and (ii) $S_n(\theta)/\sqrt{n} \Rightarrow N(0, \sigma^2)$ if $\theta = 0$ or π , where $\sigma^2(\theta) = \|\xi(\theta, X_0, X_1)\|^2$.

Proposition 1. *Assume that*

$$(7) \quad \sum_{n=1}^{\infty} \|\mathcal{P}_1 g(X_n) - \mathcal{P}_1 g(X_{n+1})\| < \infty.$$

Then (4) and (5), and consequently (6), hold for all $0 < \theta < 2\pi$.

Condition (2) is fairly mild and imposes a very weak decay rate of $\|\mathbb{E}[g(X_n)|X_0]\|$. Rootzén [12] obtained a central limit theorem under conditions which are not easily verifiable. In comparison, our conditions (4), (5) and (7) are tractable in many cases. It is easily seen that (2) is equivalent to

$$(8) \quad \sum_{k=1}^{\infty} 2^{-k} \sum_{i=1}^{2^k} \|\mathbb{E}[g(X_i)|X_0]\|^2 < \infty$$

by exchanging the order of summation. Notice that $\|\mathbb{E}[g(X_n)|X_0]\|$ is non-increasing in n in view of $\|\mathcal{P}_{-n}g(X_0)\|^2 = \|\mathbb{E}[g(X_0)|X_{-n}]\|^2 - \|\mathbb{E}[g(X_0)|X_{-n-1}]\|^2$. So another equivalent condition of (2) is $\sum_{k=1}^{\infty} \|\mathbb{E}[g(X_{2^k})|X_0]\|^2 < \infty$. Inequality (8) is needed to establish a connection between $\sigma(\theta)$ in (3) and spectral densities (cf. Proposition 2).

Let $r_k = \mathbb{E}[g(X_0)g(X_k)]$ be the covariance function and introduce the spectral distribution function $F(\theta)$, $0 \leq \theta \leq 2\pi$, via Herglotz's Theorem,

$$r_k = \int_0^{2\pi} \exp(ik\theta) dF(\theta).$$

Assume that F is absolutely continuous with the spectral density function f , namely $F(\theta) = \int_0^\theta f(u)du$.

Proposition 2. *Assume (2). Then for almost all $\theta \in [0, 2\pi]$ (Lebesgue), $f(\theta) = \sigma^2(\theta)/\pi$.*

Example 1. Iterated random functions. Let (\mathcal{X}, ρ) be a complete and separable metric space and let $X_n = F_{\varepsilon_n}(X_{n-1})$, where $F_\varepsilon(\cdot) = F(\cdot, \varepsilon)$ is the ε -section of a jointly measurable function $F : \mathcal{X} \times \Upsilon \mapsto \mathcal{X}$ and $\varepsilon, \varepsilon_n, n \in \mathbb{Z}$, are iid random variables that take values in a second measurable space Υ . Define $L_\varepsilon = \sup_{x \neq x'} \rho[F_\varepsilon(x), F_\varepsilon(x')]/\rho(x, x')$. Diaconis and Freedman [6] prove that X_n admits a unique stationary distribution (say Π) if

$$(9) \quad \mathbb{E}(L_\varepsilon^\alpha) < \infty, \mathbb{E}(\log L_\varepsilon) < 0, \text{ and } \mathbb{E}[\rho^\alpha(x_0, F_\varepsilon(x_0))] < \infty$$

for some $\alpha > 0$ and $x_0 \in \mathcal{X}$. Let $\Delta_g(\delta) = \sup\{\| [g(X) - g(X')] \mathbf{1}_{[\rho(X, X') \leq \delta]} \| : X, X' \sim \Pi\}$.

Corollary 1. *Assume (9), $\mathbb{E}[g(X_1)] = 0$ and $\mathbb{E}[|g(X_1)|^\ell] < \infty$ for some $\ell > 2$. (a) If*

$$(10) \quad \int_0^{1/2} \frac{\Delta_g^2(t)}{t|\log t|} dt < \infty,$$

then (2) holds. (b) If

$$(11) \quad \int_0^{1/2} \frac{\Delta_g(t)}{t} dt < \infty,$$

then $\sum_{n=1}^{\infty} \|\mathbb{E}[g(X_n)|X_1]\| < \infty$ and hence (7) holds.

Proof. Let $X'_0 \sim \Pi$, and let X'_0 be independent of X_0 and $(\varepsilon_k)_{k \in \mathbb{Z}}$. For $n \geq 1$, let $X'_n = F_{\varepsilon_n} \circ F_{\varepsilon_{n-1}} \circ \dots \circ F_{\varepsilon_1}(X'_0)$. Then (9) implies that there exists $\beta, C > 0$ and $0 < r < 1$ such that $\mathbb{E}[\rho^\beta(X_n, X'_n)] \leq Cr^n$ hold for all $n \geq 0$ (cf. Lemma 3 in Wu

and Woodroffe [22]). Let $p = \ell/2$, $q = p/(p - 1)$ and $\delta_n = (Cr^n)^{1/(q+\beta)}$. Since $\mathbb{E}[g(X'_n)|X_0] = 0$,

$$\begin{aligned} & \|\mathbb{E}[g(X_n)|X_0]\| \\ & \leq \| [g(X_n) - g(X'_n)] \mathbf{1}_{\rho(X_n, X'_n) < \delta_n} \| + \| [g(X_n) - g(X'_n)] \mathbf{1}_{\rho(X_n, X'_n) \geq \delta_n} \| \\ & \leq \Delta_g(\delta_n) + \| [g(X_n) - g(X'_n)]^2 \|_p^{1/2} \times [\mathbb{P}(\rho(X_n, X'_n) \geq \delta_n)]^{\frac{1}{2q}} \leq \Delta_g(\delta_n) + C' \delta_n^{1/2}. \end{aligned}$$

So (2) follows since (10) entails $\sum_{n=1}^\infty \Delta_g^2(\delta_n)/n < \infty$. (b) similarly follows. \square

Example 2. Linear processes. Let $\varepsilon_k, k \in \mathbb{Z}$, be iid random variables with mean 0 and finite variance; let $X_n = (\dots, \varepsilon_{n-1}, \varepsilon_n)$ and $g(X_n) = \sum_{i=0}^\infty a_i \varepsilon_{n-i}$, where a_i are real numbers such that $\sum_{i=0}^\infty a_i^2 < \infty$. Then (7) is reduced to $\sum_{i=1}^\infty |a_i - a_{i-1}| < \infty$, and the central limit theorem (6) holds for all $0 < \theta < 2\pi$. Notice that this cannot be extended to $\theta = 0$ if $|a_n|$ is not summable. For example, $a_n = n^{-\beta}$, $1/2 < \beta < 1$ for $n \geq 1$.

3. PROOFS

Let \mathbb{U} be the uniform probability measure on $\Theta = [0, 2\pi)$, and let $\mathcal{B}(\Theta)$ be the class of the Borel sets of Θ . Denote by $(\Theta \times \Omega, \mathcal{B}(\Theta) \times \mathcal{B}(\Omega), \mathbb{U} \times \mathbb{P})$ the product probability space of $(\Theta, \mathcal{B}(\Theta), \mathbb{U})$ and $(\Omega, \mathcal{B}(\Omega), \mathbb{P})$.

Lemma 1. *Assume (2). Then for almost all $\theta \in \Theta(\mathbb{U})$,*

$$\frac{1}{\sqrt{n}} \mathbb{E}[S_n(\theta)|X_0] \rightarrow 0 \text{ almost surely } (\mathbb{P}).$$

Proof of Lemma 1. Let $A \in \mathcal{B}(\Theta) \times \mathcal{B}(\Omega)$ be the set on which

$$\sum_{n=1}^N \frac{1}{\sqrt{n}} e^{in\theta} \mathbb{E}[g(X_n)|X_0]$$

does not converge as $N \rightarrow \infty$. Let A^ω and A_θ be the ω -section and θ -section of A , respectively. Define

$$(12) \quad \Omega_0 = \left\{ \omega \in \Omega : \sum_{n=1}^\infty \frac{1}{n} |\mathbb{E}[g(X_n)|X_0]|^2 < \infty \right\}.$$

By (2), $\mathbb{P}(\Omega_0) = 1$. For $\omega \in \Omega_0$, by Carleson's theorem, $\mathbb{U}(A^\omega) = 0$. Thus, by Fubini's theorem, for almost all $\theta \in \Theta(\mathbb{U})$, $\mathbb{P}(A_\theta) = 0$, i.e., $\sum_{n=1}^\infty e^{in\theta} \mathbb{E}[g(X_n)|X_0]/\sqrt{n}$ converges almost surely (\mathbb{P}) . Hence by Kronecker's lemma (cf. Chow and Teicher [5], Lemma 5.1.2), as $N \rightarrow \infty$,

$$\frac{1}{\sqrt{N}} \sum_{n=1}^N e^{in\theta} \mathbb{E}[g(X_n)|X_0] \rightarrow 0 \text{ a.s. } (\mathbb{P}).$$

\square

Lemma 2. *For almost all $\theta \in \Theta(\mathbb{U})$, there exists $\xi(\theta, X_0, X_1) \in \mathcal{L}^2$ such that*

$$(13) \quad \mathcal{P}_1 S_n(\theta) \rightarrow \xi(\theta, X_0, X_1) \text{ almost surely } (\mathbb{P}).$$

Proof of Lemma 2. Since the sequence $\mathbb{E}[g(X_0)|X_{1-n}] - \mathbb{E}[g(X_0)|X_{-n}]$, $n = 0, 1, \dots$, forms martingale differences,

$$\sum_{n=1}^{\infty} \|\mathcal{P}_1 g(X_n)\|^2 = \sum_{n=1}^{\infty} \|\mathcal{P}_{1-n} g(X_0)\|^2 = \|g(X_0)\|^2 < \infty.$$

Hence for almost all $\omega \in \Omega(\mathbb{P})$, $\sum_{n=1}^{\infty} |\mathcal{P}_1 g(X_n)|^2 < \infty$, which yields (13) by Carleson's theorem and the same argument as in Lemma 1. Next we show that $\xi(\theta, X_0, X_1) \in \mathcal{L}^2$. To this end, since the trigonometric bases e^{in} , $n \in \mathbb{Z}$, are orthogonal,

$$\sum_{k=1}^n \|\mathcal{P}_{1-k} g(X_0)\|^2 = \int_{\Theta} \mathbb{E} |\mathcal{P}_1 S_n(\theta)|^2 \mathbb{U}(d\theta).$$

By Fatou's lemma,

$$\begin{aligned} \|g(X_0)\|^2 &\geq \liminf_{n \rightarrow \infty} \int_{\Theta} \mathbb{E} |\mathcal{P}_1 S_n(\theta)|^2 \mathbb{U}(d\theta) \\ &\geq \int_{\Theta} \mathbb{E} \liminf_{n \rightarrow \infty} |\mathcal{P}_1 S_n(\theta)|^2 \mathbb{U}(d\theta) = \int_{\Theta} \mathbb{E} [|\xi(\theta, X_0, X_1)|^2] \mathbb{U}(d\theta). \end{aligned}$$

Hence for almost all $\theta \in \Theta(\mathbb{U})$, $\|\xi(\theta, X_0, X_1)\|^2 < \infty$. \square

Lemma 3. Assume (2). Then for almost all $\theta \in \Theta(\mathbb{U})$,

$$(14) \quad \mathbb{E}[\xi(\theta, X_0, X_1)|X_0] = 0 \quad a.s. \quad (\mathbb{P})$$

Proof of Lemma 3. The almost sure convergence (13) in Lemma 2 alone does not guarantee the \mathcal{L}^2 convergence. To prove (14), we shall show below that, under (2), the Cesàro average $\sum_{n=1}^N \mathcal{P}_1 S_n(\theta)/N$ converges to $\xi(\theta, X_0, X_1)$ in \mathcal{L}^2 . The relation (14) reveals the martingale structure, and we can apply the martingale central limit theorem.

Let the tail

$$R_N(\theta, X_0, X_1) = \sum_{n=N+1}^{\infty} e^{in\theta} \{\mathbb{E}[g(X_n)|X_1] - \mathbb{E}[g(X_n)|X_0]\}.$$

Then $R_0(\theta, X_0, X_1) = \xi(\theta, X_0, X_1)$. Again by the orthogonality of the bases e^{in} ,

$$\int_{\Theta} |R_N(\theta, X_0, X_1)|^2 \mathbb{U}(d\theta) = \sum_{n=1+N}^{\infty} |\mathcal{P}_1 g(X_n)|^2 < \infty.$$

Hence by (2),

$$\begin{aligned} \sum_{N=1}^{\infty} \frac{1}{N} \int_{\Theta} \mathbb{E} |R_N(\theta, X_0, X_1)|^2 \mathbb{U}(d\theta) &= \sum_{N=1}^{\infty} \frac{1}{N} \sum_{n=1+N}^{\infty} \mathbb{E} |\mathcal{P}_1 g(X_n)|^2 \\ &= \sum_{N=1}^{\infty} \frac{1}{N} \|\mathbb{E}[g(X_0)|X_{-N}]\|^2 < \infty. \end{aligned}$$

So for almost all $\theta \in \Theta(\mathbb{U})$,

$$\sum_{N=1}^{\infty} \frac{1}{N} \mathbb{E} |R_N(\theta, X_0, X_1)|^2 < \infty.$$

It follows from Kronecker’s lemma that as $N \rightarrow \infty$,

$$(15) \quad \frac{1}{N} \sum_{j=1}^N \mathbb{E}|R_j(\theta, X_0, X_1)|^2 \rightarrow 0,$$

which yields

$$\mathbb{E} \left| \frac{1}{N} \sum_{j=1}^N R_j(\theta, X_0, X_1) \right|^2 \rightarrow 0$$

by Cauchy’s inequality. In other words,

$$\bar{s}_N(\theta, X_0, X_1) := \frac{1}{N} \sum_{n=1}^N \mathcal{P}_1 S_n(\theta) \rightarrow \xi(\theta, X_0, X_1) \quad \text{in } \mathcal{L}^2.$$

Clearly, $\mathbb{E}[\bar{s}_N(\theta, X_0, X_1)|X_0] = 0$ a.s. (\mathbb{P}). Hence as $N \rightarrow \infty$,

$$\begin{aligned} \mathbb{E}|\mathbb{E}[\xi(\theta, X_0, X_1)|X_0]| &= \mathbb{E}|\mathbb{E}[\xi(\theta, X_0, X_1) - \bar{s}_N(\theta, X_0, X_1)|X_0]| \\ &\leq \mathbb{E}|\xi(\theta, X_0, X_1) - \bar{s}_N(\theta, X_0, X_1)| \\ &\leq \|\xi(\theta, X_0, X_1) - \bar{s}_N(\theta, X_0, X_1)\| \rightarrow 0, \end{aligned}$$

which proves (14). □

Lemma 4. *Suppose (15) holds for θ for which $\xi(\theta, X_0, X_1) \in \mathcal{L}^2(\mathbb{P})$. Then*

$$(16) \quad \begin{pmatrix} \Re \\ \Im \end{pmatrix} \frac{S_n(\theta) - \mathbb{E}[S_n(\theta)|X_0]}{\sqrt{n}} \Rightarrow N[0, \Sigma(\theta)],$$

where $\Sigma(\theta) = \frac{1}{2}\|\xi(\theta, X_0, X_1)\|^2 \text{Id}_2$ if $\theta \neq 0, \pi$, and

$$\Sigma(\theta) = \begin{pmatrix} \|\xi(\theta, X_0, X_1)\|^2 & 0 \\ 0 & 0 \end{pmatrix}, \quad \text{if } \theta = 0, \pi.$$

Proof of Lemma 4. We generalize the arguments in Woodroffe [21] where the asymptotic normality for the case $\theta = 0$ was obtained. Let $\xi_n(\theta, x_0, x_1) = \mathbb{E}[S_n(\theta)|X_1 = x_1] - \mathbb{E}[S_n(\theta)|X_0 = x_0]$, and write

$$(17) \quad \begin{aligned} S_n(\theta) - \mathbb{E}[S_n(\theta)|X_0] &= \sum_{j=1}^n e^{i\theta(j-1)} \xi(\theta, X_{j-1}, X_j) \\ &+ \sum_{j=1}^n e^{i\theta(j-1)} [\xi_{n-j+1}(\theta, X_{j-1}, X_j) - \xi(\theta, X_{j-1}, X_j)]. \end{aligned}$$

Now we claim that (15) implies that the second part in the preceding display is $o_{\mathbb{P}}(\sqrt{n})$. Actually, by Lemma 3, $\mathbb{E}[\xi_{n-j+1}(\theta, X_{j-1}, X_j) - \xi(\theta, X_{j-1}, X_j)|X_{j-1}] = 0$ almost surely \mathbb{P} . Then it suffices to establish

$$(18) \quad \frac{1}{n} \sum_{j=1}^n \|\xi_{n-j+1}(\theta, X_{j-1}, X_j) - \xi(\theta, X_{j-1}, X_j)\|^2 \rightarrow 0,$$

which follows from (15) via the stationarity of X_j . By Lemma 3, $\xi(\theta, X_{j-1}, X_j)$, $j \in \mathbb{Z}$ is a martingale difference sequence. Hence we can use the martingale central limit theorem to deduce (16) from (17). To this end, let

$$\begin{aligned} \xi(\theta, X_{j-1}, X_j) &= A_j(\theta) + iB_j(\theta), \\ \alpha_j(\theta) &= A_j(\theta) \cos[(j-1)\theta] - B_j(\theta) \sin[(j-1)\theta], \\ \beta_j(\theta) &= B_j(\theta) \cos[(j-1)\theta] + A_j(\theta) \sin[(j-1)\theta]. \end{aligned}$$

Then $A_j(\theta)$, $B_j(\theta)$, $\alpha_j(\theta)$ and $\beta_j(\theta)$ form martingale difference sequences, and

$$\sum_{j=1}^n e^{i\theta(j-1)} \xi(\theta, X_{j-1}, X_j) = \sum_{j=1}^n [\alpha_j(\theta) + i\beta_j(\theta)].$$

For a fixed $0 \leq \theta_0 < 2\pi$, let $D_j = \alpha_j(\theta) \cos \theta_0 + \beta_j(\theta) \sin \theta_0$. Then the D_j are again martingale differences. By the Cramer-Wold device, it suffices to show that

$$\frac{1}{\sqrt{n}} \sum_{j=1}^n D_j \Rightarrow N[0, \sigma^2(\theta, \theta_0)], \quad \text{where } \sigma^2(\theta, \theta_0) = (\cos \theta_0, \sin \theta_0) \Sigma(\theta) \begin{pmatrix} \cos \theta_0 \\ \sin \theta_0 \end{pmatrix}.$$

We now apply the martingale central limit theorem to $\sum_{j=1}^n D_j/\sqrt{n}$. The Lindeberg condition is automatically satisfied. Since $\mathbb{E}[\xi^2(\theta, X_{j-1}, X_j)|\mathcal{F}_{j-1}]$, $j \in \mathbb{Z}$ forms a stationary and ergodic sequence in $\mathcal{L}^1(\mathbb{P})$, by Lemma 5, the limit

$$(19) \quad V(\theta) = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{j=1}^n \mathbb{E}[\xi^2(\theta, X_{j-1}, X_j)|\mathcal{F}_{j-1}] e^{2(j-1)i\theta}$$

exists and equals 0 almost surely (\mathbb{P}) if $\theta \neq 0, \pi$, and equals $\|\xi(\theta, X_0, X_1)\|^2$ if $\theta = 0$ or π . After some algebra,

$$\begin{aligned} \Sigma_{11}(\theta) &= \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{j=1}^n \mathbb{E}[\alpha_j^2(\theta)|\mathcal{F}_{j-1}] = \frac{\|\xi(\theta, X_0, X_1)\|^2}{2} + \frac{\Re V(\theta)}{2}, \\ \Sigma_{22}(\theta) &= \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{j=1}^n \mathbb{E}[\beta_j^2(\theta)|\mathcal{F}_{j-1}] = \frac{\|\xi(\theta, X_0, X_1)\|^2}{2} - \frac{\Re V(\theta)}{2}, \\ \Sigma_{12}(\theta) &= \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{j=1}^n \mathbb{E}[\alpha_j(\theta)\beta_j(\theta)|\mathcal{F}_{j-1}] = \frac{\Im V(\theta)}{2} \end{aligned}$$

almost surely (\mathbb{P}), which completes the proof. □

Lemma 5. *Let η_n , $n \in \mathbb{Z}$, be a real-valued, stationary and ergodic sequence with $\mathbb{E}|\eta_1| < \infty$. Then for all $0 < \alpha < 2\pi$,*

$$(20) \quad \frac{1}{n} \sum_{t=1}^n e^{it\alpha} \eta_t \rightarrow 0$$

almost surely and in \mathcal{L}^1 .

Proof of Lemma 5. This result seems to be implied but not explicitly stated in the literature (see, for example, Doob ([7], pp. 469–470), Rozanov ([15], pp. 160–161), Wiener and Wintner [20]). Since $\sum_{t=1}^n e^{it\alpha} \mathbb{E}(\eta_t)/n \rightarrow 0$, we can assume, without loss of generality, that $\mathbb{E}(\eta_t) = 0$. If $\alpha/(2\pi)$ is a rational number, then (20) clearly follows from the classical ergodic theorem. In the case that $\alpha/(2\pi)$ is not a rational number, define the rotation $\rho_\alpha : \Theta \mapsto \Theta$ by $\rho_\alpha(\theta) = \theta + \alpha \pmod{2\pi}$. Then ρ_α is measure-preserving and ergodic. Let the random variable $\vartheta \sim \text{Uniform}(\Theta)$ be independent of η_n , $n \in \mathbb{Z}$. Since η_t is stationary and ergodic, the sequence $\varphi_t = e^{it\alpha + \vartheta} \eta_t$, $t \in \mathbb{Z}$, is then stationary (cf. Rozanov [15], p. 161) as well as ergodic on the product space $(\Theta \times \Omega, \mathcal{B}(\Theta) \times \mathcal{B}(\Omega), \mathbb{U} \times \mathbb{P})$. Therefore the classical ergodic theorem asserts that $n^{-1} \sum_{t=1}^n \varphi_t \rightarrow 0$ almost surely ($\mathbb{U} \times \mathbb{P}$) and in \mathcal{L}^1 , which clearly entails (20) since \mathbb{U} is a uniform distribution. □

Proof of Theorem 1. (i) This follows from Lemmas 1 and 4. (ii) By Lemmas 1, 3 and 4, for almost all $\theta, \varphi \in \Theta(\mathbb{U})$, martingale differences $\xi(\tau, X_{t-1}, X_t) = A_t(\tau) + iB_t(\tau)$, $\tau = \theta, \varphi$, can be constructed, and it suffices to show that $n^{-1/2} \sum_{t=1}^n \mathbf{v}_t \Rightarrow N[0, \Sigma(\theta, \varphi)]$, where random vectors $\mathbf{v}_t = (\alpha_t(\theta), \beta_t(\theta), \alpha_t(\varphi), \beta_t(\varphi))$ and the covariance matrix $\Sigma(\theta, \varphi) = \frac{1}{2} \text{Diag}(w(\theta), w(\theta), w(\varphi), w(\varphi))$, $w(\tau) = \|\xi(\tau, X_0, X_1)\|^2$. To this end, by (i) and the Cramer-Wold device, (ii) follows from

$$\frac{1}{n} \sum_{t=1}^n \begin{pmatrix} \alpha_t(\theta)\alpha_t(\varphi) & \alpha_t(\theta)\beta_t(\varphi) \\ \beta_t(\theta)\alpha_t(\varphi) & \beta_t(\theta)\beta_t(\varphi) \end{pmatrix} \rightarrow 0 \quad a.s. \quad (\mathbb{P}),$$

which in view of Lemma 5 is valid provided that $\varphi \neq \theta$ and $\varphi + \theta \neq 2\pi$. □

Proof of Theorem 2. Observe that (16) in Lemma 4 holds for θ for which (4) is satisfied. Therefore, (6) follows in view of (5). □

Proof of Proposition 1. Let $h_n = \sum_{t=1}^n e^{it\theta}$. Since $0 < \theta < 2\pi$, $h := \sup_{n \geq 1} |h_n| < \infty$. By (7), $\sum_{n=1}^{\infty} h_n [\mathcal{P}_1 g(X_n) - \mathcal{P}_1 g(X_{n+1})]$ converges in $\mathcal{L}^2(\mathbb{P})$. Thus (4) holds since $\|\mathcal{P}_1 g(X_n)\| \rightarrow 0$. To prove (5), let $\phi_t = \|\mathcal{P}_1 g(X_t) - \mathcal{P}_1 g(X_{t+1})\|$ and $\Phi_k = \sum_{t=k}^{\infty} \phi_t$. Then (7) entails $\sum_{j=0}^{\infty} [\sum_{t=1}^n \phi_{t+j}]^2 \leq \Phi_1 \sum_{j=0}^{\infty} \sum_{t=1}^n \phi_{t+j} = o(n)$. So (5) follows from

$$\|\mathcal{P}_{-j} S_n(\theta)\| \leq h \sum_{t=1}^n \|\mathcal{P}_{-j} g(X_t) - \mathcal{P}_{-j} g(X_{t+1})\| + h \|\mathcal{P}_{-j} g(X_{n+1})\|,$$

$\|\mathbb{E}[S_n(\theta)|X_0]\|^2 = \sum_{j=0}^{\infty} \|\mathcal{P}_{-j} S_n(\theta)\|^2$ and $\sum_{j=0}^{\infty} \|\mathcal{P}_{-j} g(X_{n+1})\|^2 \leq \|g(X_0)\|^2$ by the orthogonality of \mathcal{P}_k . □

Proof of Proposition 2. Let $K_n(\lambda) = \sin^2(n\lambda/2)/[2\pi n \sin^2(\lambda/2)]$ be the Fejér kernel. It is well known that $\|S_n(\theta)\|^2/(2\pi n) = \int_0^{2\pi} K_n(\lambda - \theta) f(\lambda) d\lambda$ (cf. Theorem 8.2.7 in Anderson ([1], p. 454)), which by the Fejér-Lebesgue Theorem (cf. Bary ([2], p. 139)) converges almost everywhere to $f(\theta)$. Therefore, by (17) and (18), for almost all θ (Lebesgue),

$$\begin{aligned} \lim_{n \rightarrow \infty} \frac{1}{n} \|\mathbb{E}[S_n(\theta)|X_0]\|^2 &= \lim_{n \rightarrow \infty} \frac{1}{n} \|S_n(\theta)\|^2 - \lim_{n \rightarrow \infty} \frac{1}{n} \|S_n(\theta) - \mathbb{E}[S_n(\theta)|X_0]\|^2 \\ (21) \qquad \qquad \qquad &= 2\pi f(\theta) - \|\xi(\theta, X_0, X_1)\|^2. \end{aligned}$$

Notice that by (8),

$$\sum_{k=1}^{\infty} 2^{-k} \int_0^{2\pi} \|\mathbb{E}[S_{2^k}(\theta)|X_0]\|^2 \mathbb{U}(d\theta) = \sum_{k=1}^{\infty} 2^{-k} \sum_{i=1}^{2^k} \|\mathbb{E}[g(X_i)|X_0]\|^2 < \infty.$$

Hence by Borel-Cantelli's Lemma, for almost all θ (Lebesgue), $2^{-k} \|\mathbb{E}[S_{2^k}(\theta)|X_0]\|^2 \rightarrow 0$ as $k \rightarrow \infty$, which by (21) entails $2\pi f(\theta) = \|\xi(\theta, X_0, X_1)\|^2 = 2\sigma^2(\theta)$ almost surely. □

ACKNOWLEDGMENT

The author is grateful to the referee for many helpful suggestions.

REFERENCES

1. Anderson, T. W. (1971). *The Statistical Analysis of Time Series*. Wiley, New York. MR44:1169
2. Bary, N. K. (1964). *A Treatise on Trigonometric Series*. Macmillan, New York. MR30:1347
3. Brockwell, P. J. and Davis, R. A. (1991). *Time Series: Theory and Methods*. Springer, New York. MR92d:62001
4. Carleson, L. (1966). On convergence and growth of partial sums of Fourier series. *Acta Math.* **116** 135–157. MR33:7774
5. Chow, Y. S. and Teicher, H. (1988). *Probability Theory*. 2nd ed. New York, Springer. MR89e:60001
6. Diaconis, P. and Freedman, D. (1999). Iterated random functions. *SIAM Rev.* **41** 41–76. MR2000c:60102
7. Doob, J. (1953). *Stochastic Processes*. Wiley, New York. MR15:445b
8. Gray, H. L., Zhang, N.-F. and Woodward, W.A. (1989). On generalized fractional processes. *J. Time Ser. Anal.* **10** 233–257. MR90m:62208
9. Ibragimov, I. A. and Linnik, Yu. V. (1971). *Independent and stationary sequences of random variables*. Wolters-Noordhoff, Groningen. MR48:1287
10. Meyn, S. P. and Tweedie, R. L. (1993). *Markov chains and stochastic stability*. Springer, London; New York. MR95j:60103
11. Olshen, R. A. (1967). Asymptotic properties of the periodogram of a discrete stationary process. *J. Appl. Probab.* **4** 508–528. MR37:3643
12. Rootzén, H. (1976). Gordin's theorem and the periodogram. *J. Appl. Probab.* **13** 365–370. MR53:14619
13. Rosenblatt, M. (1981). Limit theorems for Fourier transforms of functionals of Gaussian sequences. *Z. Wahrsch. Verw. Gebiete* **55** 123–132. MR82i:60066
14. Rosenblatt, M. (1985). *Stationary sequences and random fields*. Birkhäuser, Boston. MR88c:60077
15. Rozanov, Yu. A. (1967). *Stationary random processes*. Holden-Day, San Francisco. MR35:4985
16. Terrin, N. and Hurvich, C. M. (1994). An asymptotic Wiener-Ito representation for the low frequency ordinates of the periodogram of a long memory time series. *Stochastic Process. Appl.* **54** 297–307. MR95i:62078
17. Tong, H. (1990). *Non-linear time series: a dynamical system approach*. Oxford University Press. MR92a:62141
18. Walker, A. M. (1965). Some asymptotic results for the periodogram of a stationary time series. *J. Austral. Math. Soc.* **5** 107–128. MR31:1720
19. Walker, A. M. (2000). Some results concerning the asymptotic distribution of sample Fourier transforms and periodograms for a discrete-time stationary process with a continuous spectrum. *J. Time Ser. Anal.* **21** 95–109. MR2001c:62108
20. Wiener, N. and Wintner, A. (1941). Harmonic analysis and ergodic theory. *American Journal of Mathematics* **63** 415–426. MR2:319b
21. Woodroffe, M. (1992). A central limit theorem for functions of a Markov chain with applications to shifts. *Stochastic Process. Appl.* **41** 33–44. MR93d:60037
22. Wu, W. B. and Woodroffe, M. (2000). A central limit theorem for iterated random functions. *J. Appl. Probab.* **37** 748–755. MR2002d:60020
23. Yajima, Y. (1989). A central limit theorem of Fourier transforms of strongly dependent stationary processes. *J. Time Ser. Anal.* **10** 375–383. MR91a:62258

DEPARTMENT OF STATISTICS, THE UNIVERSITY OF CHICAGO, 5734 S. UNIVERSITY AVENUE,
CHICAGO, ILLINOIS 60637

E-mail address: `wbwu@galton.uchicago.edu`