

## AN ALGORITHM FOR LINEAR PREDICTION OF A BANACH SPACE VALUED STATIONARY STOCHASTIC PROCESS

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Wiener and Masani describe a procedure for relating nonlinear prediction of a univariate random process to linear prediction of an infinite-variate process which may not be a Hilbert-space-valued process but may be Banach-space-valued instead. An algorithm for computation of the linear predictor and the generating function of a Banach-space-valued stationary stochastic process is obtained under an extension of the boundedness condition of Wiener and Masani on the spectral density of the process.

**1. Introduction and notation.** If  $\mathcal{X}$  and  $\mathcal{Y}$  are two Banach spaces,  $\mathcal{B}(\mathcal{X}, \mathcal{Y})$  denotes the Banach space of all bounded linear operators from  $\mathcal{X}$  to  $\mathcal{Y}$ , and  $\mathcal{X}^*$  denotes the Banach space of all conjugate linear functionals on  $\mathcal{X}$ . A bisequence  $\{\xi_n: -\infty < n < \infty\}$  of elements of  $\mathcal{B}(\mathcal{X}, \mathcal{H})$  where  $\mathcal{X}$  is a Banach space and  $\mathcal{H}$  is a Hilbert space, is called a  $\mathcal{B}(\mathcal{X}, \mathcal{H})$ -valued weakly stationary stochastic process if the operator  $\xi_m^* \xi_n$  in  $\mathcal{B}(\mathcal{X}, \mathcal{X}^*)$  depends only on  $n - m$ . And then the operator sequence  $R(n) = \xi_0^* \xi_n$  defined for  $-\infty < n < \infty$  is called the covariance bisequence of the process. Assume that  $\mathcal{X}$  is separable. With this stationary stochastic process are associated the following subspaces ([6], page 922):

$M_\infty$ , the closed subspace of  $\mathcal{H}$  spanned by  
 $\{\hat{\xi}_k(x): -\infty < k < \infty, x \in \mathcal{X}\},$

$M_n$ , the closed subspace of  $\mathcal{H}$  spanned by  
 $\{\hat{\xi}_k(x): -\infty < k \leq n, x \in \mathcal{X}\},$

and

$$M_{-\infty} = \bigcap_{-\infty < n < \infty} M_n.$$

The process  $\{\xi_n: -\infty < n < \infty\}$  is said to be

- (i) singular if  $M_{-\infty} = M_n$  for  $-\infty < n < \infty$ ;
- (ii) nondeterministic if  $M_{-\infty} \neq M_n$  for some finite  $n$ ;
- (iii) regular if  $M_{-\infty} = \{0\}$ .

For  $\mathcal{I} \subset \mathcal{B}(\mathcal{X}, \mathcal{H})$  let  $\bar{\sigma}(\mathcal{I})$  denote the smallest (strongly) closed subspace of  $\mathcal{B}(\mathcal{X}, \mathcal{H})$  containing the set  $\{SB: S \in \mathcal{I}, B \in \mathcal{B}(\mathcal{X}, \mathcal{X})\}$  and  $\sigma(\mathcal{I})$  denote the smallest closed subspace of  $\mathcal{H}$  containing the set  $\{Sx: S \in \mathcal{I}, x \in \mathcal{X}\}$ . We shall use the same notation also for subsets  $\mathcal{I}$  of  $\mathcal{B}(\mathcal{H}, \mathcal{H})$ . In this notation

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then

$$\bar{\sigma}(\mathcal{I}) = \mathcal{B}(\mathcal{X}, \sigma(\mathcal{I})) \tag{[6], page 922}.$$

For the stationary stochastic  $\mathcal{B}(\mathcal{X}, \mathcal{K})$ -valued process  $\{\xi_n : -\infty < n < \infty\}$  define

$$\begin{aligned} \mathcal{M}_n &= \bar{\sigma}\{\xi_k : k \leq n\}, \\ \mathcal{M}_{-\infty} &= \bigcap_n \mathcal{M}_n, \\ \mathcal{M}_\infty &= \bar{\sigma}\{\xi_k : -\infty < k < \infty\}. \end{aligned}$$

In the above notation then,  $\mathcal{M}_n = \mathcal{B}(\mathcal{X}, \mathcal{M}_n)$ ,  $-\infty \leq n \leq \infty$ . Furthermore let  $\mathcal{B}_n, B_n$  for  $-\infty \leq n \leq \infty$  denote corresponding subspaces for a  $\mathcal{B}(\mathcal{X}, \mathcal{K})$ -valued stationary process  $\{\eta_n : -\infty < n < \infty\}$ .

Now for each  $\xi_n \in \mathcal{B}(\mathcal{X}, \mathcal{K})$ , there exists an operator  $(\xi_n | \mathcal{M}_0)$  in  $\mathcal{B}(\mathcal{X}, \mathcal{M}_0)$  such that  $\xi_n - (\xi_n | \mathcal{M}_0)$  is orthogonal to  $\mathcal{M}_0$  ([4], Theorem 3.2.5, page 10).  $(\xi_n | \mathcal{M}_0)$  is called the projection of  $\xi_n$  on  $\mathcal{M}_0$ , and is denoted by  $\hat{\xi}_n$ . Similarly define  $\hat{\eta}_n$  as  $(\eta_n | \mathcal{B}_0)$ ,  $-\infty < n < \infty$ . The operator  $G = (\xi_0 - \hat{\xi}_0)^*(\xi_0 - \hat{\xi}_0)$  is called the predictor error operator of the process. The process is said to be of full rank if  $G$  is boundedly invertible.

Time domain and spectral analysis for such processes, as given below, were obtained by A. G. Miammee [6]. However an extension of the algorithm of Weiner and Masani ([7], 6, pages 123–127) under the boundedness condition ([5], page 1), was obtained only for Hilbert-space-valued random variables using Fourier analysis of infinite matrix valued functions. In dearth of an obvious identity operator in the family of  $\mathcal{B}(\mathcal{X}, \mathcal{X}^*)$ -valued functions, a suitable boundedness condition on the spectral density of the process must be obtained to work out the corresponding algorithm for prediction.

*Time domain analysis.* For a  $\mathcal{B}(\mathcal{X}, \mathcal{K})$ -valued regular stationary stochastic process  $\{\xi_n : -\infty < n < \infty\}$  there exist mutually orthogonal isometries  $S_k$  and  $A_k \in \mathcal{B}(\mathcal{X}, \mathcal{K})$  such that

$$\xi_n = \sum_{k=0}^{\infty} S_{n-k} A_k,$$

convergence being in the strong operator topology ([6] Theorem 3.5, page 924).

*Spectral analysis.* For the  $\mathcal{B}(\mathcal{X}, \mathcal{K})$ -valued weakly stationary stochastic process  $\{\xi_n : -\infty < n < \infty\}$ , the shift operator  $\mathcal{U}$  defined on  $\mathcal{M}_\infty$  as follows

$$\mathcal{U}\xi_n x = \xi_{n+1} x, \quad x \in \mathcal{X}, \quad -\infty < n < \infty$$

has a spectral resolution  $\mathcal{U} = 1/2\pi \int_0^{2\pi} e^{-i\theta} E(d\theta)$ , where  $E$  is a projection valued measure over  $([0, 2\pi), \mathcal{B})$ ,  $\mathcal{B}$  being the algebra of Borel sets ([2], pages 359–360). Now define for  $B \in \mathcal{B}$ ,  $F(B) = \xi_0^* E(B) \xi_0$ . This  $F$  is called the spectral distribution function of  $\{\xi_n : -\infty < n < \infty\}$ . Assume now that there exists a nonnegative  $\mathcal{B}(\mathcal{X}, \mathcal{X}^*)$ -valued function  $f(\theta)$  defined on  $[0, 2\pi)$  such that

- (i)  $f(\theta)$  is strongly measurable;

- (ii)  $f(\theta)$  is Bochner integrable; and
- (iii) for each Borel measurable  $B \subset [0, 2\pi)$ ,  $F(B) = \int_B f(\theta) d\theta$ .

This  $f(\theta)$ , also denoted by  $f_\theta$ , will then be called the spectral density of the process  $\{\xi_n: -\infty < n < \infty\}$ . Let  $L_2(\mathcal{H})$  denote the Hilbert space of all  $\mathcal{H}$ -valued scalarly measurable functions on the unit circle which have square summable norm. The  $L_2(\mathcal{H})$  inner product of two functions  $g_1$  and  $g_2$  is

$$\frac{1}{2\pi} \int_0^{2\pi} (g_1(e^{i\theta}), g_2(e^{i\theta})) d\theta .$$

Then a  $\mathcal{B}(\mathcal{H}, \mathcal{H})$ -valued function  $A(e^{i\theta})$  defined on the unit circle is said to be conjugate analytic if

$$\forall x \in \mathcal{H}, \quad A(e^{i\theta})(x) \in \left\{ g \in L_2(\mathcal{H}) : \frac{1}{2\pi} \int e^{-in\theta} g(e^{i\theta}) d\theta = 0 \text{ for } n > 0 \right\} .$$

The spectral density  $f(\theta)$  is said to be factorable if there exists a conjugate analytic  $\mathcal{B}(\mathcal{H}, \mathcal{H})$ -valued function  $A(e^{i\theta})$  defined on the unit circle such that  $f(e^{i\theta}) = A^*(e^{i\theta})A(e^{i\theta})$ , in the sense that  $(f(e^{i\theta})x)(y) = (A(e^{i\theta})x, A(e^{i\theta})y)$  for all  $x, y \in \mathcal{H}$ .

Regarding factorization of the spectral density of a  $\mathcal{B}(\mathcal{H}, \mathcal{H})$ -valued regular stochastic process, the following has been established in [6], Theorem 4.5, page 930.

1.1 THEOREM. *The spectral distribution  $F$  of a regular full rank  $\mathcal{B}(\mathcal{H}, \mathcal{H})$ -valued stationary stochastic process is absolutely continuous and*

$$\frac{d}{d\theta} (F(e^{i\theta})x)(x) = \|\Phi(e^{i\theta})x\|^2$$

where

$$\Phi(e^{i\theta})(x) = \sum_{k=0}^{\infty} e^{-ik\theta} A_k(x), \quad A_k \in \mathcal{B}(\mathcal{H}, \mathcal{H})$$

and

$$G = A_0^* A_0 .$$

$\Phi$ , as defined in this theorem, is called the generating function of the process  $\{\xi_n: -\infty < n < \infty\}$ .

2. The boundedness condition on the spectral density. Let the spectral density  $f_\theta$ , of the  $\mathcal{B}(\mathcal{H}, \mathcal{H})$ -valued stationary stochastic process  $\{\xi_n: -\infty < n < \infty\}$  satisfy

$$0 < m(\theta)A^*A \leq f_\theta \leq M(\theta)A^*A \quad \text{a.e. } \theta \in [0, 2\pi)$$

for some  $A: \mathcal{H} \rightarrow \mathcal{H}$  with  $\|A\| = 1$  and  $M(\theta), 1/m(\theta), M(\theta)/m(\theta)$ , summable.

2.1 LEMMA. *Under boundedness condition 2 on the spectral density and  $N_\theta = f_\theta/a_\theta - A^*A$  with  $a_\theta = (m(\theta) + M(\theta))/2, \|N_\theta\|_B \leq (M(\theta) - m(\theta))/(M(\theta) + m(\theta)) < 1$ .*

PROOF. For each  $x \in \mathcal{H}$

$$m(\theta)(Ax, Ax) \leq (f(x), x) \leq M(\theta)(Ax, Ax),$$

i.e.,

$$\left(\frac{m(\theta)}{a_\theta} - 1\right) (A^*Ax, x) \leq \frac{(f_\theta(x), x)}{a_\theta} - (A^*Ax, x) \leq \left(\frac{M(\theta)}{a_\theta} - 1\right) (A^*Ax, x),$$

i.e.,

$$\frac{m(\theta) - M(\theta)}{m(\theta) + M(\theta)} \|Ax\|^2 \leq (N_\theta(x), x) \leq \frac{M(\theta) - m(\theta)}{M(\theta) + m(\theta)} \|Ax\|^2.$$

Using the parallelogram law, we have for each  $x, y \in \mathcal{L}$

$$\begin{aligned} |(N_\theta(x), y)| &= \frac{1}{4} \{|(N_\theta(x+y), x+y) - (N_\theta(x-y), x-y)|\} \\ &\leq \left| \frac{M(\theta) - m(\theta)}{M(\theta) + m(\theta)} \frac{(A^*Ax, y) + (A^*Ay, x)}{2} \right|. \end{aligned}$$

Since  $\|A\| = 1$ ,  $\|N_\theta\|_B \leq (M(\theta) - m(\theta))/(M(\theta) + m(\theta)) < 1$ .

**2.2 LEMMA.** *Let the spectral density  $f_\theta$  satisfy the boundedness condition 2, and the image  $A\mathcal{L}$  be dense in  $\mathcal{K}$ . If  $A$  is one-to-one onto  $A\mathcal{L}$  then*

- (i)  $A^*$  is one-to-one;
- (ii)  $A^{*-1} = (A^{-1})^*$ ; and
- (iii)  $|(A^{*-1}N_\theta A^{-1}(k), l)| \leq (M(\theta) - m(\theta))/(M(\theta) + m(\theta)) \|k\| \|l\|$  a.e.  $\theta$  for  $k, l \in A\mathcal{L}$ .

**PROOF.** (i) Since  $A\mathcal{L}$  is dense in  $\mathcal{K}$ ,  $A^*$  is defined on  $\mathcal{K}$  to  $\mathcal{L}^*$  as follows:  $\forall k \in \mathcal{K}$ ,  $A^*(k) = x^*$  where  $x^*(y) = (k, Ay) \forall y \in \mathcal{L}$ .  $A^*$  is easily seen to be one-to-one.

(ii) In fact

$$\begin{aligned} \mathcal{D}((A^{-1})^*) &= \{x^* \in \mathcal{L}^* : \exists k \in \mathcal{K} \text{ with } x^*(A^{-1}l) = (k, l) \ \forall l \in Ax\} \\ &= \{x^* \in \mathcal{L}^* : \exists k \in \mathcal{K} \text{ with } x^*(y) = (k, Ay) \ \forall y \in x\} \\ &= \text{range of } A^* = \mathcal{D}(A^{*-1}). \end{aligned}$$

Also for each  $x^*$  in  $\mathcal{D}(A^{*-1})$ ,  $A^{*-1}(x^*) = k \Leftrightarrow (A^{-1})^*(x^*) = k$ .

(iii) Now from the proof of Lemma 2.1

$$|(N_\theta(x), y)| \leq \frac{M(\theta) - m(\theta)}{M(\theta) + m(\theta)} \left| \frac{(Ax, Ay) + (Ay, Ax)}{2} \right| \text{ a.e. } \theta.$$

Thus for  $k, l \in A\mathcal{L}$

$$\begin{aligned} |(A^{*-1}N_\theta A^{-1}(k), l)| &= |(N_\theta A^{-1}k, A^{-1}l)| \\ &\leq \frac{M(\theta) - m(\theta)}{M(\theta) + m(\theta)} \left| \frac{(AA^{-1}k, AA^{-1}l) + (AA^{-1}k, AA^{-1}l)}{2} \right| \text{ a.e. } \theta. \end{aligned}$$

$$\therefore \|A^{*-1}N_\theta A^{-1}\|_B \leq \frac{M(\theta) - m(\theta)}{M(\theta) + m(\theta)}.$$

Hence the result.

**3. Relationship with the case of Hilbert-space-valued random variables.**

**MAIN THEOREM 1.** *If the spectral density  $f_\theta$  satisfies the boundedness condition 2 and  $A: \mathcal{L} \rightarrow \mathcal{H}$  is one-to-one and  $A\mathcal{L}$  dense in  $\mathcal{H}$  then there is a unique stationary stochastic process  $\{\eta_n: -\infty < n < \infty\}$  which is  $\mathcal{B}(\mathcal{H}, \mathcal{H})$ -valued and is such that*

(i)  $R_\eta(n) = A^{*-1}R_\xi(n)A^{-1}$  on  $A\mathcal{L}$ .

(ii)  $f_\eta(\theta) = 2/(M(\theta) + m(\theta))[I_{\mathcal{X}} + A^{*-1}N_\theta A^{-1}] = A^{*-1}f_\xi(\theta)A^{-1}$  on  $A\mathcal{L}$  where  $I_{\mathcal{X}}$  denotes the identity operator on  $\mathcal{X}$  and  $f_\xi(\theta)$  is  $f_\theta$  in our previous notation.

**PROOF.** By Lemma 2.2  $A^{*-1}f_\xi(\theta)A^{-1} = 2/(M(\theta) + m(\theta))[I_{\mathcal{X}} + A^{*-1}N_\theta A^{-1}]$  is a bounded operator defined on  $A\mathcal{L}$ . Let  $g_\theta$  denote its unique continuous extension to  $\mathcal{X}$ .  $g_\theta$  is then a nonnegative  $\mathcal{B}(\mathcal{X}, \mathcal{X})$ -valued continuous function defined on the unit circle. Further  $g_\theta$  is strongly measurable since  $f(\theta)$  is assumed to be so. Also by 2.2 (iii)  $\|g_\theta\| \in L_1[0, 2\pi)$ . Hence  $g_\theta$  is Bochner integrable. Thus for any  $n$ ,  $\xi_n A^{-1}$  defined on  $A\mathcal{L}$  is such that  $\forall k \in A\mathcal{L}$

$$\begin{aligned} \|\xi_n A^{-1}(k)\|^2 &= \frac{1}{2\pi} \int_0^{2\pi} (A^{*-1}f_\theta A^{-1}(k), k) d\theta \\ &= \frac{1}{2\pi} \int_0^{2\pi} (g_\theta(k), k) d\theta \\ &\leq \|g\|_{L_1[0, 2\pi)} \|k\|^2 < \infty . \end{aligned}$$

Hence  $\xi_n A^{-1}$  admits a unique continuous extension to  $\mathcal{H}$ , say  $\eta_n$ .  $\{\eta_n: -\infty < n < \infty\}$  is then a  $\mathcal{B}(\mathcal{H}, \mathcal{H})$ -valued stationary stochastic process. In fact  $\{\eta_n: -\infty < n < \infty\}$  is stationary as shown by the following reasoning.

For  $k, l \in \mathcal{H}$  we must show that  $(\eta_n k, \eta_m l)$  depends only on  $n - m$ . Since  $A\mathcal{L}$  is dense in  $\mathcal{H}$ , there exist sequences  $\{x_p\}, \{y_q\}$  in  $\mathcal{L}$  such that

$$A(x_p) \rightarrow k \text{ in } \mathcal{H} \quad \text{and} \quad A(y_q) \rightarrow l \text{ in } \mathcal{H} .$$

Then, since  $\eta_n$  and  $\eta_m$  are bounded

$$\begin{aligned} (\eta_n k, \eta_m l) &= \lim_{p \rightarrow \infty} (\eta_n(Ax_p), \eta_m(Ay_p)) \\ &= \lim_{p \rightarrow \infty} (\xi_n x_p, \xi_m y_p) \\ &= \lim_{p \rightarrow \infty} \frac{1}{2\pi} \int_0^{2\pi} \bar{e}^{i(n-m)\theta} (f_\theta x_p, y_p) d\theta \end{aligned}$$

which depends on  $m$  and  $n$  only through  $n - m$ .

Furthermore

$$\begin{aligned} (\eta_n k, \eta_m l) &= \lim_{p \rightarrow \infty} \frac{1}{2\pi} \int_0^{2\pi} e^{-i(n-m)\theta} (f_\theta A^{-1}(Ax_p), A^{-1}(Ay_p)) d\theta \\ (\eta_n k, \eta_m l) &= \lim_{p \rightarrow \infty} \frac{1}{2\pi} \int_0^{2\pi} e^{-i(n-m)\theta} (A^{*-1}f_\theta A^{-1}(Ax_p), Ay_p) d\theta \\ &= \frac{1}{2\pi} \int_0^{2\pi} e^{-i(n-m)\theta} \{ \lim_{p \rightarrow \infty} (A^{*-1}f_\theta A^{-1}(Ax_p), Ay_p) \} d\theta \\ &= \frac{1}{2\pi} \int_0^{2\pi} e^{-i(n-m)\theta} (g_\theta(k), (l)) d\theta , \end{aligned}$$

the last two steps being true since  $g_\theta$  is a bounded operator. Thus on  $A(\mathcal{H})$

$$R_{\eta_n} = (\eta_n, \eta_0) = (\xi_n A^{-1}, \xi_0 A^{-1}) = A^{*-1} R_{\xi_n} A^{-1}$$

$$f_{\eta_n}(\theta) = A^{*-1} f_{\xi_n}(\theta) A^{-1},$$

and due to continuity of all functions involved,  $R_{\eta_n}$  and  $f_{\eta_n}(\theta)$  are the unique continuous extensions of  $A^{*-1} R_{\xi_n} A^{-1}$  and  $A^{*-1} f_{\xi_n}(\theta) A^{-1}$  respectively to  $\mathcal{H}$ .

3.1 Factorization of the spectral density.

**COROLLARY.** If  $\Phi_\theta: \mathcal{H} \rightarrow \mathcal{H}$  is the generating function for the  $\mathcal{B}(\mathcal{H}, \mathcal{H})$ -valued stationary stochastic process  $\{\eta_n: -\infty < n < \infty\}$  and if  $f_\theta$  satisfies the boundedness condition 2, and  $A: \mathcal{L} \rightarrow \mathcal{H}$  is one-to-one and  $A\mathcal{L}$  dense in  $\mathcal{H}$  then  $\Phi_\theta A: \mathcal{L} \rightarrow \mathcal{H}$  is such that  $f_\theta = (\Phi_\theta A)^*(\Phi_\theta A)$ .

**PROOF.** By Main Theorem I,  $g_\theta$  is the unique continuous extension of  $A^{*-1} f_\theta A^{-1}$ . So that

$$f_\theta = A^* g_\theta A$$

$$= A^* \Phi_\theta^* \Phi_\theta A = (\Phi_\theta A)^*(\Phi_\theta A).$$

3.2 The prediction error matrix and the predictor for a Banach-space-valued process. For the  $\mathcal{B}(\mathcal{H}, \mathcal{H})$ -valued stationary stochastic process  $\{\eta_n: -\infty < n < \infty\}$  a schematic algorithm to obtain the prediction error matrix  $G_\nu$  and the linear predictor  $\hat{\eta}_\nu$  of  $\eta_\nu$  for  $\nu > 0$  based on the past  $\{\eta_n: n \leq 0\}$ , is given in [5]. We shall now find the same for the  $\mathcal{B}(\mathcal{L}, \mathcal{H})$ -valued process  $\{\xi_n: -\infty < n < \infty\}$ .

**MAIN THEOREM II.** The two stationary stochastic processes  $\{\xi_n: -\infty < n < \infty\}$  and  $\{\eta_n: -\infty < n < \infty\}$  are further related as follows:

- (i) For each integer  $\nu > 0$ ,

$$\hat{\xi}_\nu = \hat{\eta}_\nu A.$$

(ii)  $G_\xi = A^* G_\eta A$ . Note that  $G_\eta = A_0^* A_0$  where  $\Phi(e^{i\theta})(x) = \sum_{k=0}^\infty e^{-ik\theta} A_k(x)$  is the generating function of the process  $\{\eta_n: -\infty < n < \infty\}$ .

(iii)  $\hat{\xi}_\nu = \lim_{n \rightarrow \infty} \sum_{k=0}^n E_{\nu,k} \xi_{-k}$  where  $E_{\nu,k}$  is the  $k$ th Fourier coefficient of  $[e^{-i\nu\theta} \Phi(e^{i\theta})_{0+} \Phi^{-1}]$ .

**PROOF.** (i) Note that  $\xi_k = \eta_k A$  for each  $k$ . Also  $A\mathcal{L}$  is dense in  $\mathcal{H}$  and  $\eta_k$  is bounded. Therefore for each  $k$

$$\sigma\{\xi_k x: x \in \mathcal{L}\} = \sigma\{\eta_k l: l \in \mathcal{L}\}.$$

Now for each  $x \in \mathcal{L}$

$$\hat{\eta}_\nu A(x) = (\eta_\nu | \mathcal{B}_0)(Ax) = (\eta_\nu Ax | B_0) = (\xi_\nu A^{-1} Ax | B_0) = (\xi_\nu x | M_0)$$

$$= (\hat{\xi}_\nu | \mathcal{M}_0)(x) = \hat{\xi}_\nu(x).$$

(ii) Now for each  $x, y \in \mathcal{H}$

$$\begin{aligned} (A^*G_\gamma A(x))(y) &= ((\eta_1 - \hat{\eta}_1)(Ax), (\eta_1 - \hat{\eta}_1)(Ay)) \quad (\text{by definition of } G_\gamma) \\ &= (\eta_1 Ax - \hat{\eta}_1 Ax, \eta_1 Ay - \hat{\eta}_1 Ay) \\ &= (\hat{\xi}_1 A^{-1}(Ax) - \hat{\xi}_1(x), \hat{\xi}_1 A^{-1}(Ay) - \hat{\xi}_1(y)) \\ &= (\hat{\xi}_1 x - \hat{\xi}_1 x, \hat{\xi}_1 y - \hat{\xi}_1 y) \\ &= (G_{\hat{\xi}}(x))(y). \end{aligned}$$

(iii) For each integer  $\nu > 0$

$$\hat{\eta}_\nu(x) = \lim_{n \rightarrow \infty} (\sum_{k=0}^n E_{\nu k} \eta_{-k})(x) \quad ([4], \text{Theorem 7.4.11, page 108}).$$

Therefore

$$\begin{aligned} \hat{\xi}_\nu(x) &= \hat{\eta}_\nu A(x) = \hat{\eta}_\nu(Ax) \\ &= \lim_{n \rightarrow \infty} (\sum_{k=0}^n E_{\nu k} \eta_{-k})(Ax) \\ &= \lim_{n \rightarrow \infty} (\sum_{k=0}^n E_{\nu k} \hat{\xi}_{-k} A^{-1})(Ax) \\ &= \lim_{n \rightarrow \infty} \sum_{k=0}^n E_{\nu k} \hat{\xi}_{-k} A^{-1}(Ax) \\ &= \lim_{n \rightarrow \infty} \sum_{k=0}^n E_{\nu k} \hat{\xi}_{-k}(x). \end{aligned}$$

**4. Note.** For results in this chapter the boundedness assumption 2 was made on the spectral density of the process and it was further assumed that the map  $A: \mathcal{H} \rightarrow \mathcal{K}$  be one-to-one with the image of  $\mathcal{H}$  dense in  $\mathcal{K}$ . The restriction of  $A\mathcal{H}$  being dense in  $\mathcal{K}$  is easily deleted by replacing  $\mathcal{K}$  by the Hilbert space  $\mathcal{H}$  generated by  $A\mathcal{H}$  in defining the process  $\{\eta_n: -\infty < n < \infty\}$ . Generalization when  $A$  is not one-to-one calls for a closer look and may be handled as follows: let  $K(P)$  denote the kernel of any operator  $P$ . Then due to boundedness assumption 2

$$(4.1) \quad K(A) = K(\hat{f}_\theta) \quad \text{a.e. } \theta$$

where  $\hat{f}_\theta$  denotes the quadratic form of  $f_\theta$ . Let the quotient space, denoted by  $\tilde{\mathcal{H}}$ , be such that

$$\forall x \in \mathcal{H}, \quad \|\tilde{x}\| = \inf_{\delta \in K(A)} \|x - \delta\| = d(x, K(A))$$

where  $\tilde{x}$  is the equivalence class  $x + K(A)$  of elements of  $x$ . Now  $(\tilde{x}, \|\cdot\|)$  is a Banach space ([1], page 140). The linear map  $A_q$  defined on it as follows

$$A_q(\tilde{x}) = Ax \quad \text{for } x \in \tilde{\mathcal{H}}$$

is continuous in the norm of  $\tilde{\mathcal{H}}$ . This is shown as follows:

$$\|A_q\| = \sup_{\|\tilde{x}\|=1} \|A(\tilde{x})\| = \sup_{\|x\|=1, x \in \tilde{\mathcal{H}}(A)} \|Ax\|.$$

Also for each  $x \in \tilde{\mathcal{H}}$  with  $d(x, K(A)) = 1, x = x + \delta - \delta$  whatever  $\delta \in K(A)$ . So

$$\|Ax\| \leq \inf_{\delta \in K(A)} \{\|A(x + \delta)\| + \|A\delta\|\} \leq \inf_{\delta \in K(A)} \{\|x + \delta\|\} \leq 1$$

since  $A\delta = 0$  for  $\delta \in K(A)$  and  $\|A\| = 1$ . Hence  $A_q$  is continuous. Furthermore

$A_Q$  is such that

$$(A_Q^* A_Q(\bar{x}), \bar{y}) = (Ax, Ay) = (A^* Ax, y) \quad \text{for } x, y \in \mathcal{L}.$$

Thus

$$m(\theta) A_Q^* A_Q \leq f_\theta \leq M(\theta) A_Q^* A_Q \quad \text{a.e. } \theta$$

and  $A_Q: \tilde{\mathcal{L}} \rightarrow \mathcal{K}$  is one-to-one, and without loss of generality  $A_Q(\tilde{\mathcal{L}})$  is dense in  $\mathcal{K}$ .

To make sense of the definition of  $\xi_n A_Q^{-1}$  on the image of  $\tilde{\mathcal{L}}$  under  $A_Q$ , we must have  $\xi_n$  uniquely defined on  $\tilde{\mathcal{L}}$ . It is here that we would need the assumption of linearity of  $\xi_n$ . Let, for  $x$  and  $y$  in  $\mathcal{L}$ ,  $Ax = Ay$ . Then

$$\begin{aligned} \|\xi_n(x) - \xi_n(y)\|^2 &= \|\xi_n(x - y)\|^2 \\ &= (\xi_n(x - y), \xi_n(x - y)) \\ &= (\xi_0(x - y), \xi_0(x - y)) \\ &= \frac{1}{2\pi} \int_0^{2\pi} \hat{f}_\theta(x - y) d\theta \\ &= 0 \quad (\text{due to (4.1)}). \end{aligned}$$

So if  $x = y \pmod{K(A)}$  then  $\xi_n(x) = \xi_n(y)$ . Hence  $\forall x \in \mathcal{L}$  we may define  $\xi_n(\bar{x}) = \xi_n(x)$ . And the preceding procedures now apply to  $\xi_n A^{-1}$  to ultimately yield the prediction error matrix and the predictor for the process  $\{\xi_n: -\infty < n < \infty\}$ .

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