

ON A SIMPLIFIED METHOD OF THE ESTIMATION OF THE CORRELOGRAM FOR A STATIONARY GAUSSIAN PROCESS, II

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§1. Summary.

For the estimation of the correlogram of a real valued weakly stationary process $x(t)$, we usually use the estimate using the term $x(t)x(t+h)$. We try to replace the term $x(t)x(t+h)$ by the term $x(t) \operatorname{sgn}(x(t+h))$. In the previous paper [2], we showed that, when the variance is known, we can get an unbiased estimate by this replacement for a Gaussian process, and also showed its variance for a simple markov Gaussian process. In this paper, we shall evaluate its variance for a general Gaussian process, and show that this estimate is a consistent estimate under a some condition. And especially, we compare, numerically, its variance with that of usual estimate, for the second-order process.

§2. The estimate and its variance.

Let $x(t)$ be a real valued weakly stationary process with continuous time parameter t , such that $Ex(t)=0$, $Ex(t)^2=\sigma^2$, $Ex(t)x(t+h)=\sigma^2\rho_h$. We assume the variance σ^2 to be known. And, given observations $\{x(t), t=1, 2, \dots, N, \dots, N+h\}$, we consider to estimate the correlogram ρ_h , where N and h are positive integers. We shall try to replace the term $x(t)x(t+h)$ of the usual estimate

$$\tilde{\gamma}_h = \frac{1}{\sigma^2} \frac{1}{N} \sum_{t=1}^N x(t)x(t+h)$$

by the term $x(t) \operatorname{sgn}(x(t+h))$, where $\operatorname{sgn}(y)$ means 1, 0 and -1 , correspondingly as $y>0$, $y=0$ and $y<0$.

For a Gaussian process, the estimate

$$\gamma_h = \sqrt{\frac{\pi}{2}} \frac{1}{\sigma} \frac{1}{N} \sum_{t=1}^N x(t) \operatorname{sgn}(x(t+h))$$

is an unbiased estimate [2]. We shall determine the variance of this estimate. Now,

$$\operatorname{Var}(\gamma_h) = E\gamma_h^2 - \rho_h^2,$$

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$$\begin{aligned} E\gamma_h^2 &= E\left(\sqrt{\frac{\pi}{2}} \frac{1}{\sigma} \frac{1}{N} \sum_{t=1}^N x(t) \operatorname{sgn}(x(t+h))\right)^2 \\ &= \frac{\pi}{2} \frac{1}{\sigma^2} \cdot \frac{1}{N^2} E\left(\sum_{t=1}^N \sum_{s=1}^N x(t) \operatorname{sgn}(x(t+h))x(s) \operatorname{sgn}(x(s+h))\right) \end{aligned}$$

and, we shall evaluate the value of

$$E(x(t) \operatorname{sgn}(x(t+h))x(s) \operatorname{sgn}(x(s+h))).$$

i) When $t, s, t+h$ and $s+h$ are all distinct, we put

$$x(t) = Ax(s) + Bx(t+h) + Cx(s+h) + \varepsilon(t),$$

where A, B and C are constants and $\varepsilon(t)$ is a stochastic process such that

a) $E\varepsilon(t) = 0,$

b) $\varepsilon(t)$ has no correlation with $x(s), x(t+h)$ and $x(s+h).$

So, A, B and C are all determined by the relation

$$\begin{aligned} E(x(t) - Ax(s) - Bx(t+h) - Cx(s+h))x(s) &= 0, \\ E(x(t) - Ax(s) - Bx(t+h) - Cx(s+h))x(t+h) &= 0, \\ E(x(t) - Ax(s) - Bx(t+h) - Cx(s+h))x(s+h) &= 0. \end{aligned} \tag{1}$$

As $x(t)$ is a real-valued process, we have the equivalence

$$\rho_t = \rho_{-t}.$$

Using this, we can rewrite the relation (1) as follows:

$$\begin{aligned} A + B\rho_{s-t-h} + C\rho_h &= \rho_{s-t}, \\ A\rho_{s-t-h} + B + C\rho_{s-t} &= \rho_h, \\ A\rho_h + B\rho_{s-t} + C &= \rho_{s-t-h}. \end{aligned} \tag{2}$$

From the equation (2), we have

$$A = \frac{1}{\Delta} \begin{vmatrix} \rho_{s-t} & \rho_{s-t-h} & \rho_h \\ \rho_h & 1 & \rho_{s-t} \\ \rho_{s-t+h} & \rho_{s-t} & 1 \end{vmatrix}, \quad B = \frac{1}{\Delta} \begin{vmatrix} 1 & \rho_{s-t} & \rho_h \\ \rho_{s-t-h} & \rho_h & \rho_{s-t} \\ \rho_h & \rho_{s-t+h} & 1 \end{vmatrix},$$

$$\text{and } C = \frac{1}{\Delta} \begin{vmatrix} 1 & \rho_{s-t-h} & \rho_{s-t} \\ \rho_{s-t-h} & 1 & \rho_h \\ \rho_h & \rho_{s-t} & \rho_{s-t+h} \end{vmatrix},$$

where

$$\Delta = \begin{vmatrix} 1 & \rho_{s-t-h} & \rho_h \\ \rho_{s-t-h} & 1 & \rho_{s-t} \\ \rho_h & \rho_{s-t} & 1 \end{vmatrix}.$$

Therefore, we have

$$\begin{aligned} & E(x(t)/x(s), x(t+h), x(s+h)) \\ &= E(Ax(s) + Bx(t+h) + Cx(s+h) + \varepsilon(t)/x(s), x(t+h), x(s+h)) \\ &= Ax(s) + Bx(t+h) + Cx(s+h). \end{aligned}$$

And, so it holds

$$\begin{aligned} & E(x(t)x(s)/x(t+h), x(s+h)) \\ &= E[x(s)(E(x(t)/x(s), x(t+h), x(s+h)))/x(t+h), x(s+h)] \\ &= E[x(s)(Ax(s) + Bx(t+h) + Cx(s+h))/x(t+h), x(s+h)] \\ &= E[Ax(s)^2 + Bx(s)x(t+h) + Cx(s)x(s+h)/x(t+h), x(s+h)]. \end{aligned}$$

In the next place, let us put

$$x(s) = Fx(t+h) + Gx(s+h) + \eta(s),$$

where $\eta(s)$ is a stochastic process such as

$$\text{a') } E\eta(s) = 0,$$

$$\text{b') } \eta(s) \text{ has no correlation with } x(t+h) \text{ and } x(s+h).$$

From this condition, we can express as

$$E(x(s) - Fx(t+h) - Gx(s+h))x(t+h) = 0,$$

$$E(x(s) - Fx(t+h) - Gx(s+h))x(s+h) = 0.$$

(3)

Writing (3) in the correlogram's terms, we have

$$\begin{aligned} F + G\rho_{s-t} &= \rho_{s-t-h}, \\ F\rho_{s-t} + G &= \rho_h. \end{aligned} \tag{4}$$

By solving the equation (4), we have

$$F = \frac{1}{D} \begin{vmatrix} \rho_{s-t-h} & \rho_{s-t} \\ \rho_h & 1 \end{vmatrix} \text{ and } G = \frac{1}{D} \begin{vmatrix} 1 & \rho_{s-t-h} \\ \rho_{s-t} & \rho_h \end{vmatrix},$$

where

$$D = \begin{vmatrix} 1 & \rho_{s-t} \\ \rho_{s-t} & 1 \end{vmatrix}.$$

Substituting the above expression, we get

$$\begin{aligned} & E(x(t)x(s)/x(t+h), x(s+h)) \\ &= E[A(Fx(t+h) + Gx(s+h) + \eta(s))^2 + B(Fx(t+h) + Gx(s+h) + \eta(s))x(t+h) \\ & \quad + C(Fx(t+h) + Gx(s+h) + \eta(s))x(s+h)/x(s+h), x(t+h)] \\ &= (AF^2 + BF)x(t+h)^2 + (2AFG + BG + CF)x(t+h)x(s+h) \\ & \quad + (AG^2 + CG)x(s+h)^2 + AE(\eta(s)^2/x(t+h), x(s+h)). \end{aligned}$$

And, as $\eta(s)$ is independent of $x(t+h)$ and $x(s+h)$, we have

$$\begin{aligned} & E(\eta(s)^2/x(t+h), x(s+h)) \\ &= E[(x(s) - Fx(t+h) - Gx(s+h))^2/x(t+h), x(s+h)] \\ &= E[(x(s) - Fx(t+h) - Gx(s+h))^2/x(t+h) = 0, x(s+h) = 0] \\ &= E[x(s)^2/x(t+h) = 0, x(s+h) = 0] = \frac{\sigma^2 \Delta}{D}. \end{aligned}$$

Consequently, it follows

$$\begin{aligned} & E(x(t) \operatorname{sgn}(x(t+h))x(s) \operatorname{sgn}(x(s+h))) \\ &= E[\operatorname{sgn}(x(t+h)) \operatorname{sgn}(x(s+h))(E(x(t)x(s)/x(t+h), x(s+h)))] \\ &= (AF^2 + BF)E(x(t+h)^2 \operatorname{sgn}(x(t+h)) \operatorname{sgn}(x(s+h))) \\ & \quad + (2AFG + BG + CF)E(|x(t+h)||x(s+h)|) \\ & \quad + (AG^2 + CG)E(x(s+h)^2 \operatorname{sgn}(x(t+h)) \operatorname{sgn}(x(s+h))) \\ & \quad + A \frac{\sigma^2 \Delta}{D} E(\operatorname{sgn}(x(t+h))\operatorname{sgn}(x(s+h))). \end{aligned}$$

Now, we shall put, for simplicity, $x(t+h)=x$ and $x(s+h)=y$ and further put

$$f(x, y) = \frac{1}{2\pi\sigma^2\sqrt{D}} e^{-(x^2-2\rho_{s-t}xy+y^2)/2\sigma^2D}$$

Then we have

$$\begin{aligned} & E(x(t+h)^2 \operatorname{sgn}(x(t+h)) \operatorname{sgn}(x(s+h))) \\ &= \int_{y=0}^{\infty} \int_{x=0}^{\infty} x^2 f(x, y) dx dy - \int_{y=0}^{\infty} \int_{x=-\infty}^0 x^2 f(x, y) dx dy - \int_{y=-\infty}^0 \int_{x=0}^{\infty} x^2 f(x, y) dx dy \\ & \quad + \int_{y=-\infty}^0 \int_{x=-\infty}^0 x^2 f(x, y) dx dy. \end{aligned}$$

Being

$$\begin{aligned} \int_{y=0}^{\infty} \int_{x=-\infty}^0 x^2 f(x, y) dx dy &= \int_{y=0}^{\infty} \int_{x=0}^{\infty} x^2 f(-x, y) dx dy = \int_{y=0}^{\infty} \int_{x=0}^{\infty} x^2 f(x, -y) dx dy \\ &= \int_{y=-\infty}^0 \int_{x=0}^{\infty} x^2 f(x, y) dx dy \end{aligned}$$

and

$$\int_{y=-\infty}^0 \int_{x=-\infty}^0 x^2 f(x, y) dx dy = \int_{y=0}^{\infty} \int_{x=0}^{\infty} x^2 f(-x, -y) dx dy = \int_{y=0}^{\infty} \int_{x=0}^{\infty} x^2 f(x, y) dx dy,$$

so it holds

$$\begin{aligned} & E(x(t+h)^2 \operatorname{sgn}(x(t+h)) \operatorname{sgn}(x(s+h))) \\ &= 2 \left(\int_{y=0}^{\infty} \int_{x=0}^{\infty} x^2 f(x, y) dx dy - \int_{y=0}^{\infty} \int_{x=0}^{\infty} x^2 f(x, -y) dx dy \right). \end{aligned}$$

Let us use the expansion (Rice [4], section 3.5)

$$\int_0^{\infty} \int_0^{\infty} u^l v^m \exp(-u^2 - v^2 - 2auv) du dv = \frac{1}{4} \sum_{k=0}^{\infty} \frac{(-2a)^k}{k!} \Gamma\left(\frac{l+k+1}{2}\right) \Gamma\left(\frac{m+k+1}{2}\right)$$

and put

$$I(-2a, l, m) = \sum_{k=0}^{\infty} \frac{(-2a)^k}{k!} \Gamma\left(\frac{l+k+1}{2}\right) \Gamma\left(\frac{m+k+1}{2}\right).$$

Consequently, we get

$$\begin{aligned} & E(x(t+h)^2 \operatorname{sgn}(x(t+h)) \operatorname{sgn}(x(s+h))) \\ &= 2 \times \frac{\sigma^2 D^{3/2}}{2\pi} (I(2\rho_{s-t}, 2, 0) - I(-2\rho_{s-t}, 2, 0)) = \frac{\sigma^2 D^{3/2}}{\pi} S_1(\rho_{s-t}) \end{aligned}$$

where

$$S_1(\rho_{s-t}) = 2 \left(\sum_{m=0}^{\infty} \frac{(2\rho_{s-t})^{2m+1}}{(2m+1)!} \Gamma(m+2) \Gamma(m+1) \right).$$

Similarly,

$$\begin{aligned} & E(|x(t+h)||x(s+h)|) \\ &= 2 \times \frac{\sigma^2 D^{3/2}}{2\pi} (I(2\rho_{s-t}, 1, 1) + I(-2\rho_{s-t}, 1, 1)) = \frac{\sigma^2 D^{3/2}}{\pi} S_2(\rho_{s-t}), \\ & E(x(s+h)^2 \operatorname{sgn}(x(t+h)) \operatorname{sgn}(x(s+h))) \\ &= 2 \times \frac{\sigma^2 D^{3/2}}{2\pi} (I(2\rho_{s-t}, 0, 2) - I(-2\rho_{s-t}, 0, 2)) = \frac{\sigma^2 D^{3/2}}{\pi} S_1(\rho_{s-t}) \end{aligned}$$

and

$$\begin{aligned} & E(\operatorname{sgn}(x(t+h)) \operatorname{sgn}(x(s+h))) \\ &= 2 \times \frac{\sqrt{D}}{4\pi} (I(2\rho_{s-t}, 0, 0) - I(-2\rho_{s-t}, 0, 0)) = \frac{\sqrt{D}}{2\pi} S_3(\rho_{s-t}), \end{aligned}$$

where

$$S_2(\rho_{s-t}) = 2 \left(\sum_{m=0}^{\infty} \frac{(2\rho_{s-t})^{2m}}{(2m)!} \Gamma(m+1)^2 \right)$$

and

$$S_3(\rho_{s-t}) = 2 \left(\sum_{m=0}^{\infty} \frac{(2\rho_{s-t})^{2m+1}}{(2m+1)!} \Gamma(m+1)^2 \right).$$

As the result, we obtain

$$\begin{aligned} & E[x(t) \operatorname{sgn}(x(t+h)) x(s) \operatorname{sgn}(x(s+h))] \\ &= (AF^2 + BF) \frac{\sigma^2 D^{3/2}}{\pi} S_1(\rho_{s-t}) + (2AFG + BG + CF) \frac{\sigma^2 D^{3/2}}{\pi} S_2(\rho_{s-t}) \\ &+ (AG^2 + CG) \frac{\sigma^2 D^{3/2}}{\pi} S_1(\rho_{s-t}) + A \frac{\sigma^2 \Delta}{2\pi \sqrt{-D}} S_3(\rho_{s-t}). \end{aligned}$$

ii) When $s=t+h$, $s+h=t+2h$. The situation is the same when $t=s+h$. In this case, we have

$$\begin{aligned} & E(x(t)x(s) \operatorname{sgn}(x(s+h)) \operatorname{sgn}(x(t+h))) \\ &= E(x(t)x(t+h) \operatorname{sgn}(x(t+h)) \operatorname{sgn}(x(t+2h))) \\ &= E[x(t+h) \operatorname{sgn}(x(t+h)) \operatorname{sgn}(x(t+2h)) E(x(t)/x(t+h), x(t+2h))]. \end{aligned}$$

As the above, we shall put

$$x(t) = Hx(t+h) + Kx(t+2h) + \delta(t)$$

where H and K are constants and $\delta(t)$ is a stochastic process such as

$$a'') \quad E\delta(t) = 0,$$

$$b'') \quad \delta(t) \text{ has no correlation with } x(t+h) \text{ and } x(t+2h).$$

H and K are determined by the conditions

$$\begin{aligned} E(x(t) - Hx(t+h) - Kx(t+2h))x(t+h) &= 0, \\ E(x(t) - Hx(t+h) - Kx(t+2h))x(t+2h) &= 0. \end{aligned} \tag{5}$$

This conditions are equivalent to

$$\begin{aligned} H + K\rho_h &= \rho_h, \\ H\rho_h + K &= \rho_{2h}. \end{aligned} \tag{6}$$

By solving (6), we get

$$H = \frac{1}{D_h} \begin{vmatrix} \rho_h & \rho_h \\ \rho_{2h} & 1 \end{vmatrix} \quad \text{and} \quad K = \frac{1}{D_h} \begin{vmatrix} 1 & \rho_h \\ \rho_h & \rho_{2h} \end{vmatrix},$$

where

$$D_h = \begin{vmatrix} 1 & \rho_h \\ \rho_h & 1 \end{vmatrix}.$$

We have

$$E(x(t)/x(t+h), x(t+2h)) = Hx(t+h) + Kx(t+2h)$$

and

$$\begin{aligned} & E[x(t)x(t+h) \operatorname{sgn}(x(t+h)) \operatorname{sgn}(x(t+2h))] \\ &= HE(x(t+h)^2 \operatorname{sgn}(x(t+h)) \operatorname{sgn}(x(t+2h))) + KE(|x(t+h)||x(t+2h)|). \end{aligned}$$

Using the same method as in i), we get

$$E(x(t)x(t+h) \operatorname{sgn}(x(t+h)) \operatorname{sgn}(x(t+2h))) = H \frac{\sigma^2 D_h^{3/2}}{\pi} S_1(\rho_h) + K \frac{\sigma^2 D_h^{3/2}}{\pi} S_2(\rho_h).$$

iii) When $t=s$, it holds that

$$E(x(t)^2 \operatorname{sgn}^2(x(t+h))) = Ex(t)^2 = \sigma^2.$$

Therefore, using the above results, we obtain, by putting $s-t=k$,

$$\begin{aligned} \text{Var.}(\gamma_n) &= E^2\gamma_n - \rho_n^2 \\ &= \frac{1}{N^2} \left\{ \sum_{k=1}^{h-1} + \sum_{k=h+1}^{N-1} \right\} (N-k) \left[(AF^2 + BF)D^{3/2}S_1(\rho_k) + (2AFG + BG + CF)D^{3/2}S_2(\rho_k) \right. \\ &\quad \left. + (AG^2 + CG)D^{3/2}S_1(\rho_k) + \frac{AD}{2D^{1/2}} S_3(\rho_k) \right] \\ &\quad + \frac{1}{N^2} (N-h)[HD_n^{3/2}S_1(\rho_h) + KD_n^{3/2}S_2(\rho_h)] + \frac{\pi}{2} \cdot \frac{1}{N} - \rho_n^2. \end{aligned}$$

3. Comparison of γ_n with $\tilde{\gamma}_n$.

Now we shall compare the estimate γ_n with the estimate $\tilde{\gamma}_n$, which is usually used. The estimate γ_n and the estimate $\tilde{\gamma}_n$ are both unbiased estimates. Here the comparison is made on the point of variance.

It holds, for a stationary Gaussian process with mean 0, that

$$\begin{aligned} &E(x(t)x(t+h)x(s)x(s+h)) \\ &= (E(x(t)x(t+h))(E(x(s)x(s+h))) + (E(x(t)x(s))(E(x(t+h)x(s+h))) \\ &\quad + (E(x(t)x(s+h))(E(x(s)x(t+h))), \end{aligned}$$

when $t < s$ and $t+h \neq s$. Using the above relation, we obtain

$$\begin{aligned} \text{Var.}(\tilde{\gamma}_n) &= E(\tilde{\gamma}_n^2) - \rho_n^2 \\ &= E\left(\frac{1}{\sigma^2} \frac{1}{N} \sum_{t=1}^N x(t)x(t+h)\right)^2 - \rho_n^2 \\ &= \frac{1}{\sigma^4} \frac{1}{N^2} \sum_{t=1}^N \sum_{s=1}^N E x(t)x(t+h)x(s)x(s+h) - \rho_n^2 \\ &= \frac{2}{N^2} \sum_{k=1}^{N-1} (N-k)(\rho_k^2 + \rho_n^2 + \rho_{n+k}\rho_{n-k}) + \frac{1}{N} (1+2\rho_n^2) - \rho_n^2. \end{aligned}$$

Let us compare the variance of γ_n with that of $\tilde{\gamma}_n$, numerically. For this, we shall consider the second-order process in the sense of Bartlett [1]. That is, $x(t)$ is subjected to the equation

$$d\hat{x}(t) + \alpha\hat{x}(t)dt + \beta x(t)dt = dy(t), \tag{7}$$

where $\hat{x}(t)$ is a mean square differential coefficient of $x(t)$, $d\hat{x}(t)$ is the change in $\hat{x}(t)$ in dt and $y(t)$ is the orthogonal process of the accumulated impulse effects.

Then we find that correlogram ρ_τ satisfies the equation

$$\rho_\tau'' + \alpha\rho_\tau' + \beta\rho_\tau = 0 \quad (\tau > 0),$$

where $\rho_\tau' = d\rho_\tau/d\tau$, etc., whence we have

$$\rho_\tau = Ae^{\lambda_1\tau} + Be^{\lambda_2\tau} \quad (\tau > 0),$$

where λ_1 and λ_2 are the roots of $\lambda^2 + \alpha\lambda + \beta = 0$. Furthermore ρ_τ must satisfy the condition

$$\rho_0 = 1 \quad \text{and} \quad \rho_0' = 0.$$

This leads finally to

$$\rho_\tau = \frac{\lambda_1}{\lambda_1 - \lambda_2} e^{\lambda_1\tau} - \frac{\lambda_2}{\lambda_1 - \lambda_2} e^{\lambda_2\tau} \quad (\tau > 0).$$

Table 1

h	ρ_h	$N=50$		$N=250$	
		Var. (γ_h)	Var. ($\tilde{\gamma}_h$)	Var. (γ_h)	Var. ($\tilde{\gamma}_h$)
1	0.9572	0.0720	0.2487	0.0149	0.0516
2	0.8536	0.0772	0.2269	0.0159	0.0471
3	0.7192	0.0850	0.1985	0.0173	0.0411
4	0.5759	0.0954	0.1706	0.0194	0.0353
5	0.4384	0.1074	0.1480	0.0218	0.0306
6	0.3154	0.1199	0.1327	0.0244	0.0273
7	0.2116	0.1315	0.1243	0.0268	0.0256
8	0.1282	0.1412	0.1212	0.0289	0.0250
9	0.0647	0.1487	0.1214	0.0305	0.0250
10	0.0189	0.1539	0.1230	0.0317	0.0254
11	-0.0119	0.1573	0.1251	0.0324	0.0259
12	-0.0307	0.1592	0.1268	0.0329	0.0263
13	-0.0403	0.1602	0.1280	0.0331	0.0265
14	-0.0432	0.1606	0.1286	0.0332	0.0267
15	-0.0416	0.1608	0.1289	0.0332	0.0267
16	-0.0373	0.1608	0.1289	0.0332	0.0268
17	-0.0316	0.1607	0.1288	0.0332	0.0267
18	-0.0254	0.1607	0.1287	0.0332	0.0267
19	-0.0194	0.1607	0.1286	0.0332	0.0267
20	-0.0140	0.1607	0.1285	0.0332	0.0267
21	-0.0095	0.1608	0.1285	0.0332	0.0267
22	-0.0058	0.1608	0.1285	0.0332	0.0266
23	-0.0030	0.1608	0.1285	0.0332	0.0266
24	-0.0009	0.1608	0.1285	0.0332	0.0266
25	0.0004	0.1608	0.1285	0.0332	0.0266
30	0.0016	0.1608	0.1285	0.0332	0.0267

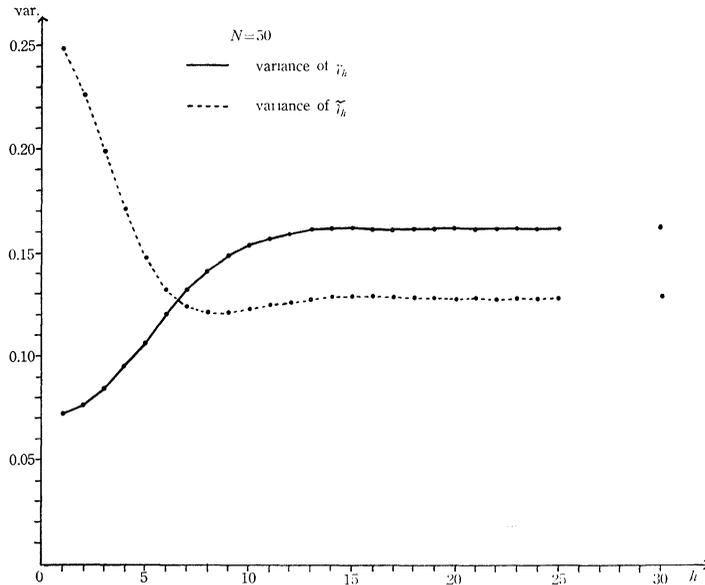


Fig. 1

For numerical computation, we shall take

$$\alpha = -2 \log 0.8 \quad \text{and} \quad \beta = 2 (\log 0.8)^2.$$

In this case, the correlogram is

$$\rho_\tau = \sqrt{2} (0.8)^{|\tau|} \cos (|\tau| \log 0.8 + \pi/4).$$

By taking $N=50$ and 250 , the numerical results are shown in Table 1 and Figure 1.

This results are like as in the case of a simple Markov process [2]. For a small value of lag h , the variances of the estimate γ_h are smaller than that of the estimate $\tilde{\gamma}_h$.

Originally, the model (7) is discussed in Takahasi and Husimi [5]. So we have taken this model in this time and discussed from the statistical point of view. As we have shown, γ_h is a fairly good estimate for a Stationary Gaussian process.

4. Consistency of the estimate γ_h .

Let us further assume that the correlogram ρ_τ has the following property:

for any positive number ε , there exists a number τ_ε such that $|\rho_\tau| < \varepsilon$ is satisfied for any number τ such as $\tau > \tau_\varepsilon$, i.e. $\lim_{\tau \rightarrow \infty} \rho_\tau = 0$.

In this case, we can prove that γ_h is a consistent estimate. The proof is as follows,

In the expression of the variance of γ_h , we shall put, for simplicity,

$$U_1(k) = AF^2 + BF, \quad U_2(k) = 2AFG + BG + CF, \quad U_3(k) = AG^2 + CG.$$

Then, it holds

$$\begin{aligned} \frac{1}{N^2} \sum_{k=1}^{h-1} (N-k) & \left[U_1(k) D^{3/2} S_1(\rho_k) + U_2(k) D^{3/2} S_2(\rho_k) \right. \\ & \left. + U_3(k) D^{3/2} S_1(\rho_k) + \frac{AA}{2D^{1/2}} S_3(\rho_k) \right] = O\left(\frac{1}{N}\right) \end{aligned}$$

and

$$\frac{1}{N^2} (N-h) [HD_h^{3/2} S_1(\rho_h) + KD_h^{3/2} S_2(\rho_h)] = O\left(\frac{1}{N}\right).$$

Now we shall evaluate the value of

$$\frac{1}{N^2} \sum_{k=h+1}^{N-1} (N-k) \left[U_1(k) D^{3/2} S_1(\rho_k) + U_2(k) D^{3/2} S_2(\rho_k) + U_3(k) D^{3/2} S_1(\rho_k) + \frac{AA}{2D^{1/2}} S_3(\rho_k) \right].$$

For any positive number ε , there exist a positive number $K = K(\varepsilon)$ such that

$$|\rho_k| < \varepsilon \quad \text{and} \quad |\rho_{k-h}| < \varepsilon$$

are satisfied for any k being larger than K .

It holds

$$|A| = \frac{1}{A} \begin{vmatrix} \rho_k & \rho_{k-h} & \rho_h \\ \rho_h & 1 & \rho_k \\ \rho_{k+h} & \rho_k & 1 \end{vmatrix} = \left| \frac{\rho_k + \rho_k \rho_{k+h} \rho_{k-h} + \rho_h^2 \rho_k - \rho_h \rho_{k+h} - \rho_h \rho_{k-h} - \rho_k^3}{1 + 2\rho_k \rho_h \rho_{k-h} - \rho_h^2 - \rho_{k-h}^2 - \rho_k^2} \right|$$

and, for any $k > K$,

$$\begin{aligned} & |\rho_k + \rho_k \rho_{k+h} \rho_{k-h} + \rho_h^2 \rho_k - \rho_h \rho_{k+h} - \rho_h \rho_{k-h} - \rho_k^3| \\ & \leq |\rho_k| + |\rho_k \rho_{k+h} \rho_{k-h}| + |\rho_h^2 \rho_k| + |\rho_h \rho_{k+h}| + |\rho_h \rho_{k-h}| + |\rho_k^3| \\ & < 6\varepsilon, \\ & |1 + 2\rho_k \rho_h \rho_{k-h} - \rho_h^2 - \rho_{k-h}^2 - \rho_k^2| \\ & \geq 1 - \rho_h^2 - 2|\rho_k \rho_h \rho_{k-h}| - \rho_{k-h}^2 - \rho_k^2 \\ & \geq 1 - \rho_h^2 - 4\varepsilon^2 = (1 - \rho_h^2) \left(1 - \frac{4\varepsilon^2}{1 - \rho_h^2}\right). \end{aligned}$$

Now we can say

$$1 - \frac{4\varepsilon^2}{1 - \rho_h^2} \geq \frac{1}{2}.$$

So we have

$$|A| \leq \frac{12}{1 - \rho_h^2} \varepsilon = a\varepsilon, \quad a = \frac{12}{1 - \rho_h^2}.$$

In the next place,

$$\begin{aligned} |B| &= \left| \frac{\rho_h + \rho_h \rho_{k+h} \rho_{k-h} + \rho_h \rho_k^2 - \rho_k \rho_{k-h} - \rho_k \rho_{k+h} - \rho_h^3}{1 + 2\rho_k \rho_h \rho_{k-h} - \rho_h^2 - \rho_{k-h}^2 - \rho_k^2} \right| \\ &\leq \frac{|\rho_h - \rho_h^3| + 4\varepsilon^2}{(1 - \rho_h^2) \left(1 - \frac{4\varepsilon^2}{1 - \rho_h^2}\right)} \\ &= |\rho_h| + \frac{4\varepsilon^2 |\rho_h| + 4\varepsilon^2}{(1 - \rho_h^2) \left(1 - \frac{4\varepsilon^2}{1 - \rho_h^2}\right)} \\ &\leq |\rho_h| + b\varepsilon^2. \end{aligned}$$

Similarly we obtain

$$|C| \leq \varepsilon c, \quad |F| \leq \varepsilon f \quad \text{and} \quad |G| \leq |\rho_h| + \varepsilon^2 g.$$

In the above expression, a , b , c , f and g are constants which are independent of k and N .

Let us evaluate the value of $S_1(\rho_k)$, $S_2(\rho_k)$ and $S_3(\rho_k)$.

$$\begin{aligned} |S_1(\rho_k)| &= 2 \left| \sum_{m=0}^{\infty} \frac{(2\rho_k)^{2m+1}}{(2m+1)!} \Gamma(m+2) \Gamma(m+1) \right| \\ &\leq 4|\rho_k| \sum_{m=0}^{\infty} (2\rho_k)^{2m} \leq 4\varepsilon \sum_{m=0}^{\infty} (2\varepsilon)^{2m} = \frac{4\varepsilon}{1 - (2\varepsilon)^2} \leq l_1 \varepsilon, \\ |S_2(\rho_k)| &= 2 \left| \sum_{m=0}^{\infty} \frac{(2\rho_k)^{2m}}{(2m)!} \Gamma(m+1)^2 \right| \\ &= 2 \left(1 + (2\rho_k)^2 \left(\sum_{m=1}^{\infty} \frac{(2\rho_k)^{2(m-1)}}{(2m)!} \Gamma(m+1)^2 \right) \right) \\ &\leq 2 \left(1 + (2\varepsilon)^2 \frac{1}{1 - (2\varepsilon)^2} \right) \leq 2(1 + l_2 \varepsilon^2) \end{aligned}$$

and

$$|S_3(\rho_k)| = 2 \left| \sum_{m=0}^{\infty} \frac{(2\rho_k)^{2m+1}}{(2m+1)!} \Gamma(m+1)^2 \right|$$

$$\leq 4|\rho_k| \left(\sum_{m=1}^{\infty} (2\rho_k)^{2m} \right) \leq \frac{4\varepsilon}{1-(2\varepsilon)^2} \leq l_3\varepsilon,$$

where l_1, l_2 and l_3 are constants which are independent of k and N . From the above results, it holds

$$\begin{aligned} |U_1(k)D^{3/2}S_1(\rho_k)| &\leq (af^2\varepsilon^3 + f|\rho_h|\varepsilon + bf\varepsilon^3) \cdot 1 \cdot l_1\varepsilon \leq \varepsilon^2 d_1, \\ |U_2(k)D^{3/2}S_2(\rho_k)| &\leq (2af|\rho_h|\varepsilon^2 + 2afg\varepsilon^4 + |\rho_h|^2 + b|\rho_h|\varepsilon^2 + g|\rho_h|\varepsilon^2 \\ &\quad + bg\varepsilon^4 + fc\varepsilon^2) \cdot 1 \cdot 2(1 + l_2\varepsilon^2) \leq 2(\rho_h^2 + \varepsilon^2 d_2), \\ |U_3(k)D^{3/2}S_1(\rho_k)| &\leq (a(|\rho_h| + \varepsilon^2 g)^2 \varepsilon + c(|\rho_h| + \varepsilon^2 g)\varepsilon) \cdot 1 \cdot l_1\varepsilon \leq d_3\varepsilon^2 \end{aligned}$$

and

$$\left| \frac{A\mathcal{A}}{2D^{1/2}} S_3(\rho_k) \right| \leq |A||\mathcal{A}||S_3(\rho_k)| \leq (a\varepsilon)(1 - \rho_h^2 + 4\varepsilon^2)(l_3\varepsilon) \leq d_4\varepsilon^2,$$

where d_1, d_2, d_3 and d_4 are constants which are independent of k and N . Accordingly, we get

$$\begin{aligned} &\frac{1}{N^2} \sum_{k=K+1}^{N-1} (N-k) \left[U_1(k)D^{3/2}S_1(\rho_k) + U_2(k)D^{3/2}S_2(\rho_k) + U_3(k)D^{3/2}S_1(\rho_k) + \frac{A\mathcal{A}}{2D^{1/2}} S_3(\rho_k) \right] \\ &\leq \frac{1}{N^2} \sum_{k=K+1}^{N-1} (N-k) [\varepsilon^2 d_1 + 2\rho_h^2 + 2\varepsilon^2 d_2 + \varepsilon^2 d_3 + \varepsilon^2 d_4] \\ &= (\varepsilon^2 d_1 + 2\rho_h^2 + 2\varepsilon^2 d_2 + \varepsilon^2 d_3 + \varepsilon^2 d_4) \left(\frac{1}{N^2} \sum_{k=K+1}^{N-1} (N-k) \right) \\ &= (\varepsilon^2 d_1 + 2\rho_h^2 + 2\varepsilon^2 d_2 + \varepsilon^2 d_3 + \varepsilon^2 d_4) \frac{1}{2} \left(1 - \frac{K+1}{N} \right) \left(1 - \frac{K}{N} \right) \\ &= \rho_h^2 - \frac{(2K+1)}{N} \rho_h^2 + \frac{K(K+1)}{N^2} \rho_h^2 + \frac{\varepsilon^2}{2} (d_1 + 2d_2 + d_3 + d_4) \left(1 - \frac{K+1}{N} \right) \left(1 - \frac{K}{N} \right) \\ &= \rho_h^2 + O\left(\frac{1}{N}\right) + O(\varepsilon^2). \end{aligned}$$

And it holds that

$$\begin{aligned} &\frac{1}{N^2} \sum_{k=h+1}^K (N-k) \left[U_1(k)D^{3/2}S_1(\rho_k) + U_2(k)D^{3/2}S_2(\rho_k) + U_3(k)D^{3/2}S_1(\rho_k) + \frac{A\mathcal{A}}{2D^{1/2}} S_3(\rho_k) \right] \\ &= O\left(\frac{1}{N}\right). \end{aligned}$$

Finally, we obtain

$$\text{Var.}(\gamma_h) = O\left(\frac{1}{N}\right) + O(\varepsilon^2),$$

so

$$P(|\gamma_h - \rho_h| > \theta) \leq \frac{\text{Var.}(\gamma_h)}{\theta^2} = \frac{1}{\theta^2} \left(O\left(\frac{1}{N}\right) + O(\varepsilon^2) \right).$$

This shows that the estimate γ_h is a consistent estimate.

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