

## ON THE OSCILLATION FUNCTIONS OF GAUSSIAN PROCESSES

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### 1. Introduction and results obtained.

By a *Gaussian process* we shall understand a separable, measurable, jointly Gauss distributed process with the time parameter on  $[0, 1]$ , continuous in the (second order) mean.

As to the regularity of the sample path of a stationary Gaussian process, we have Yu. K. Belayev's theorem of alternatives [1] which reads as follows: the sample function (path) of a stationary Gaussian process is either continuous with probability one or unbounded on every interval with probability one.

What will happen for a non-stationary Gaussian process? Our purpose is to answer this question.

Given a Gaussian process  $x = x(t, \omega)$ ,  $0 \leq t \leq 1$ ,  $\omega \in \Omega(\mathcal{B}, P)$ , we shall define the *oscillation function* of  $x$  by

$$W_x(t, \omega) = \lim_{\varepsilon \downarrow 0} \sup_{u, v \in (t-\varepsilon, t+\varepsilon) \cap [0, 1]} |x(v, \omega) - x(u, \omega)|,$$

where we apply the usual convention  $(+\infty) - (+\infty) = (-\infty) - (-\infty) = 0$ , etc. Because of the separability of our process  $x$ , the supremum can be taken only for the  $u$  and  $v$  in the separant  $Q$  of  $x$  which is countable, so that  $W_x(t, \omega)$  is measurable in  $\omega$  for each  $t \in [0, 1]$ .

An interesting fact is that the oscillation function of a Gaussian process is a deterministic function. Precisely speaking, we have the following theorem which will be proved in Section 2.

**THEOREM 1.** *There exists a function  $\alpha = \alpha_x(t)$ ,  $0 \leq t \leq 1$ , which does not depend on  $\omega$ , such that*

$$P[W_x(t, \omega) = \alpha(t) \text{ for every } t \in [0, 1]] = 1.$$

In view of this theorem we call  $\alpha$  the *oscillation function* of the Gaussian process  $x$ .

Using the fact that the probability law of the process  $x(t) - E(x(t))$ ,  $0 \leq t \leq 1$ , is invariant under reflection, we shall prove the following theorem in Section 3:

**THEOREM 2.** *For each  $t \in [0, 1]$ , we have*

$$P \left[ \overline{\lim}_{s \rightarrow t} x(s) = x(t) + \frac{1}{2}\alpha(t), \underline{\lim}_{s \rightarrow t} x(s) = x(t) - \frac{1}{2}\alpha(t) \right] = 1.$$

It is clear that, with probability one, the sample function of  $x(t)$  is continuous at every point  $t$  where  $\alpha(t)$  vanishes.

We have also the following theorem which will be proved in Section 4.

**THEOREM 3.** *If, for some constant  $a$ ,  $\alpha(t) \geq a > 0$  on a dense subset  $D$  of an open interval  $I \subset [0, 1]$ , then*

$$P \left[ \overline{\lim}_{s \rightarrow t} x(s) = \infty, \underline{\lim}_{s \rightarrow t} x(s) = -\infty \text{ for every } t \in I \right] = 1.$$

In Section 5 and 6 we shall prove the following properties that characterize oscillation functions.

**THEOREM 4.** (a) *The oscillation function of a Gaussian process satisfies*

$$\begin{aligned} (\alpha, 1) \quad & \alpha(t) \text{ is upper semi-continuous,} \\ (\alpha, 2) \quad & \{t : a \leq \alpha(t) < \infty\} \text{ is nowhere dense for every } a > 0. \end{aligned}$$

(b) *Conversely, given a function  $\alpha: [0, 1] \rightarrow [0, \infty]$  satisfying  $(\alpha, 1)$  and  $(\alpha, 2)$ , we can construct a (not necessarily unique) Gaussian process whose oscillation function is  $\alpha$ .*

Let us derive Belayev's theorem of alternatives from Theorems 1 and 3. Suppose  $x(t)$  is a stationary Gaussian process. The oscillation function  $\alpha(t)$  of the restriction of  $x$  to  $0 \leq t \leq 1$  is constant because of the stationarity. If the constant is 0, then almost all sample functions of  $x$  are continuous; if it is positive, then almost all sample functions are, by Theorem 3, unbounded both below and above on every interval.

## 2. Proof of Theorem 1.

We can assume that  $E x(t) = 0$ , because  $E x(t)$  is continuous in  $t$ . Let  $R(s, t)$ ,  $t, s \in [0, 1]$ , be the covariance function of  $x$ . Then  $R$  is real, symmetric, positive-definite and continuous on  $I \times I$ . Using Mercer's theorem, we can expand  $R$  as follows:

$$(2.1) \quad R(t, s) = \sum_n \varphi_n(t) \varphi_n(s) / \lambda_n,$$

where  $\{\lambda_n\}$  and  $\{\varphi_n\}$  are, respectively, the positive eigenvalues and the corresponding real (normalized) eigenfunctions for the integral operator with the kernel  $R(t, s)$ , that is,

$$(2.2) \quad \varphi_n(t) = \lambda_n \int_0^1 R(t, s) \varphi_n(s) ds, \quad 0 \leq \lambda_1 \leq \lambda_2 \leq \dots,$$

and the sum in (2.1) converges absolutely and uniformly on  $I \times I$ .

We shall define a sequence of random variables  $x_n$ ,  $n=1, 2, \dots$ , as the Fourier coefficients of the sample function of  $x(t)$  with respect to  $\{\varphi_n\}$ :

$$(2.3) \quad x_n = \int_0^1 x(t) \varphi_n(t) dt.$$

Observing that

$$E \left[ \int_0^1 x(s)^2 ds \right] = \int_0^1 R(s, s) ds < \infty,$$

we have

$$P \left[ \int_0^1 x(s)^2 ds < \infty \right] = 1,$$

so that  $x_n$  is well-defined.

A simple computation shows that

$$E(x_n x_m) = 0, \quad n \neq m, \quad E(x_n^2) = \lambda_n^{-1},$$

which implies that  $x_n$ ,  $n=1, 2, \dots$ , are independent, each having the Gauss distribution with mean 0 and variance  $\lambda_n^{-1}$ . Observing that

$$E \left[ \left| x(t) - \sum_1^N \varphi_n(t) x_n \right|^2 \right] = R(t, t) - \sum_1^N \lambda_n^{-1} \varphi_n(t)^2 \rightarrow 0$$

as  $n \rightarrow \infty$ , we have

$$(2.4) \quad P \left[ x(t) = \sum_{n=1}^{\infty} \varphi_n(t) x_n \right] = 1 \quad \text{for each } t;$$

the infinite series converges to  $x(t)$  in the mean for each  $t$  and so it converges with probability one for each  $t$  because of the independence of  $x_n$ ,  $n=1, 2, \dots$ .

Let us define the *maximum oscillation*  $W_y(s, t, \omega)$  of a separable process on the interval  $[s, t]$  by

$$(2.5) \quad W_y(s, t, \omega) = \lim_{n \uparrow \infty} \lim_{p \uparrow \infty} \sup_{\substack{u, v \in (s-n^{-1}, t+n^{-1}) \cap [0, 1] \\ |u-v| < p^{-1}}} |y(u, \omega) - y(v, \omega)|,$$

where the interval  $[0, 1]$  can be replaced by the separant  $Q$  of  $y$ .

We shall now prove that  $W_x(s, t, \omega)$  is a constant; more precisely, that there exists a function  $\alpha(s, t)$  independent of  $\omega$  such that

$$(2.6) \quad P[W_x(s, t, \omega) = \alpha(s, t)] = 1$$

for each pair  $s \leq t$ .

Since  $\varphi_j(t)$  is continuous in  $t$ , we have

$$(2.7) \quad P[W_x(s, t, \omega) = W_{y_n}(s, t, \omega)] = 1,$$

where

$$y_n(t) = x(t) - \sum_{j=1}^n \varphi_j(t) x_j = \sum_{j=n+1}^{\infty} \varphi_j(t) x_j.$$

The separant  $Q$  of  $x$  is also that of  $y_n$  because of the continuity of  $\varphi_j(t)$ . By virtue of (2.4),  $y_n(t)$  is measurable with respect to  $\mathcal{B}(x_k, k \geq n)$  for each  $t$ . But  $W_{y_n}(s, t, \omega)$  is measurable with respect to  $\mathcal{B}(y_n(t), t \in Q)$ . Since  $Q$  is countable,  $W_{y_n}(s, t, \omega)$  is measurable with respect to  $\mathcal{B}(x_k, k \geq n)$  and so  $W_x(s, t, \omega)$  is also measurable with respect to  $\mathcal{B}(x_k, k \geq n)$  for every  $n$ , by (2.7). Since the  $x_n, n = 1, 2, \dots$ , are independent, Kolmogorov's zero-one law shows that  $W_x(s, t, \omega)$  is a constant with probability one.

We shall now strengthen (2.6) to get

$$(2.6') \quad P[W_x(s, t, \omega) = \alpha(s, t) \text{ for every pair } s \leq t] = 1.$$

It follows from (2.6) that

$$(2.6'') \quad P[W_x(s, t, \omega) = \alpha(s, t) \text{ for every rational pair } s \leq t] = 1.$$

Since  $W_x(s, t, \omega)$  is left-continuous in  $s$  and right-continuous in  $t$ , (2.6'') implies (2.6'). Writing  $W_x(t, \omega)$  and  $\alpha(t)$  for  $W_x(t, t, \omega)$  and  $\alpha(t, t)$ , respectively, we get from (2.6')

$$(2.7) \quad P[W_x(t, \omega) = \alpha(t) \text{ for every } t] = 1.$$

### 3. Proof of Theorem 2.

We shall use the same notation as in Section 2. Using Kolmogorov's zero-one law in the same way as before, we can see that  $\overline{\lim}_{s \rightarrow t} (x(s, \omega) - x(t, \omega))$  is a constant, say  $\beta(t)$ , with probability one. Since the process  $y(t) \equiv -x(t)$  has the same Gaussian probability law as the process  $x$ , we have

$$\overline{\lim}_{s \rightarrow t} (-x(s) + x(t)) = \beta(t),$$

that is,

$$\underline{\lim}_{s \rightarrow t} (x(s) - x(t)) = -\beta(t)$$

with probability one. By definition we have

$$\begin{aligned} W_x(t, \omega) &= \overline{\lim}_{s \rightarrow t} x(s) - \underline{\lim}_{s \rightarrow t} x(s) \\ &= \overline{\lim}_{s \rightarrow t} (x(s) - x(t)) - \underline{\lim}_{s \rightarrow t} (x(s) - x(t)). \end{aligned}$$

Therefore,  $\alpha(t)$  must be equal to  $2\beta(t)$ . This completes the proof of Theorem 2.

#### 4. Proof of Theorem 3.

In the following lemma and throughout this paper an open subset of  $[0, 1]$  means a subset open in  $[0, 1]$ . For example,  $[0, u)$  is open and  $0$  is an interior point of this interval.

**LEMMA 4.1.** *Let  $x(t)$ ,  $0 \leq t \leq 1$ , be a separable process continuous in probability, and  $D$  a dense subset of an open subinterval  $I$  of  $[0, 1]$ . For each  $t \in I$ , we can then find a sequence  $s_n \in D$  such that  $s_n \rightarrow t$  and that*

$$(4.1) \quad P \left[ \overline{\lim}_{n \rightarrow \infty} x(s_n) = \overline{\lim}_{s \rightarrow t} x(s) \right] = 1,$$

and hence a fortiori

$$(4.1') \quad P \left[ \overline{\lim}_{\substack{s \rightarrow t \\ s \in D}} x(s) = \overline{\lim}_{s \rightarrow t} x(s) \right] = 1.$$

**PROOF.** Let  $Q = \{t_n\}$  be a separant of  $x(t)$  and let  $\{U_n\}$  be a sequence of neighborhoods of  $t$  converging to  $t$ . Let  $\{y_n(\omega)\}$  be a sequence converging to  $\bar{x}(t) = \underline{\lim}_{s \rightarrow t} x(s)$  strictly from below, for example

$$y_n(\omega) = \min(\bar{x}(t), n) - 1/n.$$

Since  $Q$  is a separant of  $x(t)$ , we can find  $u_{n1}, u_{n2}, \dots, u_{np_n} \in U_n \cap Q$  such that

$$P[\max_k x(u_{nk}) > y_n(\omega)] > 1 - 2^{-n}.$$

By Borel-Cantelli's lemma we have

$$P[\lim_n \max_k x(u_{nk}) \geq \bar{x}(t)] = 1.$$

Writing  $\{u_n\}$  for  $\{u_{11}, \dots, u_{1p_1}, u_{21}, \dots, u_{2p_2}, \dots\}$ , we have

$$(4.2) \quad P \left[ \overline{\lim}_{n \rightarrow \infty} x(u_n) \geq \bar{x}(t) \right] = 1.$$

Since  $x(t)$  is continuous in probability, we can find

$$s_n \in (u_n - 1/n, u_n + 1/n) \cap D$$

such that

$$P[|x(u_n) - x(s_n)| > 2^{-n}] < 2^{-n}, \quad n = 1, 2, \dots$$

Using Borel–Cantelli’s lemma again, we have

$$(4.3) \quad P[\overline{\lim}_n x(u_n) = \overline{\lim}_n x(s_n)] = 1,$$

which, combined with (4.2), implies (4.1) and so (4.1’).

We shall now prove Theorem 3. Using (4.1) and Theorem 2, we can see that the event

$$\Omega_1 = \left\{ \omega : \overline{\lim}_{\substack{s \rightarrow t \\ s \in D}} x(s, \omega) = x(t, \omega) + \frac{1}{2}\alpha(t) \text{ for every } t \in D \right\}$$

has probability one, since  $D$  is a countable dense subset of  $I$ . For every  $\omega \in \Omega_1$  and every  $t \in D$ , we have

$$\begin{aligned} \overline{\lim}_{\substack{s \rightarrow t \\ s \in D}} x(s, \omega) &= \overline{\lim}_{\substack{s \rightarrow t \\ s \in D}} \overline{\lim}_{\substack{u \rightarrow s \\ u \in D}} x(u, \omega) \\ &= \overline{\lim}_{\substack{s \rightarrow t \\ s \in D}} (x(s, \omega) + \frac{1}{2}\alpha(s)) \geq \overline{\lim}_{\substack{s \rightarrow t \\ s \in D}} x(s, \omega) + \frac{1}{2}\alpha. \end{aligned}$$

But this is impossible, unless

$$\overline{\lim}_{\substack{s \rightarrow t \\ s \in D}} x(s, \omega) = \infty,$$

that is, unless  $\overline{\lim}_{s \rightarrow t} x(s, \omega) = \infty$ .

Therefore

$$P \left[ \overline{\lim}_{s \rightarrow t} x(s, \omega) = \infty \text{ for every } t \in D \right] = 1.$$

Similarly we have

$$P \left[ \underline{\lim}_{s \rightarrow t} x(s, \omega) = -\infty \text{ for every } t \in D \right] = 1.$$

This completes our proof, since  $D$  is dense in  $I$ .

**5. Proof of Theorem 4(a).**

Let  $\alpha(t)$  be the oscillation function of a Gaussian process  $x(t)$ ,  $0 < t < 1$ . Then we have

$$P[W_x(t, \omega) = \alpha(t) \text{ for every } t] = 1$$

by the definition of  $\alpha(t)$  in Section 2. By the definition of  $W_x(t, \omega)$ , it holds that

$$\overline{\lim}_{s \rightarrow t} W_x(s, \omega) \leq W_x(t, \omega),$$

so that we have

$$\overline{\lim}_{s \rightarrow t} \alpha(s) \leq \alpha(t),$$

which shows that  $\alpha$  is upper semi-continuous. Hence it follows that  $T_a = \{t: \alpha(t) \geq a\}$  is a closed subset of  $[0, 1]$ . If  $T_a - T_\infty$  contains a dense subset  $D$  of an open interval for some  $a > 0$ , then  $D \subset T_\infty$  by Theorem 3, in contradiction with  $D \subset T_a - T_\infty$ . Therefore,  $T_a - T_\infty$  is nowhere dense for  $a > 0$ . This completes the proof of Theorem 4(a).

**6. Proof of Theorem 4(b).**

We shall denote the mean square norm of a random variable  $x$  by  $\|x\|$ ,

$$\|x\|^2 = E(x^2).$$

Consider a Brownian motion  $B(t)$ ,  $0 \leq t \leq 1$ , and a stationary Gaussian process  $S(t)$ ,  $-\infty < t < \infty$ , with  $ES(t) = 0$ ,  $ES(t)^2 = 1$  and  $\alpha(t, S) \equiv \infty$ . The existence of the latter process was proved by Belayev [1]. We can assume that these two processes are independent. Let  $L$  be the  $\|\cdot\|$ -closure of all finite linear combinations of  $B(t)$ ,  $0 \leq t \leq 1$ , and  $S(t)$ ,  $0 \leq t \leq 1$ . It is clear that any process  $x(t)$ ,  $0 \leq t \leq 1$ , such that  $x(t) \in L$  for each  $t$  is jointly Gauss distributed.

We shall prove Theorem 4(b) by constructing a Gaussian process  $x(t) \in L$ ,  $0 \leq t \leq 1$ , with  $\alpha(t, x) = \alpha(t)$  for any given function

$$\alpha : [0, 1] \rightarrow [0, \infty] \text{ satisfying } (\alpha, 1) \text{ and } (\alpha, 2).$$

Let us start with some lemmas.

**LEMMA 6.1.** *Given  $I = [u, v] \subset [0, 1]$  and  $\varepsilon > 0$ , we can construct a Gaussian process  $x(t) \in L$ ,  $0 \leq t \leq 1$ , satisfying*

- (a)  $x(t, \omega) = 0$  for  $t \in [0, 1] - I^\circ$  ( $I^\circ$  = the interior of  $I$ ),
- (b)  $\alpha(t, x) = \infty$  for  $t \in I$ ,
- (c)  $\|x(t)\| \leq \varepsilon$  for  $t \in [0, 1]$ .

**PROOF.** Take a continuous function  $f(t)$  such that  $0 < f(t) < \varepsilon$  in  $I^\circ$  and  $f(t) = 0$  elsewhere. Then  $x(t, \omega) \equiv f(t)S(t, \omega)$  is a Gaussian process satisfying our conditions.

**LEMMA 6.2.** *Given  $0 < a < \infty$ ,  $\varepsilon > 0$ , and  $I = [u, v] \subset [0, 1]$ , we can construct a Gaussian process  $x(t) \in L$ ,  $0 \leq t \leq 1$ , satisfying the following conditions:*

- (a)  $x(t, \omega)$  has continuous paths,
- (b)  $x(t, \omega) = 0$  for  $t \in [0, 1] - I^\circ$ ,
- (c)  $E x(t) = 0$ ,  $\|x(t)\| < \varepsilon$  for every  $t$ ,
- (d)  $P(|\sup_I x(t) - a| > \varepsilon) < \varepsilon$ .

Such a process will be denoted by  $x(t; I, a, \varepsilon)$ .

**PROOF.** Let  $B(t)$  be a Brownian motion and define a process  $y(t)$  by

$$\begin{aligned} y(t) &= 0, & 0 \leq t \leq u, \\ &= \frac{a(B(t) - B(u))}{(2(t-u) \log \log(t-u)^{-1})^{\frac{1}{2}}}, & u \leq t \leq v' \equiv \min(v, u+9), \\ &= \frac{a(B(v') - B(u))}{(2(v'-u) \log \log(v'-u)^{-1})^{\frac{1}{2}}}, & v' \leq t \leq 1. \end{aligned}$$

Then  $y(t)$  is jointly Gauss distributed with  $E y(t) = 0$  and the sample path of  $y(t)$  is continuous except at  $t = u$ . The continuity in the mean follows from

$$E[y(t)^2] = \frac{a^2}{2 \log \log(t-u)^{-1}} \rightarrow 0 \quad \text{as } t \downarrow u.$$

By the law of the iterated logarithm we have

$$P \left[ \overline{\lim}_{t \downarrow u} y(t) = a \right] = 1.$$

We now determine  $u < s_1 < s_2 < s_3 < s_4 < v$  as follows. By taking  $s_4$  sufficiently close to  $u$ , we have

$$\begin{aligned} E[y(t)^2] &< \varepsilon^2, \\ P \left[ \sup_{u < t < s_4} y(t) < a + \varepsilon \right] &> 1 - \frac{1}{2}\varepsilon, \\ P \left[ \sup_{u < t < s_4} y(t) > a - \varepsilon \right] &> 1 - \frac{1}{2}\varepsilon. \end{aligned}$$



By taking  $s_2$  sufficiently close to  $u$  and  $s_3$  sufficiently close to  $s_4$ , we have

$$P \left[ \sup_{s_2 \leq t \leq s_3} y(t) > a - \varepsilon \right] > 1 - \frac{1}{2}\varepsilon .$$

We shall take  $s_1$  in  $(u, s_2)$  arbitrarily.

Let  $f(t)$  be a polygonal function of  $t$  vanishing on  $[0, s_1] \cup [s_4, 1]$ , equal to 1 on  $[s_2, s_3]$  and linear in each of  $[s_1, s_2]$  and  $[s_3, s_4]$ . Then  $x(t) = f(t) y(t)$  is a Gaussian process satisfying our conditions.

**LEMMA 6.3.** *Suppose that  $\alpha_1(t)$  and  $\alpha_2(t)$  satisfy  $(\alpha, 1)$  and the following condition (stronger than  $(\alpha, 2)$ ):*

$$(\alpha, 2') \quad \{t : \alpha_2(t) > 0\} \text{ is nowhere dense .}$$

*For any Gaussian process  $x_1(t)$  with  $\alpha(t, x_1) = \alpha_1(t)$  and any  $\varepsilon > 0$ , we can construct a Gaussian process  $x_2(t) \in L$ ,  $0 \leq t \leq 1$ , satisfying the conditions:*

- (a)  $\alpha(t, x_1 + x_2) = \alpha_1(t) + \alpha_2(t)$ ,
- (b)  $\|x_2(t)\| < \varepsilon$ ,
- (c)  $P[\sup_t |x_2(t)| > \sup_t \alpha_2(t)] < \varepsilon$ .

**PROOF.** We can assume that  $c = \sup \alpha_2(t) > 0$ . If otherwise,  $x_2(t) \equiv 0$  will satisfy our conditions trivially.

Write  $\alpha(t)$  for  $\alpha_1(t) + \alpha_2(t)$ . The set  $\{(t, \alpha(t)) : \alpha(t) > 0\}$  is a subset of  $[0, 1] \times [0, \infty]$ . Let  $\{(t_n, \alpha(t_n))\}_n$  be a countable dense subset of  $\{(t, \alpha(t)) : \alpha(t) > 0\}$ . Then the sets  $\{t_n\}_n$  are dense in  $\{t : \alpha(t) > 0\}$  and so dense in its closure  $F$ . By our assumptions  $(\alpha, 2')$ ,  $F$  is nowhere dense and its complement  $G$  is a dense open subset of  $[0, 1]$ . Since  $\alpha(t) \geq \alpha(t, x_1)$ , we have  $\alpha(t, x_1) = 0$  for  $t \in G$ , so that the sample path of  $x_1(t)$  is continuous in  $t \in G$  with probability one.

Using Theorem 2 and Lemma 4.1, we can find  $\{t_{1n}\}_n$  in  $G$  tending to  $t_1$  as  $n \rightarrow \infty$  such that

$$P \left[ \overline{\lim}_{n \rightarrow \infty} x_1(t_{1n}) = x(t_1) + \frac{1}{2}\alpha_1(t_1) \right] = 1 .$$

Since the path of  $x_1(t)$  is continuous in  $t \in G$ , we can find, for each  $t_{1n}$ , a closed interval  $I_{1n} \subset G$  containing  $t_{1n}$  in its interior such that

$$P \left[ x_1(t_{1n}) \geq \inf_{I_{1n}} x_1(s) \geq x_1(t_{1n}) - 2^{-n} \right] < 2^{-n} .$$

This implies

$$P \left[ \overline{\lim}_n \inf_{I_{1n}} x_1(s) = \overline{\lim}_{n \rightarrow \infty} x_1(t_{1n}) \right] = 1$$

by Borel–Cantelli’s lemma. Thus we have

$$P \left[ \overline{\lim}_{n \rightarrow \infty} \inf_{I_{1n}} x_1(s) = x(t_1) + \frac{1}{2} \alpha_1(t_1) \right] = 1.$$

By taking  $I_{1n}$  sufficiently small, we can achieve that the  $\{I_{1n}\}_n$  are disjoint. Then  $\sum_n |I_{1n}| \leq 1$  where  $|\cdot|$  denotes length. Therefore  $|I_{1n}| \rightarrow 0$  and so  $I_{1n}$  tends to  $t_1$  by  $t_{1n} \rightarrow t_1$ .

It is clear that  $\bigcup_n I_{1n} \cup \{t_1\}$  is a closed set which does not contain  $t_2$ . Therefore we can find a neighborhood  $U$  of  $t_2$  which does not intersect this closed set. In the same way as above, we can find a sequence of disjoint intervals  $I_{2n} \subset G \cap U$ ,  $n = 1, 2, \dots$ , tending to  $t_2$  such that

$$P \left[ \overline{\lim}_{n \rightarrow \infty} \inf_{I_{2n}} x_1(s) = x_1(t_2) + \frac{1}{2} \alpha_1(t_2) \right] = 1.$$

Continuing this procedure we can get a double sequence of disjoint closed intervals  $I_{kn} \subset G$ ,  $k, n = 1, 2, \dots$ , such that  $I_{kn}$  tends to  $t_k$  as  $n \rightarrow \infty$  for each  $k$  and that

$$(6.1) \quad P \left[ \overline{\lim}_{n \uparrow \infty} \inf_{I_{kn}} x_1(s) = x_1(t_k) + \frac{1}{2} \alpha_1(t_k) \right] = 1, \quad k = 1, 2, \dots.$$

By removing a finite number of intervals from  $\{I_{kn}\}_n$  we can achieve that  $I_{kn} \subset (t_k - 1/k, t_k + 1/k)$  for each  $k$ .

Take  $\varepsilon_{kn} > 0$  such that

$$\sum_{kn} \varepsilon_{kn} < \min \left( \frac{1}{2} \varepsilon, \frac{1}{2} c \right)$$

and set

$$x_{kn}(t) = x(t; I_{kn}, a_{kn}, \varepsilon_{kn}) \quad (\text{see Lemma 6.2}),$$

where  $a_{kn} = \frac{1}{2} \alpha_2(t_{kn})$  if this is finite and  $= n$  otherwise, so that  $a_{kn} \uparrow \frac{1}{2} \alpha_2(t_{kn})$  as  $n \rightarrow \infty$  for each  $k$ . We shall prove that

$$x_2(t) = \sum_{kn} x_{kn}(t)$$

is a Gaussian process satisfying our conditions.

Since this implies

$$\begin{aligned} x_2(t) &= x_{kn}(t) && \text{on } I_{kn}, \quad k, n = 1, 2, \dots, \\ &= 0 && \text{elsewhere,} \end{aligned}$$

$x_2(t)$  is well-defined and  $x_2(t) \in L$ . Therefore  $x_2(t)$  is jointly Gauss distributed, separable and measurable.

By  $\|x_{kn}(t)\| < \varepsilon_{kn}$  and  $\sum \varepsilon_{kn} < \infty$ , the series  $\sum_{kn} x_{kn}(t)$  converges in the

mean uniformly in  $t$  and so  $x_2(t)$  is continuous in the mean and we have

$$\|x_2(t)\| < \sum_{kn} \|x_{kn}(t)\| < \varepsilon ,$$

which proves (b).

Observing that

$$\begin{aligned} P \left[ \sup_t x_2(t) > c \right] &\leq \sum_{kn} P \left[ \sup_{t \in I_{kn}} x_2(t) > c \right] \\ &\leq \sum_{kn} P \left( \sup_t x_{kn}(t) > a_{kn} + \varepsilon_{kn} \right) \\ &\leq \sum_{kn} \varepsilon_{kn} < \frac{1}{2} \varepsilon , \end{aligned}$$

we have

$$P(\sup_t |x_2(t)| > c) < \varepsilon ,$$

since the probability law of the sample path of  $x_2(t)$  is symmetric by  $E x_2(t) = 0$ . Thus (c) is proved.

Now we shall prove that  $\alpha(t, x_2) \leq \alpha_2(t)$ .

If  $t_0 \in G$ , then  $t_0$  has a positive distance from  $F$ . Since  $I_{kn}$  is in the  $1/k$ -neighborhood of  $t_k \in F$ , a small neighborhood  $U$  ( $\subset G$ ) of  $t_0$  does not intersect  $I_{kn}$  with  $k \geq k_0, n = 1, 2, \dots$ , for some  $k_0$ . Since  $I_{kn} \rightarrow t_k \in F$  for each  $k$ ,  $U$  can intersect only a finite number of intervals among  $\{I_{kn}\}_{kn}$ . Let us denote these intervals by  $I_{k(i), n(i)}, i = 1, 2, \dots, m$ . Then  $x_2(t)$  is the sum of  $x_{k(i), n(i)}, i = 1, 2, \dots, m$ , as far as  $t$  lies in  $U$ . Therefore the path of  $x_2(t)$  is continuous in  $U$  and so  $\alpha(t_0, x) = 0 \leq \alpha_2(t_0)$ .

If  $t_0 \in F$ , then  $x_2(t_0) = 0$  by our construction. Take an arbitrary  $\delta > 0$ . Then there exists a neighborhood  $U_1$  of  $t_0$  such that

$$\sup_{s \in U_1} \alpha_2(s) < \alpha_2(t_0) + \delta .$$

Take a neighborhood  $U_2$  of  $t_0$  such that  $\bar{U}_2 \subset U_1$ . Then the distance  $\varrho(U_2, U_1^c)$  is positive. Since the  $\{I_{kn}\}_{kn}$  are disjoint and  $\sum_{kn} |I_{kn}| \leq 1$ , we have only a finite number of intervals among  $\{I_{kn}\}_{kn}$  with the length  $\geq \varrho(U_2, U_1^c)$  and only such intervals can intersect both  $U_2$  and  $U_1^c$ . Since each  $I_{kn}$  has positive distance from  $t_0$ , we have a neighborhood  $U_3$  ( $\subset U_2$ ) of  $t_0$  such that  $I_{kn} \subset U_1$  as far as  $I_{kn}$  intersects  $U_3$ .

Write  $\Sigma'$  for the summation over those indices  $(k, n)$  for which  $I_{kn}$  intersects  $U_3$ . Then any interval  $I_{kn}$  with the index  $(k, n)$  appearing in  $\Sigma'$  is contained in  $U_1$ . By taking  $U_3$  small enough, we can achieve that

$$\sum_{kn} \varepsilon_{kn} < \delta .$$

We then have

$$\begin{aligned} P \left[ \sup_{s \in \bar{U}_8} x_2(s) > \frac{1}{2} \alpha_2(t_0) + 2\delta \right] \\ \leq \sum' P \left[ \sup_{s \in \bar{U}_1} x_{kn}(s) > \sup_{s \in \bar{U}_1} \alpha_2(s) + \delta \right] \\ \leq \sum' P(\sup x_{kn}(s) > a_{kn} + \varepsilon_{kn}) < \sum' \varepsilon_{kn} < \delta, \end{aligned}$$

by the construction in Lemma 6.2. Therefore we get

$$P \left[ \overline{\lim}_{s \rightarrow t_0} x_2(s) > \frac{1}{2} \alpha_2(t_0) + 2\delta \right] < \delta$$

for every  $\delta > 0$ . Letting  $\delta \downarrow 0$ , we have

$$P \left[ \overline{\lim}_{s \rightarrow t_0} x_2(s) \geq x_2(t_0) + \frac{1}{2} \alpha_2(t_0) \right] = 0. \quad (\text{Note } x_2(t_0) = 0.)$$

This implies that  $\alpha(t_0, x_2) \leq \alpha_2(t_0)$  by Theorem 2.

Thus  $\alpha(t, x_2) \leq \alpha_2(t)$  is proved for every  $t$ . By the definition of the oscillation function we have

$$\alpha(t, x_1 + x_2) \leq \alpha(t, x_1) + \alpha(t, x_2) \leq \alpha_1(t) + \alpha_2(t) = \alpha(t).$$

We shall now prove that

$$\alpha(t, x_1 + x_2) \geq \alpha(t).$$

Consider first the case  $t = t_k$ . It holds that

$$\begin{aligned} (6.2) \quad P \left[ \overline{\lim}_{s \rightarrow t_k} (x_1(s) + x_2(s)) \geq x_1(t_k) + x_2(t_k) + \frac{1}{2} \alpha(t_k) \right] \\ \geq P \left[ \overline{\lim}_{n \rightarrow \infty} \sup_{I_{kn}} [x_1(s) + x_2(s)] \geq x_1(t_k) + x_2(t_k) + \frac{1}{2} \alpha(t_k) \right] \\ \geq P \left[ \overline{\lim}_{n \rightarrow \infty} \left( \inf_{I_{kn}} x_1(s) + \sup_{I_{kn}} x_2(s) \right) \geq x_1(t_k) + x_2(t_k) + \frac{1}{2} \alpha(t_k) \right] \\ \geq P \left[ \overline{\lim}_{n \rightarrow \infty} \inf_{I_{kn}} x_1(s) + \overline{\lim}_{n \rightarrow \infty} \sup_{I_{kn}} x_2(s) \geq x_1(t_k) + x_2(t_k) + \frac{1}{2} \alpha(t_k) \right]. \end{aligned}$$

Since we have

$$P[\sup_{I_{kn}} x_2(s) < a_{kn} - \varepsilon_{kn}] < \varepsilon_{kn}$$

by virtue of  $x_2(s) = x_{kn}(s)$  on  $I_{kn}$ , we get

$$(6.3) \quad P \left[ \overline{\lim}_{n \rightarrow \infty} \sup_{I_{kn}} x_2(s) \geq x_2(t_k) + \frac{1}{2} \alpha_2(t_k) \right] = 1$$

by  $x_2(t_k) = 0$  and  $\sum_n \varepsilon_{kn} < \infty$ . By (6.1), (6.2) and (6.3) we get

$$P \left[ \overline{\lim}_{s \rightarrow t_k} (x_1(s) + x_2(s)) \geq x_1(t_k) + x_2(t_k) + \frac{1}{2}(t_k) \right] = 1,$$

that is, by Theorem 2,

$$\alpha(t_k, x_1 + x_2) \geq \alpha(t_k).$$

For  $t \neq t_k$ ,  $k = 1, 2, \dots$ , the point  $(t, \alpha(t))$  is an accumulation point of  $(t_n, \alpha(t_n))$ ,  $n = 1, 2, \dots$ . Therefore we have a subsequence  $\{s_n\}$  of  $\{t_n\}$  such that

$$\alpha(t) = \lim_n \alpha(s_n).$$

By Theorem 4 (a)  $(\alpha, 1)$  we have

$$\alpha(t, x_1 + x_2) \geq \overline{\lim}_n \alpha(s_n, x_1 + x_2) = \overline{\lim}_n \alpha(s_n) = \alpha(t),$$

which completes the proof of Lemma 6.3.

Now we shall come back to the proof of Theorem 4 (b). We shall first assume

$(\alpha, 2'')$   $\{t : \alpha(t) \geq c\}$  is nowhere dense for every  $c > 0$ ;

this is stronger than  $(\alpha, 2)$  but weaker than  $(\alpha, 2')$ . Set

$$\begin{aligned} \alpha_0(t) &= 0, \\ \alpha_1(t) &= \max\left(\alpha(t), \frac{1}{2}\right) - \frac{1}{2}, \\ \alpha_n(t) &= \max\left(\min\left(\alpha(t), 2^{-n+1}\right), 2^{-n}\right) - 2^{-n}, \quad n = 2, 3, \dots \end{aligned}$$

It is then easy to verify the following properties of  $\alpha_n(t)$ :

$$\begin{aligned} 0 &\leq \alpha_n(t) \leq 2^{-n-1}, \quad n = 2, 3, \dots, \\ \sum_0^n \alpha_i(t) &\uparrow \alpha(t) \\ \{t : \alpha_n(t) > 0\} &\text{ is nowhere dense.} \end{aligned}$$

Starting with the Gaussian process  $x_0(t) \equiv 0$  whose oscillation function is  $\alpha_0(t) \equiv 0$ , we can use Lemma 6.3 to define a sequence of Gaussian processes  $x_n(t) \in L$ ,  $0 \leq t \leq 1$ ,  $n = 1, 2, \dots$ , satisfying

- (a)  $\alpha(t, \sum_0^n x_i) = \sum_0^n \alpha_i(t)$ ,
- (b)  $\|x_n(t)\| < 2^{-n}$ ,
- (c)  $P[\sup_t |x_n(t)| > \sup_t \alpha_n(t)] < 2^{-n}$ .

Now set

$$x(t) = \sum_n x_n(t).$$

By Borel-Cantelli's lemma it follows from (c) and  $\alpha_n(t) \leq 2^{-n-1}$ ,  $n \geq 2$ , that this infinite series converges uniformly in  $t$  with probability one.

Therefore  $x(t)$  is well-defined, separable, measurable and jointly Gauss distributed, and we have

$$\alpha(t, x) = \lim_n \alpha(t, \sum_0^n x_i) = \lim_n \sum_0^n \alpha_i(t) = \alpha(t).$$

It follows from (b) that this infinite series converges also in the mean, uniformly in  $t$ , so that  $x(t)$  is continuous in the mean.

We shall now remove the assumption that  $T_c = \{t: \alpha(t) \geq c\}$  is nowhere dense.

Let  $I_1, I_2, \dots$  be the maximal intervals contained in the set  $T_\infty = \{t: \alpha(t) = \infty\}$ . Since, by  $(\alpha, 2)$ ,  $\{t: c \leq \alpha(t) < \infty\}$  is nowhere dense,  $I_1, I_2, \dots$  are also the maximal intervals contained in the set  $T_c$  ( $c > 0$ ).

We now define

$$\begin{aligned} \beta(t) &= 0, & t \in I_n^\circ, & \quad n = 1, 2, \dots, \\ &= \alpha(t) & \text{elsewhere.} & \end{aligned}$$

Then  $\beta(t)$  satisfies  $(\alpha, 1)$  and  $(\alpha, 2'')$ . Therefore we can construct a Gaussian process  $y(t) \in L$ ,  $0 \leq t \leq 1$ , such that  $\alpha(t, y) = \beta(t)$ , as we proved above.

By Lemma 6.1, we can construct a sequence of Gaussian processes  $y_n(t) \in L$ ,  $0 \leq t \leq 1$ ,  $n = 1, 2, \dots$ , such that  $\alpha(t, y_n) = \infty$  on  $I_n$ ,  $y_n(t) = 0$  on  $[0, 1] - I_n^\circ$  and  $\|y_n(t)\| < 2^{-n}$ . Now consider

$$x(t) = y(t) + \sum_n y_n(t).$$

Then

$$\begin{aligned} x(t) &= y_n(t) + y(t), & t \in I_n^\circ, & \quad n = 1, 2, \dots, \\ &= y(t), & \text{elsewhere,} & \end{aligned}$$

and  $x(t) \in L$ ,  $0 \leq t \leq 1$ . Therefore  $x(t)$  is jointly Gaussian, measurable and separable. Its continuity in the mean follows from  $\|y_n(t)\| < 2^{-n}$ .

To complete our proof, we need only to show that  $\alpha(t, x) = \alpha(t)$ . Since  $x(t) = y(t)$  on the set  $G = [0, 1] - \bigcup_n \overline{I_n}$  which is open in  $[0, 1]$ , we have

$$\alpha(t, x) = \alpha(t, y) = \beta(t) = \alpha(t), \quad t \in G.$$

Since  $x(t) = y_n(t) + y(t)$  and  $y(t)$  is continuous in  $I_n^\circ$ , we have

$$\alpha(t, x) = \alpha(t, y_n) = \infty = \alpha(t), \quad t \in \bigcup_n I_n^\circ.$$

If  $t \in \overline{\bigcup_n I_n} - \bigcup_n I_n^\circ$ , then  $t$  is an accumulation point of  $\bigcup_n I_n^\circ$  and so we get

$$\alpha(t, x) \geq \overline{\lim}_{\substack{s \rightarrow t \\ s \in \bigcup_n I_n^\circ}} \alpha(s, x) = \infty$$

by Theorem 4 (a)  $(\alpha, 1)$ .

## REFERENCE

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