

# A NOTE ON ROSENBLATT DISTRIBUTIONS

By J. M. P. Albin

*Chalmers University of Technology & University of Göteborg*

Rosenblatt processes arise as functional limits in non-central limit theorems for strongly dependent Gaussian sequences. Using local central- and  $\chi^2$ -limit techniques we show that the marginal distributions of these processes belong to the Type I-domain of attraction of extremes. This in turn makes it possible to obtain bounds on local extremes for Rosenblatt processes.

**1. Introduction.** A random variable  $Y$  is Rosenblatt distributed provided that

$$\mathbf{E}\{e^{i\theta Y}\} = \exp\left\{\sum_{k=2}^{\infty} \frac{(2i\theta)^k}{2k} \int_{x \in [0,1]^k} |x_1 - x_k|^{-2\gamma} \prod_{j=2}^k |x_j - x_{j-1}|^{-2\gamma} dx\right\} \quad \text{for } \theta \in \mathbb{R},$$

where  $\gamma \in (0, \frac{1}{2})$  is a parameter, and then we write  $Y \in \mathfrak{R}(\gamma)$ . These distributions were introduced by Rosenblatt (1961), and named after him by Taqqu (1975).

Let  $\eta$  be an  $N(0, 1)$ -distributed random variable. Then the Hermite polynomials  $H_n(x) = (-1)^n e^{x^2/2} \frac{d^n}{dx^n} e^{-x^2/2}$  form an ON-basis in  $\mathbb{L}^2(\mathbb{R}, \eta) \equiv \{G \in \mathbb{L}^0(\mathbb{R}) : \mathbf{E}\{G(\eta)^2\} < \infty\}$ . Writing  $J_n \equiv \mathbf{E}\{G(\eta)H_n(\eta)\}$  we thus have  $\mathbf{E}\{[\sum_{n=m}^N J_n H_n(\eta) - G(\eta)]^2\} \rightarrow 0$  as  $N \rightarrow \infty$  for  $G \in \mathcal{G}_m \equiv \{G \in \mathbb{L}^2(\mathbb{R}, \eta) : J_0 = \dots = J_{m-1} = 0\}$ .

**Theorem A.** [TAQQU (1975), DOBRUSHIN & MAJOR (1979)]. *Let  $\{X_i\}_{i \in \mathbb{Z}}$  be a stationary zero-mean Gaussian sequence. Assume that the covariance*

$$r(N) \equiv \mathbf{E}\{X_N X_0\} \rightarrow 0 \quad \text{and} \quad \sum_{i=1}^N \sum_{j=1}^N r(i-j)^2 \sim L(N)^2 \quad \text{as } N \rightarrow \infty,$$

where  $L$  is a regularly varying function with index  $\gamma$ . Writing  $\{B(t)\}_{t \in \mathbb{R}}$  for standard Brownian motion and choosing a  $G \in \mathcal{G}_2$ , we then have

$$\begin{aligned} \frac{1}{L(N)} \sum_{i=1}^{[Nt]} G(X_i) &\rightarrow \frac{J_2}{2K_\gamma} \int_{x \in \mathbb{R}^2} \int_{s=0}^{s=t} [(s-x_1)^+(s-x_2)^+]^{-(1+\gamma)/2} ds dB(x_1) dB(x_2) \\ &\equiv \frac{J_2}{2K_\gamma} \xi(t) \quad \text{weakly in } \mathcal{D}([0, 1]) \quad \text{as } N \rightarrow \infty, \end{aligned}$$

where  $K_\gamma^2 = \mathbf{Var}\{\xi(1)\}$ . Moreover  $K_\gamma^{-1} t^{\gamma-1} \xi(t) \in \mathfrak{R}(\gamma)$  for each  $t > 0$ .

In Sections 2 and 3 we prove the following theorems:

---

Research supported by NFR grant M-AA/MA 9207-309.

Key words and phrases. Central Limit Theorem,  $\chi^2$  Limit Theorem, Convolution Kernel, Domain of Attraction, Extreme Values, Laplace Transform, Local Limit Theorem, Non-Central Limit Theorem, Rosenblatt Distribution, Tauberian Theorem.

Adress to author: Dept. of Math., CTH & GU, S-412 96 Gothenburg, SWEDEN.

**Theorem 1.** *The distribution function  $F$  of a Rosenblatt distributed random variable  $Y \in \mathfrak{R}(\gamma)$  has a density function  $f$  such that*

$$\lim_{u \rightarrow -\infty} w(u) f(u - w(u)x) / F(u) = e^{-x} \quad \text{for } x \in \mathbb{R}, \quad (1.1)$$

for some non-negative function  $w$ . Thus  $F$  belongs to the Type I-domain of attraction for minima with auxiliary function  $w$ , i.e.,

$$\lim_{u \rightarrow -\infty} F(u - w(u)x) / F(u) = e^{-x} \quad \text{for } x \in \mathbb{R}. \quad (1.2)$$

**Theorem 2.** *The distribution function  $F$  of a Rosenblatt distributed random variable  $Y \in \mathfrak{R}(\gamma)$  has a density function  $f$  such that*

$$\lim_{u \rightarrow \infty} W f(u + Wx) / (1 - F(u)) = e^{-x} \quad \text{for } x \in \mathbb{R}, \quad (1.3)$$

where  $W \equiv \sup\{s \in \mathbb{R} : \mathbf{E}\{e^{sY}\} < \infty\} \in (0, \infty)$ . Thus  $F$  belongs to the Type I-domain of attraction for maxima with constant auxiliary function  $W$ , i.e.,

$$\lim_{u \rightarrow \infty} (1 - F(u + Wx)) / (1 - F(u)) = e^{-x} \quad \text{for } x \in \mathbb{R}. \quad (1.4)$$

The proof of (1.1) and (1.3) is an adaption of the method of Feigin & Yashchin (1983) and Davis & Resnick (1991). Their idea is to derive a so-called strong Tauberian result by proving a local limit theorem for a suitably normalized and Esscher-transformed version of the distribution under consideration.

Strong Tauberian theorems origin in the asymptotic treatment of convolution kernels by Hirschmann & Widder (1955, Chapter V). Feigin & Yashchin (1983) gave a generalization to more general Laplace transforms (than convolution kernels), but under rather restrictive technical conditions. As did Davis & Resnick (1991) in their study of sums of non-negative random variables, we found that these conditions are not met by our framework. Thus a treatment adapted to the specific situation is required. But the scheme of Feigin & Yashchin (1983) remains the main inspiration.

Application of results from extreme value theory requires belongance to a domain of attraction: Methods in statistics for extremes are directly linked to these domains [e.g., Resnick (1987)], and extremal theory for stochastic processes also relies on attraction [e.g., Berman (1982) and Albin (1990, 1998)]. In Section 4 we show how Theorems 1 and 2 combine with a results of Albin (1998) to yield bounds on the probability of a local extrema for the Rosenblatt process  $\xi(t)$  in Theorem A.

Theorem A suggests that  $\mathfrak{R}(\gamma)$ -distributions are related to  $\chi^2$ -distributions: Letting  $\eta_1, \eta_2, \dots$  denote independent  $N(0, 1)$ -variables the precise statement becomes [Taqqu (1975, Section 6), Dobrushin & Major (1979, Proposition 2)]

$$Y =_{\mathcal{L}} \sum_{j=1}^{\infty} \lambda_j (\eta_j^2 - 1) \quad \text{where} \quad \lambda_1 = \dots = \lambda_{j_0} > \lambda_{j_0+1} \geq \dots > 0 \quad \text{and} \quad \sum_{j=1}^{\infty} \lambda_j^2 < \infty. \quad (1.5)$$

In (1.5) we have  $\sum_{j=1}^{\infty} \lambda_j = \infty$ . This is important since otherwise we could write  $Y =_{\mathcal{L}} \|\hat{Y}\|^2 - \sum_{j=1}^{\infty} \lambda_j$  where  $\hat{Y} = \sum_{j=1}^{\infty} \sqrt{\lambda_j} \eta_j e_j$  is Gaussian with values in the Hilbert space spanned by an ON-basis  $\{e_j\}_{j=1}^{\infty}$ . But then the fact that  $Y$  belongs to the Type I-domain of attraction would follow from the corresponding result for  $\|\hat{Y}\|^2$  [e.g., Albin (1992, pp. 139-140) and Albin (1996, Proposition 1)].

Now note that in view of (1.5) the Laplace transform  $\phi$  of  $Y$  is given by

$$\phi(s) = \mathbf{E}\{\exp[-sY]\} = \exp\left\{-\sum_{j=1}^{\infty} \left(\frac{1}{2} \ln(1+2\lambda_j s) - \lambda_j s\right)\right\} \quad \text{for } s \in (-(2\lambda_1)^{-1}, \infty).$$

**2. Proof of Theorem 1.** The Esscher-transform  $Y_s$  of  $Y$  at  $s \in (-(2\lambda_1)^{-1}, \infty)$  is a random variable with distribution  $dF_{Y_s}(x) = e^{-sx} dF(x) / \phi(s)$ . Here we have

$$m(s) \equiv \mathbf{E}\{Y_s\} = -\sum_{j=1}^{\infty} \frac{2\lambda_j^2 s}{1+2\lambda_j s} \quad \text{and} \quad \sigma(s)^2 \equiv \mathbf{Var}\{Y_s\} = \sum_{j=1}^{\infty} \frac{2\lambda_j^2}{(1+2\lambda_j s)^2}.$$

The normalized variable  $Z_s \equiv (Y_s - m(s)) / \sigma(s)$  has characteristic function

$$\begin{aligned} \mu_s(x) &\equiv \mathbf{E}\{\exp[ixZ_s]\} \\ &= \phi(s - ix/\sigma(s)) \exp\{-ix m(s)/\sigma(s)\} / \phi(s) \\ &= \exp\left\{-\sum_{j=1}^{\infty} \left[\frac{1}{2} \ln\left(1 - \frac{2\lambda_j ix}{(1+2\lambda_j s)\sigma(s)}\right) + \frac{\lambda_j ix}{(1+2\lambda_j s)\sigma(s)}\right]\right\} \quad \text{for } x \in \mathbb{R}. \end{aligned}$$

Since  $\lim_{s \rightarrow \infty} s \sigma(s) = \infty$  it follows readily that

$$\lim_{s \rightarrow \infty} \mu_s(x) = e^{-x^2/2} \quad \text{for } x \in \mathbb{R}, \quad \text{so that } Z_s \rightarrow_{\mathcal{L}} N(0, 1) \quad \text{as } s \rightarrow \infty. \quad (2.1)$$

To proceed we observe the easy fact that

$$|\mu_s(x)| = \exp\left\{-\frac{1}{4} \sum_{j=1}^{\infty} \ln\left(1 + \frac{4\lambda_j^2 x^2}{(1+2\lambda_j s)^2 \sigma(s)^2}\right)\right\} \quad \text{for } x \in \mathbb{R}. \quad (2.2)$$

Choosing a  $c > 0$  such that  $\ln(1+y^2) \geq cy^2$  for  $|y| \leq 1$ , we therefore get

$$\begin{aligned} &\overline{\lim}_{s \rightarrow \infty} \int_{K < |x| \leq s\sigma(s)} |\mu_s(x)| dx \\ &\leq \overline{\lim}_{s \rightarrow \infty} \int_K^{s\sigma(s)} 2 \exp\left\{-\frac{1}{4} \sum_{j=1}^{\infty} \frac{c\lambda_j^2 x^2}{(1+2\lambda_j s)^2 \sigma(s)^2}\right\} dx \leq \int_K^{\infty} 2 \exp\{-\frac{1}{8} cx^2\} dx \rightarrow 0 \end{aligned} \quad (2.3)$$

as  $K \rightarrow \infty$  [recall that  $s\sigma(s) \rightarrow \infty$ ]. Invoking the trivial facts that

$$\int_1^\infty \left(1 + \frac{4}{9}x^2\right)^{-\nu} dx \leq \left(1 + \frac{4}{9}\right)^{1-\nu} \int_0^\infty \left(1 + \frac{4}{9}x^2\right)^{-1} dx = \frac{\pi}{3} \left(\frac{13}{9}\right)^{1-\nu} \quad \text{for } \nu > 1,$$

and that  $n(s) \equiv \#\{j : \lambda_j s > 1\} \rightarrow \infty$  as  $s \rightarrow \infty$ , we further obtain

$$\begin{aligned} & \int_{|x| > s\sigma(s)} |\mu_s(x)| dx \\ &= 2 \int_{s\sigma(s)}^\infty \exp\left\{-\frac{n(s)}{4} \ln\left(1 + \frac{4x^2}{9s^2\sigma(s)^2}\right) - \frac{1}{4} \sum_{\{j : \lambda_j s \leq 1\}} \ln\left(1 + \frac{4\lambda_j^2 x^2}{9\sigma(s)^2}\right)\right\} dx \\ &\leq 2s\sigma(s) \int_1^\infty \left(1 + \frac{4}{9}x^2\right)^{-n(s)/4} \exp\left\{-\frac{1}{4} \sum_{\{j : \lambda_j s \leq 1\}} \ln(1 + 4\lambda_j^2 s^2)\right\} dx \\ &\leq 2 \left(\sum_{j=1}^\infty \frac{2\lambda_j^2 s^2}{(1+2\lambda_j s)^2}\right)^{1/2} \frac{\pi}{3} \left(\frac{13}{9}\right)^{1-n(s)/4} \exp\left\{-\frac{1}{4}c \sum_{\{j : \lambda_j s \leq 1\}} \lambda_j^2 s^2\right\} \\ &\leq \frac{\sqrt{8}\pi}{3} \left(\frac{13}{9}\right)^{1-n(s)/4} \left(\sqrt{\frac{1}{2}n(s)} + \sqrt{\sum_{\{j : \lambda_j s \leq 1\}} \lambda_j^2 s^2} \exp\left\{-\frac{1}{4}c \sum_{\{j : \lambda_j s \leq 1\}} \lambda_j^2 s^2\right\}\right) \\ &\rightarrow 0 \quad \text{as } s \rightarrow \infty. \end{aligned} \tag{2.4}$$

Since (2.2) shows that  $|\mu_s(\cdot)| \in \mathbb{L}^1(\mathbb{R})$ ,  $Z_s$  has a density  $f_s$  given by the inverse Fourier transform of  $\mu_s(\cdot)$ . Combining (2.1) and (2.3)-(2.4) we thus conclude

$$\begin{aligned} \sup_{y \in \mathbb{R}} \left| f_s(y) - \frac{\exp\{-\frac{1}{2}y^2\}}{\sqrt{2\pi}} \right| &= \sup_{y \in \mathbb{R}} \left| \frac{1}{2\pi} \int_{-\infty}^\infty e^{-iyx} (\mu_s(x) - \exp\{-\frac{1}{2}x^2\}) dx \right| \\ &\leq \frac{1}{2\pi} \int_{-\infty}^\infty |\mu_s(x) - \exp\{-\frac{1}{2}x^2\}| dx \\ &\rightarrow 0 \quad \text{as } s \rightarrow \infty. \end{aligned} \tag{2.5}$$

Since  $Z_s$  has a density,  $Y$  has a density  $f$  that satisfies

$$f(m(s) + x\sigma(s)) = \sigma(s)^{-1} \phi(s) \exp\{s(m(s) + x\sigma(s))\} f_s(x). \tag{2.6}$$

Choosing  $x=0$  and using (2.5) we now obtain

$$f(m(s)) \sim (2\pi)^{-1/2} \sigma(s)^{-1} \phi(s) \exp\{sm(s)\} \quad \text{as } s \rightarrow \infty. \tag{2.7}$$

Combining (2.5)-(2.7) we get [again recalling that  $s\sigma(s) \rightarrow \infty$ ]

$$f(m(s) - x/s) = \sigma(s)^{-1} \phi(s) \exp\{sm(s)\} e^{-x} f_s(x/(s\sigma(s))) \sim e^{-x} f(m(s))$$

as  $s \rightarrow \infty$ . Another application of (2.5) therefore yields

$$\frac{e^{-x} sF(m(s))}{f(m(s) - x/s)} \sim \frac{sF(m(s))}{f(m(s))} = \int_0^\infty \frac{f(m(s) - y/s)}{f(m(s))} dy = \int_0^\infty e^{-y} \frac{f_s(y/(s\sigma(s)))}{f_s(0)} dy \rightarrow 1$$

as  $s \rightarrow \infty$ . Consequently (1.1) holds with  $w(u) = (m^{-1}(u))^{-1}$ .

The fact that (1.1) implies (1.2) is well-known and follows e.g., from an application of the theorem by Scheffé (1947).  $\square$

**3. Proof of Theorem 2.** Let  $\hat{Y}_s$  be a variable with density  $f_{\hat{Y}_s}(x) = e^{-sx}(x - m(s))^2 f(x) / (V(s)\phi(s))$  for  $s \in (-(2\lambda_1)^{-1}, \infty)$ . Then we have

$$\hat{m}(s) \equiv \mathbf{E}\{\hat{Y}_s\} = m(s) - V'(s)/V(s) \sim \frac{j_0/2+2}{(2\lambda_1)^{-1}+s} \quad (3.1)$$

$$\hat{\sigma}(s)^2 \equiv \mathbf{Var}\{\hat{Y}_s\} = V(s) + V''(s)/V(s) - V'(s)^2/V(s)^2 \sim \frac{j_0/2+2}{((2\lambda_1)^{-1}+s)^2} \quad (3.2)$$

as  $s \downarrow -(2\lambda_1)^{-1}$ , where  $V(s) \equiv \sigma(s)^2$ . It follows that

$$V(s - ix/\hat{\sigma}(s)) \sim (j_0/2) / (1 - ix/\sqrt{j_0/2+2}) \quad \text{as } s \downarrow -(2\lambda_1)^{-1}.$$

Further the normalized variable  $\hat{Z}_s \equiv (\hat{Y}_s - \hat{m}(s))/\hat{\sigma}(s)$  has characteristic function

$$\begin{aligned} \hat{\mu}_s(x) &\equiv \mathbf{E}\{\exp[ixZ_s]\} \\ &= (V(s - ix/\hat{\sigma}(s))/V(s)) (\phi(s - ix/\hat{\sigma}(s))/\phi(s)) \exp\{-ix \hat{m}(s)/\hat{\sigma}(s)\} \\ &= (V(s - ix/\hat{\sigma}(s))/V(s)) \\ &\quad \times \exp\left\{\frac{ix(m(s) - \hat{m}(s))}{\hat{\sigma}(s)} - \frac{1}{2} \sum_{j=1}^{\infty} \left[ \ln\left(1 - \frac{ix/\hat{\sigma}(s)}{(2\lambda_j)^{-1}+s}\right) + \frac{ix/\hat{\sigma}(s)}{(2\lambda_j)^{-1}+s} \right]\right\} \\ &\rightarrow (1 - ix/\sqrt{j_0/2+2})^{-(j_0/2+2)} \exp\{-ix\sqrt{j_0/2+2}\} \quad \text{as } s \downarrow -(2\lambda_1)^{-1} \quad (3.3) \end{aligned}$$

for  $x \in \mathbb{R}$ . Consequently  $\hat{Z}_s \rightarrow_{\mathcal{L}} (\chi^2(j_0+4) - (j_0+4))/\sqrt{2j_0+8} \equiv \chi$ .

To proceed we observe the easy fact that

$$\begin{aligned} &|\hat{\mu}_s(x)| \\ &= \left( \sum_{j=1}^{\infty} \frac{1/(2V(s))}{((2\lambda_j)^{-1}+s)^2 + x^2/\hat{\sigma}(s)^2} \right) \exp\left\{-\frac{1}{4} \sum_{j=1}^{\infty} \ln\left(1 + \frac{x^2/\hat{\sigma}(s)^2}{((2\lambda_j)^{-1}+s)^2}\right)\right\} \\ &\leq \frac{j_0/(2V(s))}{((2\lambda_1)^{-1}+s)^2 + x^2/\hat{\sigma}(s)^2} \\ &\quad + \left( \sum_{j>j_0} \frac{1/(2V(s))}{((2\lambda_j)^{-1}+s)^2 + x^2/\hat{\sigma}(s)^2} \right) \exp\left\{-\frac{1}{4} \sum_{j>j_0} \ln\left(1 + \frac{x^2/\hat{\sigma}(s)^2}{((2\lambda_j)^{-1}+s)^2}\right)\right\}. \quad (3.4) \end{aligned}$$

Here (3.2) combines with the fact that  $V(s) \sim (j_0/2) / ((2\lambda_1)^{-1}+s)^2$  to give

$$\begin{aligned} &\overline{\lim}_{s \downarrow -(2\lambda_1)^{-1}} \int_K^{\infty} \frac{j_0/(2V(s))}{((2\lambda_1)^{-1}+s)^2 + x^2/\hat{\sigma}(s)^2} dx \\ &= \overline{\lim}_{s \downarrow -(2\lambda_1)^{-1}} \frac{j_0\hat{\sigma}(s)/(2V(s))}{(2\lambda_1)^{-1}+s} \left[ \frac{\pi}{2} - \arctan\left(\frac{K/\hat{\sigma}(s)}{(2\lambda_1)^{-1}+s}\right) \right] \rightarrow 0 \quad \text{as } K \rightarrow \infty. \quad (3.5) \end{aligned}$$

As  $s \downarrow -(2\lambda_1)^{-1}$  we further have

$$\int_K^{\hat{\sigma}(s)} \sum_{j>j_0} \frac{1/(2V(s))}{((2\lambda_j)^{-1}+s)^2+x^2/\hat{\sigma}(s)^2} \leq \frac{\hat{\sigma}(s)}{V(s)} \sum_{j>j_0} \frac{2\lambda_j^2}{(1+2\lambda_j s)^2} \rightarrow 0 \quad (3.6)$$

and

$$\begin{aligned} & \int_{\hat{\sigma}(s)}^{\infty} \left( \sum_{j>j_0} \frac{1/(2V(s))}{((2\lambda_j)^{-1}+s)^2+x^2/\hat{\sigma}(s)^2} \right) \exp \left\{ -\frac{1}{4} \sum_{j>j_0} \ln \left( 1 + \frac{x^2/\hat{\sigma}(s)^2}{((2\lambda_j)^{-1}+s)^2} \right) \right\} dx \\ & \leq \int_1^{\infty} \left( \sum_{j>j_0} \frac{2\lambda_j^2 \hat{\sigma}(s)/V(s)}{(1+2\lambda_j s)^2} \right) \exp \left\{ -\frac{1}{4} \sum_{j=j_0+1}^{j_0+5} \ln \left( 1 + \frac{4\lambda_j^2 x^2}{(1+2\lambda_j s)^2} \right) \right\} dx \\ & \leq \frac{\hat{\sigma}(s)}{V(s)} \left( \sum_{j>j_0} \frac{2\lambda_j^2}{(1-\lambda_j/\lambda_1)^2} \right) \int_1^{\infty} \left( 1 + \frac{4\lambda_{j_0+5}^2 x^2}{(1+2\lambda_{j_0+1} s)^2} \right)^{-1} dx \\ & \rightarrow 0. \end{aligned} \quad (3.7)$$

Since (3.4) shows that  $|\hat{\mu}_s(\cdot)| \in \mathbb{L}^1(\mathbb{R})$ ,  $\hat{Z}_s$  has a density  $\hat{f}_s$  given by the inverse Fourier transform of  $\hat{\mu}_s(\cdot)$ . Combining (3.3) and (3.5)-(3.7) we thus get [cf. (2.5)]

$$\hat{f}_s(0) - f_\chi(0) = \frac{1}{2\pi} \int_{-\infty}^{\infty} (\hat{\mu}_s(x) - \mathbf{E}\{\exp[-ix\chi]\}) dx \rightarrow 0 \quad \text{as } s \downarrow -(2\lambda_1)^{-1}.$$

Since

$$f(\hat{m}(s)) = \hat{f}_s(0) \phi(s) e^{s \hat{m}(s)} (\hat{m}(s) - m(s))^2 (V(s)/\hat{\sigma}(s)),$$

and [cf. (3.1)-(3.2)]

$$\frac{1}{2}(j_0/2+2) (\hat{m}(s) - m(s)) \sim \hat{m}(s) \sim \sqrt{j_0/2+2} V(s)/\hat{\sigma}(s),$$

it follows that

$$f(\hat{m}(s)) \sim f_\chi(0) \phi(s) e^{j_0/2+2} e^{-\hat{m}(s)/(2\lambda_1)} ((j_0/2+2)/2)^2 \hat{m}(s)^{-2} (j_0/2+2)^{-1/2} \hat{m}(s).$$

But here  $\phi(s) \sim C \hat{m}(s)^{j_0/2}$  for some constant  $C > 0$ , and thus we conclude

$$f(u) \sim f_\chi(0) C u^{j_0/2} e^{j_0/2+2} e^{-u/(2\lambda_1)} ((j_0/2+2)/2)^2 u^{-2} (j_0/2+2)^{-1/2} u \quad \text{as } u \rightarrow \infty.$$

Now (1.3) and (1.4) follow from elementary computations.  $\square$

## REFERENCES

- Albin, J.M.P. (1990). On extremal theory for stationary processes. *Ann. Probab.* **18** 92-128.  
Albin, J.M.P. (1992). Extremes and crossings for differentiable stationary processes with application to Gaussian processes in  $\mathfrak{R}^m$  and Hilbert space. *Stochastic Process. Appl.* **42** 119-147.  
Albin, J.M.P. (1996). Minima of  $H$ -valued Gaussian processes. *Ann. Probab.* **24** 788-824.

- Albin, J.M.P. (1998). On extremal theory for self-similar processes. Accepted for publication in *Ann. Probab.*
- Berman, S.M. (1982). Sojourns and extremes of stationary processes. *Ann. Probab.* **10** 1-46.
- Davis, R.A. & Resnick, S.I. (1991). Extremes of moving averages of random variables with finite endpoint. *Ann. Probab.* **19** 312-328.
- Dobrushin, R.L. & Major, P. (1979). Non-central limit theorems for non-linear functionals of Gaussian fields. *Z. Wahrsch. Verw. Gebiete* **50** 27-52.
- Feigin, P.D. & Yashchin, E. (1983). On a strong Tauberian result. *Z. Wahrsch. Verw. Gebiete* **65** 35-48.
- Hirschmann, I.I. & Widder, D.V. (1955). *The Convolution Transform*. Princeton Univ. Press.
- Resnick, S.I. (1987). *Extreme Values, Regular Variation, and Point Processes*. Springer, New York.
- Rosenblatt, M. (1961). Independence and dependence. *Proc. 4th Berkeley Sympos. Math. Statist.* 431-443. Univ. of California Press.
- Scheffé, H. (1947). A useful convergence theorem for probability distributions. *Ann. Math. Statist.* **18** 434-438.
- Taqqu, M.S. (1975). Weak convergence to fractional Brownian motion and to the Rosenblatt process. *Z. Wahrsch. Verw. Gebiete* **31** 287-302.