

## LIMITING DISTRIBUTION OF THE MAXIMUM OF A NULL RECURRENT DIFFUSION PROCESS

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### Abstract

A limit theorem for the maximum processes of a class of null recurrent linear diffusions is proved. The limiting distribution is a mixture of the Mittag-Leffler distribution.

### 1. Introduction

Let  $X = (X(t))_{t \geq 0}$  be a regular, recurrent diffusion process on an interval  $I = (r_1, r_2) \subset \mathbf{R}$  ( $-\infty \leq r_1 < 0 < r_2 \leq \infty$ ) with the local generator

$$(1.1) \quad \mathcal{L} = a(x) \frac{d^2}{dx^2} + b(x) \frac{d}{dx} \quad (a(x) > 0)$$

and let  $X^*(t) = \max\{X(s); 0 \leq s \leq t\}$ . In the present paper we are interested in the limiting laws of

$$(1.2) \quad \frac{1}{\psi(t)} (X^*(t) - q(t)) \quad (t \rightarrow \infty)$$

for suitable normalizing functions  $\psi(t) > 0$  and  $q(t)$ .

On this subject we should mention the classical result of Berman [1]. He proved that, if the diffusion is positive recurrent, then the problem is reduced to that for the maximum of i.i.d. random variables and therefore, by the well-known Fisher-Tippett theorem, all possible limit distributions are the Gumbel, the Fréchet, and the Weibull distribution.

On the other hand, in the case of null recurrent diffusions, [1] says that, in some cases, the *Mittag-Leffler distribution* is possible. By Mittag-Leffler distribution we mean the distribution  $\mu_{\alpha,t}$  ( $0 \leq \alpha \leq 1, t \geq 0$ ) on  $[0, \infty)$  characterized by

$$\int_{[0, \infty)} e^{-sx} \mu_{\alpha,t}(dx) = \sum_{k=0}^{\infty} \frac{(-s)^k}{\Gamma(k\alpha + 1)} t^{k\alpha}, \quad s > 0$$

(see [4, p. 453] or [11]). Especially, if  $\alpha = 0, 1/2$  or  $1$ , then  $\mu_{\alpha,t}$  is an exponential

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distribution, a truncated normal distribution, or the unit mass at  $x = t$ , respectively. The distribution function of  $\mu_{\alpha,1}$  is

$$g_\alpha(x) = \frac{1}{\pi\alpha} \int_0^x \sum_{j=1}^{\infty} \frac{(-1)^{j-1}}{j!} \sin \pi\alpha \cdot \Gamma(\alpha j + 1) u^{j-1} du \quad (x > 0)$$

provided that  $0 < \alpha < 1$ . Another characterization of  $\mu_{\alpha,t}$  ( $0 < \alpha < 1$ ) is the following: Let  $Z_\alpha = (Z_\alpha(t))_{t \geq 0}$  be  $\alpha$ -stable subordinator (increasing Lévy process) such that

$$(1.3) \quad E[e^{-sZ_\alpha(t)}] = e^{-ts^\alpha}, \quad s > 0, t > 0.$$

Then the one-dimensional marginal distribution of the inverse process  $Z_\alpha^{-1}(t)$  obeys  $\mu_{\alpha,t}$  (cf. [4, p. 453]). Note that  $Z_\alpha^{-1}(\cdot)$  is  $\alpha$ -self-similar:

$$(1.4) \quad (Z_\alpha^{-1}(ct))_t \stackrel{d}{=} (c^\alpha Z_\alpha^{-1}(t))_t, \quad \forall c > 0,$$

which follows immediately from  $(Z_\alpha(ct))_t \stackrel{d}{=} (c^{1/\alpha} Z_\alpha(t))_t$  (here, ' $\stackrel{d}{=}$ ' denotes the equivalence in law). This characterization of  $\mu_{\alpha,t}$  in terms of  $Z_\alpha$  helps us to understand why [1] says that  $\mu_{\alpha,t}$  is possible for the limiting distribution of (1.2) if we recall that the inverse process  $(X^*)^{-1}(t)$  has (time-inhomogenous) independent increments due to the strong Markov property of the diffusion. However, as far as the authors know, no concrete examples satisfying the conditions given in [1] are known except for the case  $\alpha = 1/2$ .

The aim of the present article is to give a limit theorem for (1.2) where the limit distribution is not the Mittag-Leffler distribution itself but is its 'mixture'. Our main result will be given in Section 2, and here we only give a typical example. Let  $1 < \rho < 2$  and consider the diffusion corresponding to

$$\mathcal{L} = \frac{1}{2} \left( \frac{d^2}{dx^2} + \frac{\rho-1}{x} 1_{(-\infty, -1)}(x) \frac{d}{dx} \right), \quad -\infty < x < \infty.$$

Then,  $X_t^*/t^\alpha$  ( $\alpha = (2-\rho)/2$ ), converges in law to the product of two independent random variables; one is  $\mu_{\alpha,t}$ -distributed and the other Fréche-distributed (see Example 2.4).

*Remark 1.1.* As we mentioned above our problem is closely related to the study of  $\tau_x := (X^*)^{-1}(x)$ , which is the first-hitting time of  $X$  to  $x$ . Therefore, our problem may be regarded as the study of the limit theorem for  $\tau_x$  as  $x \rightarrow \infty$ . On this subject we should mention the results of Yamazato (e.g. [12]). However, we are treating quite different type of diffusions and there seems no direct relations.

## 2. Main results

We first rewrite

$$(2.1) \quad \mathcal{L} = a(x) \frac{d^2}{dx^2} + b(x) \frac{d}{dx} \quad (a(x) > 0)$$

into the form of Feller’s canonical representation. To this end it is convenient to rewrite (2.1) as

$$(2.2) \quad \mathcal{L} = a(x) \left( \frac{d^2}{dx^2} - V'(x) \frac{d}{dx} \right) \quad (a(x) > 0),$$

where

$$V(x) = - \int_0^x \frac{b(u)}{a(u)} du, \quad -\infty < x < \infty.$$

Now define

$$(2.3) \quad s(x) = \int_0^x e^{V(u)} du \quad (x \in I)$$

and

$$(2.4) \quad m(x) = \int_0^x \frac{1}{a(u)} e^{-V(u)} du \quad (x \in I).$$

Here,  $\int_0^x = - \int_x^0$  if  $x < 0$  as usual. So far we did not mention detailed conditions on  $a(x)$  and  $b(x)$ , but we shall assume that  $a(x)$  and  $b(x)$  are measurable functions such that  $V(x)$ ,  $s(x)$  and  $m(x)$  are finite for all  $x \in I$ . Throughout the paper we shall confine ourselves to the case where  $s(x) \rightarrow -\infty (x \downarrow r_1)$ ,  $s(x) \rightarrow \infty (x \uparrow r_2)$  so that  $s^{-1}(x)$  is defined for all  $x \in \mathbf{R}$ , which condition means that the process is recurrent. The function  $s(x)$  is referred to as the *scale function*, and the Lebesgue-Stieltjes measure  $dm(x)$  is called the *speed measure* or the *canonical measure* of  $X$  (see e.g. [5]). Using above functions we can rewrite  $\mathcal{L}$  as follows:

$$\mathcal{L} = a(x) e^{V(x)} \frac{d}{dx} \left( e^{-V(x)} \frac{d}{dx} \right) = \frac{d}{dm(x)} \frac{d}{ds(x)}.$$

Next, in order to describe the limiting distribution of (1.2) we prepare the following stochastic process (c.f. [3]). By a *canonical extremal process* we mean a nonnegative, nondecreasing process  $(\xi(t))_{t \geq 0}$  with the following finite-dimensional marginal distributions; for  $0 \leq t_1 < \dots < t_n$  and  $0 < x_1 < \dots < x_n$ ,

$$(2.5) \quad P(\xi(t_1) \leq x_1, \dots, \xi(t_n) \leq x_n) = G(x_1)^{t_1} G(x_2)^{t_2 - t_1} \dots G(x_n)^{t_n - t_{n-1}}$$

where  $G(x) = e^{-1/x}$  (Fréche distribution). Such a process can be obtained as the maximum process of a Poisson point process with the characteristic measure  $\nu(dx) = x^{-2} dx$  so that  $e^{-\nu([x, \infty))} = G(x)$  (for the definition of Poisson point process see [7]). Note that  $\xi(\cdot)$  is 1-self-similar;

$$(2.6) \quad \left( \frac{1}{c} \xi(ct) \right)_{t \geq 0} \stackrel{d}{=} (\xi(t))_{t \geq 0}, \quad \forall c > 0.$$

Also note that  $\xi(\cdot)$  is stochastically continuous (i.e.,  $P\{\xi(t) = \xi(t - 0)\} = 1$  ( $\forall t > 0$ )), which is clear from  $E[1/\xi(t)] = 1/t$ .

Our main result is the following:

Throughout the paper ‘ $\xrightarrow{f.d.}$ ’ denotes the convergence of all finite-dimensional marginal distributions.

**THEOREM 2.1.** *Let  $\gamma > 0$  and put  $\alpha = 1/(\gamma + 1)$ .*

*If*

$$(2.7) \quad \lim_{x \rightarrow -\infty} \frac{-m(s^{-1}(x))}{|x|^\gamma} = c > 0, \quad \lim_{x \rightarrow \infty} \frac{m(s^{-1}(x))}{x^\gamma} = 0,$$

*then,*

$$\left( \frac{c^\alpha}{\lambda^\alpha} s(X^*(\lambda t)) \right)_{t \geq 0} \xrightarrow{f.d.} \left( \frac{1}{C_\alpha} \xi(Z_\alpha^{-1}(t)) \right)_{t \geq 0} \quad (\lambda \rightarrow \infty),$$

where  $(\xi(t))_{t \geq 0}$  is a canonical extremal process which is independent of  $(Z_\alpha(t))_{t \geq 0}$  and

$$(2.8) \quad C_\alpha = \frac{\Gamma(1 - \alpha)}{\Gamma(1 + \alpha)} \{\alpha(1 - \alpha)\}^\alpha.$$

**THEOREM 2.2.** *If, in addition to the assumptions of Theorem 2.1,*

$$(2.9) \quad \lim_{\lambda \rightarrow \infty} \frac{s^{-1}(\lambda x) - q(\lambda)}{\varphi(\lambda)} = G(x), \quad x > 0,$$

for some  $\varphi(\lambda) (> 0)$ ,  $q(\lambda)$ , and continuous  $G(x) (x > 0)$ , then

$$\frac{1}{\varphi((t/c)^\alpha)} \{X^*(t) - q((t/c)^\alpha)\} \xrightarrow{d} G\left(\frac{1}{C_\alpha} \xi(1) Z_\alpha^{-1}(1)\right) \quad (t \rightarrow \infty).$$

The proofs will be given in Section 4.

*Remark 2.3.* The function  $G(x) (x > 0)$  in (2.9) is necessarily of the same type as one of the following three functions

$$x^\beta, \quad -x^{-\beta}, \quad \log x \quad (\beta > 0),$$

and the law of  $G(\xi(1))$  is the Fréche, the Weibull, and the Gumbel distribution, respectively.

*Example 2.4.* Let  $0 < \rho_+ < \rho_- < 2$  and let

$$\mathcal{L} = \frac{1}{2} \left( \frac{d^2}{dx^2} + \frac{\rho(x) - 1}{x} \frac{d}{dx} \right), \quad -\infty < x < \infty,$$

where

$$\rho(x) = \begin{cases} \rho_- & (x < -1) \\ 1 & (|x| \leq 1) \\ \rho_+ & (x > 1) \end{cases}.$$

Then

$$e^{V(x)} = \begin{cases} |x|^{1-\rho_-} & (x < -1) \\ x & (|x| \leq 1) \\ x^{1-\rho_+} & (x > 1) \end{cases}$$

$$s(x) = \begin{cases} \frac{-1}{2-\rho_-} (|x|^{2-\rho_-} - 1) - 1 & (x < -1) \\ x & (|x| \leq 1) \\ \frac{1}{2-\rho_+} (x^{2-\rho_+} - 1) + 1 & (x > 1) \end{cases}$$

$$m(x) = \begin{cases} -\frac{2}{\rho_-} (|x|^{\rho_-} - 1) - 2 & (x < -1) \\ 2x & (|x| \leq 1) \\ \frac{2}{\rho_+} (x^{\rho_+} - 1) + 2 & (x > 1) \end{cases}$$

Therefore, putting  $\gamma = \rho_-/(2 - \rho_-)$ ,  $\beta = 1/(2 - \rho_+)$ , we have

$$\lim_{x \rightarrow -\infty} \frac{-m(s^{-1}(x))}{|x|^\gamma} = \frac{2(2 - \rho_-)^\gamma}{\rho_-}, \quad \lim_{x \rightarrow \infty} \frac{m(s^{-1}(x))}{x^\beta} = 0$$

and

$$\lim_{x \rightarrow \infty} \frac{s(x)}{x^{1/\beta}} = \beta, \quad \text{so that} \quad \lim_{\lambda \rightarrow \infty} \frac{s^{-1}(\lambda x)}{\lambda^\beta} = \left(\frac{x}{\beta}\right)^\beta, \quad x > 0.$$

Therefore, we have

$$\left(\frac{c}{t}\right)^{\alpha\beta} X^*(t) \xrightarrow{d} \left(\frac{1}{\beta C_\alpha} \xi(1) Z_\alpha^{-1}(1)\right)^\beta \quad (t \rightarrow \infty),$$

where  $\alpha = 1/(\gamma + 1) = (2 - \rho_-)/2$  and

$$c = \frac{2(2 - \rho_-)^\gamma}{\rho_-} = \frac{2(2 - \rho_-)^{(1/\alpha)-1}}{\rho_-}$$

### 3. Preliminaries

The basic idea of the proofs is to represent all necessary processes as functionals of a fixed Brownian motion.

Let  $B = (B(t))_{t \geq 0}$  be a one-dimensional standard Brownian motion starting at 0 and  $\{\ell(t, x); t \geq 0, x \in \mathbf{R}\}$  be the local time of  $B$  with respect to the measure  $2 dx$ :

$$\int_0^t 1_E(B(s)) ds = 2 \int_E \ell(t, x) dx, \quad E \in \mathcal{B}(\mathbf{R}).$$

One of the standard ways to construct a diffusion  $(X(t))_{t \geq 0}$  with the generator

$$(3.1) \quad \mathcal{L} = a(x) \frac{d^2}{dx^2} + b(x) \frac{d}{dx} = \frac{d}{dm(x)} \frac{d}{ds(x)}$$

is the following: Let  $\tilde{m}(x) = m(s^{-1}(x))$  and let

$$(3.2) \quad A(t) = \int_{\mathbf{R}} \ell(t, x) d\tilde{m}(x), \quad t \geq 0.$$

Then, it is well known that

$$(3.3) \quad Y(t) = B(A^{-1}(t)), \quad t \geq 0$$

is a diffusion with the generator  $\tilde{\mathcal{L}} = \frac{d}{d\tilde{m}(x)} \frac{d}{dx}$ , and therefore,

$$(3.4) \quad X(t) := s^{-1}(Y(t)), \quad (t \geq 0)$$

corresponds to (3.1) with the initial condition  $X(0) = 0$  (see Itô-McKean [6]). Therefore, in what follows we shall adopt (3.4) for the ‘definition’ of  $(X(t))_{t \geq 0}$ . Note that (3.3) and (3.4) imply

$$(3.5) \quad X^*(t) = s^{-1}(Y^*(t)) \quad \text{and} \quad Y^*(t) = B^*(A^{-1}(t)), \quad t \geq 0,$$

where  $X^*(t)$ ,  $Y^*(t)$  and  $B^*(t)$  are the maximum processes of  $X(t)$ ,  $Y(t)$  and  $B(t)$ , respectively.

Throughout the paper let us say that a càdlàg stochastic process  $(Z(t))_{t \geq 0}$  is parametrized by  $(x(t), y(t))$  if  $x(\cdot)$  is a càdlàg process,  $y(\cdot)$  is a non-negative, nondecreasing càdlàg process, and if  $Z(t) = x(y^{-1}(t))$  a.s.. For example, (3.5) means that  $X^*(t)$  and  $Y^*(t)$  are parametrized by  $(s^{-1}(B^*(t)), A(t))$  and  $(B^*(t), A(t))$ , respectively. In this way the study of  $X^*(t)$  (or  $Y^*(t)$ ) may be reduced to that of  $(B^*(t), A(t))$ .

LEMMA 3.1. For every  $\lambda > 0$ ,

$$\left( \frac{1}{\lambda} Y^*(c\lambda^{1/\alpha} t) \right)_{t \geq 0}$$

is parametrized by

$$(3.6) \quad \left( \frac{1}{\lambda} B^*(\lambda^2 t), \frac{1}{c\lambda^{1/\alpha}} A(\lambda^2 t) \right)_{t \geq 0}.$$

*Proof.* Simply compute the inverse process of the second component and use (3.5).  $\square$

To find the limiting distribution of (3.6) we prepare

LEMMA 3.2. For every  $\lambda > 0$ ,

$$(3.7) \quad \left( \frac{1}{\lambda} B^*(\lambda^2 t), \frac{1}{c\lambda^{1/\alpha}} A(\lambda^2 t) \right)_{t \geq 0} \stackrel{d}{=} \left( B^*(t), \frac{1}{c} \int_{\mathbf{R}} \ell(t, x) d\tilde{m}_\lambda(x) \right)_{t \geq 0}$$

where

$$\tilde{m}_\lambda(x) = \frac{1}{\lambda^{(1/\alpha)-1}} \tilde{m}(\lambda x), \quad x \in \mathbf{R}.$$

*Proof.* Since

$$\left( \frac{1}{\lambda} B(\lambda^2 t), \ell(\lambda^2 t, x) \right)_{t \geq 0} \stackrel{d}{=} (B(t), \ell(t, x/\lambda))_{t \geq 0},$$

we have  $\left( \frac{1}{\lambda} B^*(\lambda^2 t) \right)_t \stackrel{d}{=} (B^*(t))_t$  and, simultaneously,

$$(3.8) \quad \frac{1}{\lambda^{1/\alpha}} A(\lambda^2 t) \left( = \frac{1}{\lambda^{1/\alpha}} \int_{\mathbf{R}} \ell(\lambda^2 t, x) d\tilde{m}(x) \right)$$

is equivalent in law to

$$(3.9) \quad \frac{\lambda}{\lambda^{1/\alpha}} \int_{\mathbf{R}} \ell(t, x) d\tilde{m}(\lambda x) = \int_{\mathbf{R}} \ell(t, x) d\tilde{m}_\lambda(x). \quad \square$$

We next find the limiting process of (3.7):

LEMMA 3.3. Under the assumptions of Theorem 2.1,

$$(3.10) \quad \left( \frac{1}{\lambda} B^*(\lambda^2 t), \frac{1}{c\lambda^{1/\alpha}} A(\lambda^2 t) \right)_{t \geq 0} \xrightarrow{d} (B^*(t), A_\alpha(t))_{t \geq 0}$$

over the function space  $C([0, \infty); \mathbf{R}^2)$ , where

$$A_\alpha(t) = \int_{\mathbf{R}} \ell(t, x) dm^{(\alpha)}(x), \quad m^{(\alpha)}(x) = \begin{cases} -(-x)^{(1/\alpha)-1} & (x < 0) \\ 0 & (x \geq 0) \end{cases}.$$

*Proof.* We first note that (2.7) implies

$$\begin{aligned} \frac{1}{c} \tilde{m}_\lambda(x) &= \frac{1}{c} m(s^{-1}(\lambda x)) = \frac{1}{c} x^\gamma \frac{m(s^{-1}(\lambda x))}{(\lambda x)^\gamma} \\ &\rightarrow m^{(\alpha)}(x) \quad (\lambda \rightarrow \infty), \quad \forall x \in \mathbf{R}. \end{aligned}$$

Therefore,  $\frac{1}{c} d\tilde{m}_\lambda(x)$  converges vaguely to  $dm^{(\alpha)}(x)$ ; i.e.,

$$\frac{1}{c} \int_{\mathbf{R}} f(x) d\tilde{m}_\lambda(x) \rightarrow \int_{\mathbf{R}} f(x) dm^{(\alpha)}(x) \quad (\lambda \rightarrow \infty)$$

for all continuous function  $f(x)$  vanishing outside a compact set. Thus we have

$$(3.11) \quad \frac{1}{c} \int_{\mathbf{R}} \ell(t, x) d\tilde{m}_\lambda(x) \rightarrow \int_{\mathbf{R}} \ell(t, x) dm^{(\alpha)}(x)$$

for every fixed  $t \geq 0$ . In fact, this convergence is automatically uniform in  $t$  on every finite interval because the both sides are nondecreasing and the right-hand side is continuous by Pólya's extension of Dini's theorem (see e.g. [2, 1.11.22]). Now combining (3.11) with Lemma 3.2 we can deduce (3.10).  $\square$

PROPOSITION 3.4. *Under the assumptions of Theorem 2.1,*

$$\left( \frac{c^\alpha}{\lambda^\alpha} Y^*(\lambda t) \right)_{t \geq 0} \xrightarrow{f.d.} (B^*(A_\alpha^{-1}(t)))_{t \geq 0} \quad (\lambda \rightarrow \infty).$$

*Proof.* In (3.10), each side is a parametrization of  $(1/\lambda)Y^*(c\lambda^{1/\alpha}t)$  or of  $B^*(A_\alpha^{-1}(t))$ . Therefore, Lemma 3.1 implies that

$$\left( \frac{1}{\lambda} Y^*(c\lambda^{1/\alpha}t) \right)_{t \geq 0} \xrightarrow{f.d.} (B^*(A_\alpha^{-1}(t)))_{t \geq 0} \quad (\lambda \rightarrow \infty).$$

For this kind of arguments see Appendix. Now change the variable (replace  $c\lambda^{1/\alpha}$  by  $\lambda$ ).  $\square$

For the proof of Theorem 2.1 our next task is to show that the limit process  $B^*(A_\alpha^{-1}(t))$  in Proposition 3.4 is distributed like  $\xi(Z_\alpha^{-1}(t))$  in Theorem 2.1 up to a multiplicative constant  $C_\alpha$ . To this end let us represent  $Z_\alpha(\cdot)$  and  $\xi(\cdot)$  as functionals of the Brownian motion  $B(\cdot)$ :

Let  $A_\alpha(t)$  be as before and let

$$(3.12) \quad T_\alpha(t) = A_\alpha(\ell^{-1}(t, 0)) \left( = \int_{\mathbf{R}} \ell(\ell^{-1}(t, 0), x) dm^{(\alpha)}(x) \right), \quad t \geq 0.$$

(Here,  $\ell^{-1}(t, 0) := \inf\{s; \ell(s, 0) > t\}$ .) Then, it is well-known that  $(T_\alpha(t))_{t \geq 0}$  is an  $\alpha$ -stable subordinator such that

$$(3.13) \quad E[e^{-sT_\alpha(t)}] = e^{-C_\alpha t s^\alpha}, \quad t \geq 0, s > 0,$$

where  $C_\alpha$  is the same as in (2.8) (see e.g. [9]). Therefore, comparing (1.3) and (3.13), we see that  $(T_\alpha(t/C_\alpha))_{t \geq 0}$  is identical in law to  $(Z_\alpha(t))_{t \geq 0}$ . Thus in what follows it is harmless to assume that

$$(3.14) \quad Z_\alpha(t) = T_\alpha(t/C_\alpha).$$

We next construct a process  $\xi(t)$  given in Theorem 2.1; i.e., a process which is independent of  $Z_\alpha$  and has the marginal distribution (2.5). An answer is

$$\xi(t) = B^*(\ell^{-1}(t)), \quad t \geq 0, \quad \ell(t) = \ell(t, 0).$$

Indeed, this is a canonical extremal process because the right-hand side is the maximum process of a  $(0, \infty)$ -valued Poisson point process with characteristic

measure  $\nu(dx) = x^{-2} dx$ , which fact is well-known in the excursion theory for the Brownian motion (see [7, Sec. 4.3]). It remains to check that  $B^*(\ell^{-1}(\cdot))$  is independent of  $Z_\alpha(\cdot)$ . However, it is clear because  $B^*(\ell^{-1}(\cdot))$  is a functional of positive excursions while  $Z_\alpha(\cdot)$  is a functional of negative excursions (positive excursions and negative excursions are independent).

LEMMA 3.5. *Let  $\zeta(t)$  and  $Z_\alpha(t)$  be as above. Then, for every  $t \geq 0$ ,*

$$B^*(A_\alpha^{-1}(t)) = \zeta(T_\alpha^{-1}(t)) = \zeta\left(\frac{1}{C_\alpha} Z_\alpha^{-1}(t)\right) \quad a.s.$$

*Proof.* Since the latter equality follows from (3.14) we shall prove the first only. By the definition of  $T_\alpha(t)$  (see (3.12)), we have

$$T_\alpha^{-1}(t) = \ell(A_\alpha^{-1}(t)),$$

where  $\ell(t) = \ell(t, 0)$ . Combining this with  $\zeta(t) = B^*(\ell^{-1}(t))$  we roughly have

$$(3.15) \quad \zeta(T_\alpha^{-1}(t)) = B^*(\ell^{-1} \circ \ell \circ A_\alpha^{-1}(t)) = B^*(A_\alpha^{-1}(t)).$$

This heuristic argument involves a problem because, precisely speaking,  $\ell^{-1} \circ \ell(t) = t$  fails. To be strict (3.15) should be replaced by

$$\zeta(T_\alpha^{-1}(t-0) - 0) \leq B^*(A_\alpha^{-1}(t)) \leq \zeta(T_\alpha^{-1}(t))$$

(see Theorem 5.1 in Appendix). Therefore, it remains to show that  $\zeta(T_\alpha^{-1}(t-0) - 0) = \zeta(T_\alpha^{-1}(t))$  with probability one for every fixed  $t \geq 0$ . Since  $T_\alpha^{-1}(t-0) = T_\alpha^{-1}(t)$  a.s. (when  $t$  is fixed), it is sufficient to prove

$$P(\zeta(T_\alpha^{-1}(t) - 0) = \zeta(T_\alpha^{-1}(t))) = 1, \quad \forall t > 0.$$

However, by the independence (see (i)), the left-hand side equals

$$\int_{(0, \infty)} P(\zeta(s-0) = \zeta(s)) \mu_{T_\alpha^{-1}(t)}(ds) = 1$$

because  $\zeta(\cdot)$  is stochastically continuous as we mentioned before. □

Now we have that the limit process in Theorem 2.1 and that in Proposition 3.4 are equivalent in law;

PROPOSITION 3.6.

$$(3.16) \quad (B^*(A_\alpha^{-1}(t)))_{t \geq 0} \stackrel{d}{=} \left( \frac{1}{C_\alpha} \cdot \zeta(Z_\alpha^{-1}(t)) \right)_{t \geq 0}$$

*Proof.* By Lemma 3.5 the left-hand side is identical in law to

$$\left( \zeta\left(\frac{1}{C_\alpha} \cdot Z_\alpha^{-1}(t)\right) \right)_{t \geq 0}$$

and, by the 1-self-similarity of  $\xi(\cdot)$  (see (2.6)), the right-hand side is equivalent in law to the right-hand side of (3.16).  $\square$

COROLLARY 3.7.

$$B^*(A_\alpha^{-1}(1)) \stackrel{d}{=} \frac{1}{C_\alpha} \cdot \xi(1) \cdot Z_\alpha^{-1}(1)$$

*Proof.* The left-hand side is identical in law to  $\frac{1}{C_\alpha} \xi(Z_\alpha^{-1}(1))$  by Proposition 3.6. Since  $\xi(\cdot)$  and  $Z_\alpha^{-1}(1)$  are independent and  $\xi(\cdot)$  is 1-self-similar, we see that  $\xi(Z_\alpha^{-1}(1))$  is equivalent in law to  $Z_\alpha^{-1}(1) \cdot \xi(1)$ .  $\square$

**4. Proofs of Theorems 2.1 and 2.2**

*Proof of Theorem 2.1.* Combining Propositions 3.4 and 3.6 we have

$$\left( \frac{c^\alpha}{\lambda^\alpha} Y^*(\lambda t) \right)_{t \geq 0} \xrightarrow{f.d.} \left( \frac{1}{C_\alpha} \cdot \xi(Z_\alpha^{-1}(t)) \right)_{t \geq 0} \quad (\lambda \rightarrow \infty).$$

Then recall that  $Y^*(t) = s(X^*(t))$  (see (3.5)).  $\square$

*Proof of Theorem 2.2.* Let

$$G_\lambda(x) = \frac{s^{-1}((\lambda/c)^\alpha x) - q((\lambda/c)^\alpha)}{\varphi((\lambda/c)^\alpha)}, \quad x > 0.$$

Then (2.9) implies

$$(4.1) \quad \lim_{\lambda \rightarrow \infty} G_\lambda(x) = G(x), \quad x > 0.$$

Note that the convergence in (4.1) is uniform on every compact set in  $(0, \infty)$  because  $G_\lambda(x)$  is monotone and  $G(x)$  is continuous. Therefore, (4.1) and Theorem 2.1 imply

$$(4.2) \quad G_\lambda \left( \frac{c^\alpha}{\lambda^\alpha} s(X^*(\lambda t)) \right)_{t \geq 0} \xrightarrow{f.d.} G \left( \frac{1}{C_\alpha} \xi(Z_\alpha^{-1}(t)) \right)_{t \geq 0} \quad (\lambda \rightarrow \infty),$$

that is,

$$\frac{1}{\varphi((\lambda/c)^\alpha)} \{X^*(\lambda t) - q((\lambda/c)^\alpha)\} \xrightarrow{f.d.} G \left( \frac{1}{C_\alpha} \xi(Z_\alpha^{-1}(t)) \right)_{t \geq 0}.$$

Especially,

$$\frac{1}{\varphi((\lambda/c)^\alpha)} \{X^*(\lambda) - q((\lambda/c)^\alpha)\} \xrightarrow{d} G \left( \frac{1}{C_\alpha} \xi(Z_\alpha^{-1}(1)) \right).$$

Since  $\xi(Z_x^{-1}(1))$  is equivalent in law to  $Z_x^{-1}(1)\xi(1)$  by the self-similarity of  $(\xi(t))_{t \geq 0}$ , we have the assertion of the theorem.  $\square$

**5. Appendix**

In the present paper we said that a càdlàg process  $(Z(t))_{t \geq 0}$  is parametrized by two càdlàg processes  $X(\cdot)$  and  $Y(\cdot)$  if  $Y(\cdot)$  is nondecreasing and if  $Z(t) = X(Y^{-1}(t))$  a.s. (see Section 3). In this section we prove two theorems on the parametrized processes.

**THEOREM 5.1.** *Let  $f(t), g(t), h(t)$  be nondecreasing, right-continuous and nonnegative functions defined on  $[0, \infty)$  and define  $f_h(t) = f(h(t))$  and  $g_h(t) = g(h(t))$ . Then,*

$$f_h(g_h^{-1}(t - 0) - 0) \leq f(g^{-1}(t)) \leq f_h(g_h^{-1}(t)), \quad t > 0.$$

*Proof.* Draw the graph  $G(g, f) = \{(g(s), f(s)); s \geq 0\}$  and see how  $f(g^{-1}(t))$  is determined. Then observe that  $G(g_h, f_h) \subset G(g, f)$ .  $\square$

Let  $D = D([0, \infty) : \mathbf{R})$  be the space of all  $\mathbf{R}$ -valued càdlàg functions endowed with the usual Skorohod  $J_1$ -topology (see [10] for the definition). We denote by  $\Phi (\subset D)$  the totality of càdlàg nondecreasing functions  $f : [0, \infty) \rightarrow [0, \infty)$  and let  $\Phi_\infty = \{f \in \Phi : \lim_{x \rightarrow \infty} f(x) = \infty\}$ . For  $f \in \Phi$ , we always define  $f(-0) = 0$  for convenience' sake.

**THEOREM 5.2.** *Let  $(X_\lambda(t))_{t \geq 0}, (Y_\lambda(t))_{t \geq 0}, (X(t))_{t \geq 0}$  and  $(Y(t))_{t \geq 0}$  be stochastic processes with sample paths in  $\Phi$  and suppose that  $P(\bar{Y}_\lambda \in \Phi_\infty) = P(Y \in \Phi_\infty) = 1$  so that the inverse processes  $(Y_\lambda^{-1}(t))_{t \geq 0}$  and  $(Y^{-1}(t))_{t \geq 0}$  make sense.*

(i) *If*

$$(5.1) \quad (X_\lambda(t), Y_\lambda(t)) \xrightarrow{d} (X(t), Y(t)) \quad \text{in } D \times D$$

*and if*

$$(5.2) \quad P\{X(Y^{-1}(t - 0) - 0) = X(Y^{-1}(t))\} = 1, \quad \forall t \geq 0$$

*then,*

$$X_\lambda(Y_\lambda^{-1}(t)) \xrightarrow{f.d.} X(Y^{-1}(t)).$$

(ii) *Each of the following two conditions is sufficient for (5.2):*

(A1)  $(X(t))_{t \geq 0}$  *has continuous paths and*

$$P\{Y^{-1}(t - 0) = Y^{-1}(t)\} = 1 \quad (\forall t \geq 0).$$

(A2)  $(X(t))_{t \geq 0}$  *and*  $(Y(t))_{t \geq 0}$  *are independent and*

$$P\{X(t) = X(t - 0)\} = P\{Y^{-1}(t) = Y^{-1}(t - 0)\} = 1 \quad (\forall t \geq 0).$$

*Proof.* By Skorohod's theorem (5.1) can be realized by an almost-sure convergence: On a suitable probability space we can construct càdàg processes  $\hat{X}_\lambda, \hat{X}, \hat{Y}_\lambda, \hat{Y}$  with the following properties.

- (1)  $(\hat{X}_\lambda, \hat{Y}_\lambda)$  is equivalent in law to  $(X_\lambda, Y_\lambda)$
- (2)  $(\hat{X}, \hat{Y})$  is equivalent in law to  $(X, Y)$
- (3)  $(\hat{X}_\lambda, \hat{Y}_\lambda) \xrightarrow{J_1} (\hat{X}, \hat{Y})$  with probability one.

Since  $J_1$ -convergence implies the convergence at all continuity points of the limit function, it follows from (1) that, with probability one,

$$\hat{X}(t-0) \leq \liminf_{\lambda \rightarrow \infty} \hat{X}_\lambda(t-0) \leq \limsup_{\lambda \rightarrow \infty} \hat{X}_\lambda(t) \leq \hat{X}(t), \quad \forall t \geq 0$$

and

$$\hat{Y}^{-1}(t-0) \leq \liminf_{\lambda \rightarrow \infty} \hat{Y}_\lambda^{-1}(t-0) \leq \limsup_{\lambda \rightarrow \infty} \hat{Y}_\lambda^{-1}(t) \leq \hat{Y}^{-1}(t), \quad \forall t \geq 0.$$

(Recall that we defined  $X(t-0) = Y^{-1}(t-0) = 0$  when  $t = 0$ .) Therefore,

$$\begin{aligned} \hat{X}(\hat{Y}^{-1}(t-0) - 0) &\leq \liminf_{\lambda \rightarrow \infty} \hat{X}_\lambda(\hat{Y}_\lambda^{-1}(t-0) - 0) \\ &\leq \limsup_{\lambda \rightarrow \infty} \hat{X}_\lambda(\hat{Y}_\lambda^{-1}(t)) \leq \hat{X}(\hat{Y}^{-1}(t)), \quad \forall t \geq 0 \end{aligned}$$

Thus we can deduce the assertion of (i). Let us prove (ii). Since it is clear that (A1) is sufficient, let us see that (A2) implies (5.2). For every fixed  $t \geq 0$ , we assume that  $P\{Y^{-1}(t) = Y^{-1}(t-0)\} = 1$ . Therefore, it is sufficient to show that

$$P\{X(Y^{-1}(t) - 0) = X(Y^{-1}(t))\} = 1.$$

But this is easy because  $X$  and  $Y$  are independent;

$$P\{X(Y^{-1}(t) - 0) = X(Y^{-1}(t))\} = \int_{[0, \infty)} P\{X(u) = X(u-0)\} \mu_{Y^{-1}(t)}(du) = 1. \quad \square$$

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