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Séminaire de probabilités (Strasbourg), tome 21 (1987), p. 246-261 http://www.numdam.org/item?id=SPS_1987_21_246_0

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LIMIT DISTRIBUTION FOR 1-DIMENSIONAL DIFFUSION IN A REFLECTED BROWNIAN MEDIUM

By H. Tanaka

Introduction

In analogy with Sinai's problem [8] on a random walk in a random medium, Brox [1] considered the diffusion process X(t) described by the stochastic differential equation

(1)
$$dX(t) = dB(t) - \frac{1}{2}W'(X(t))dt$$
, $X(0) = 0$,

where {W(x), $x \in \mathbb{R}$ } is a Brownian medium independent of another Brownian motion B(t), and proved that $(\log t)^{-2}X(t)$ converges in distribution as $t \to \infty$. Similar results in the case of a considerably wider class of self-similar random media were obtained by Schumacher [7]. Recently Kesten [5] obtained the exact form of the limit distribution for Sinai's random walk as well as for a diffusion in a Brownian medium. See also [2] for a related problem.

In this paper we substitute W(x) in (1) by a nonnegative reflected Brownian medium and find the corresponding limit distribution. The result was already anounced in [9] without proof but the Laplace transform of the limit distribution given in [9: §3] is not correct. We give here a full proof to the whole result of [9: §3] with a correction (see Theorem 1 and 2 below). Our method is similar to that of [1].

<u>Theorem 1</u>. Let X(t) be a solution of (1) where $W_{+} = \{W(x), x \ge 0\}$ and $W_{-} = \{W(-x), x \ge 0\}$ are independent reflected Brownian motions on the half line $(0, \infty)$ starting from 0 which are also independent of the Brownian motion B(t). Then the distribution of $(\log t)^{-2}X(t)$ converges as $t \rightarrow \infty$ to the distribution μ defined by

(2)
$$\mu = \int m_W Q(dW)$$

where m_W is the probability measure on \mathbb{R} defined by (3.1) and \mathbb{Q} is the probability measure on the space of media $\mathbb{W} = \mathbb{C}(\mathbb{R} orestyle 0, \infty)) \wedge \{\mathbb{W}:\mathbb{W}(0)=0\}$ such that \mathbb{W}_+ are independent reflected Brownian motions on $(0, \infty)$.

Theorem 2. μ has a symmetric density and for $\lambda > 0$

(3)
$$\int_{0}^{\infty} e^{-\lambda x} \mu(dx) = \int_{0}^{\infty} \frac{\sinh\sqrt{2\lambda}}{\sqrt{2\lambda} \cosh\sqrt{2\lambda} + t \sinh\sqrt{2\lambda}} \cdot \frac{dt}{(1+t)^{2}}$$

The present case is not contained in the framework of (7] since the nonnegative reflected medium W(x) has (uncountably) many points giving its minimum. The case of a nonpositive reflected Brownian medium was discussed in (9). Some generalizations will be discussed in (5).

Acknowledgment. I wish to thank Professor H.Kesten for pointing out mistakes of the first version of this paper.

§1. Preliminaries and exit times from valleys

Let W and Q be defined as in Theorem 1. For each $W \in W$ solutions of the stochastic differential equation (1) define a diffusion process in \mathbb{R} with generator

(1.1)
$$\frac{1}{2} e^{W(x)} \frac{d}{dx} (e^{-W(x)} \frac{d}{dx})$$

Such a diffusion can be constructed from a Brownian motion B(t)' as follows ([4]). Let Ω be the space of continuous functions $\omega : [0, \infty) \rightarrow \mathbb{R}$ with $\omega(0) = 0$, and denote by P the Wiener measure on Ω . Denote the value of ω at time t by $\omega(t)$ or by B(t) and put

$$\begin{split} \mathrm{L}(\mathrm{t},\mathrm{x}) &= \lim_{\varepsilon \neq 0} \frac{1}{\varepsilon} \int_{0}^{\mathrm{t}} \mathbb{I}_{\left[\mathrm{x},\mathrm{x}+\varepsilon\right)}(\mathrm{B}(\mathrm{s})) \mathrm{d}\mathrm{s} \qquad (\text{local time}), \\ \mathrm{S}(\mathrm{x}) &= \int_{0}^{\mathrm{x}} \mathrm{e}^{\mathrm{W}(\mathrm{y})} \mathrm{d}\mathrm{y} , \\ \mathrm{A}(\mathrm{t}) &= \int_{0}^{\mathrm{t}} \mathrm{e}^{-2\mathrm{W}(\mathrm{S}^{-1}(\mathrm{B}(\mathrm{s})))} \mathrm{d}\mathrm{s} = \int_{\mathrm{IR}} \mathrm{e}^{-2\mathrm{W}(\mathrm{S}^{-1}(\mathrm{x}))} \mathrm{L}(\mathrm{t},\mathrm{x}) \mathrm{d}\mathrm{x} , \quad \mathrm{t} \ge 0 , \\ \mathrm{S}^{-1}, \ \mathrm{A}^{-1} = \text{the inverse functions }. \end{split}$$

Then the process $X(t, W) = S^{-1}(B(A^{-1}(t)))$ defined on the probability space (Ω, P) is a diffusion process with generator (1.1) starting at 0. If we set $(W^{X})(\cdot) = W(\cdot + x)$, then $X^{X}(t, W) = x + X(t, W^{X})$ is a diffusion process with generator (1.1) starting at x. Let

$$T(x_1, x_2) = \inf \{t \ge 0 : B(t) \notin (x_1, x_2)\}$$
,

¹⁾ The Brownian motion here is not the same as the one in (1) but we use the same notation B(t) .

$$\begin{split} & L(x_1, x_2, x) = L(T(x_1, x_2), x) , x \in \mathbb{R} , \\ & S_{\lambda}(x) = \int_0^x e^{\lambda W(y)} dy , \\ & X_{\lambda}(t) = X(t, \lambda W) , X_{\lambda}^x(t) = x + X(t, \lambda W^x) . \end{split}$$

Next we define a valley. Given $W \in W$, a quartet $V = (a,b_1,b_2,c)$ is called a <u>valley</u> of W if

(i)
$$a < b_1 < 0 < b_2 < c$$
,
(ii) $W(b_1) = W(b_2) = 0$, $W(a) = W(c) = D$,
(iii) $0 < W(x) < W(a)$ for $a < x < b_1$,
 $0 < W(x) < W(c)$ for $b_2 < x < c$,
(iv) $A_{-} = \sup \{W(y) - W(x) : a < x < y < b_2\} < D$,

$$A_{+} = \sup \{W(x) - W(y) : b_{1} < x < y < c\} < D$$
.

We call D (resp. $A = A \checkmark A_{+}^{2}$) the <u>depth</u> (resp. the <u>inner directed</u> <u>ascent</u>) of V. It is clear that there exist valleys of W with A < 1 < D for almost all reflected Brownian media W.

In what follows let $W \in W$ be given and $V = (a, b_1, b_2, c)$ be a valley of W with the depth D and the inner directed ascent A. We put

$$T^{\mathbf{X}}_{\lambda}$$
 = $T^{\mathbf{X}}_{\lambda}(a, c)$ = inf {t ≥ 0 : $X^{\mathbf{X}}_{\lambda}(t) \notin (a, c)$ }.

The following three lemmas were proved in [1].

Lemma 1. For a < x < c

$$\mathbb{I}_{\lambda}^{\mathbf{x}}(\mathbf{a}, \mathbf{c}) \stackrel{d}{=} \int_{\mathbf{a}}^{\mathbf{c}} \mathbb{L}(\widehat{\mathbf{S}}_{\lambda}(\mathbf{a}), \widehat{\mathbf{S}}_{\lambda}(\mathbf{c}), \widehat{\mathbf{S}}_{\lambda}(\mathbf{y})) e^{-\lambda W(\mathbf{y})} d\mathbf{y} ,$$

where

$$\widehat{S}_{\lambda}(y) = \int_{x}^{y} e^{\lambda W(z)} dz$$

d and = means the equality in distribution.

Lemma 2. For each $\lambda > 0$

$$\{L(\lambda \mathbf{x}_1, \lambda \mathbf{x}_2, \lambda \mathbf{x}), \mathbf{x} \in \mathbb{R}\} \stackrel{d}{=} \{\lambda L(\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}), \mathbf{x} \in \mathbb{R}\}.$$

2) $a \lor b = max \{a, b\}$, $a \land b = min \{a, b\}$.

 $\underline{\text{Lemma 3}}. \text{ For } \lambda > 0 \text{ and } W \in \mathbb{W}$ $(1.2) \qquad \{X(t, \lambda W_{\lambda}), t \ge 0\} \stackrel{d}{=} \{\lambda^{-2}X(\lambda^{4}t, W), t \ge 0\},$

where W_{λ} (ϵW) is defined by

$$W_{\lambda}(x) = \lambda^{-1}W(\lambda^2 x)$$
, $x \in \mathbb{R}$.

The following lemma plays an essential role in our discussions.

Lemma 4. For any $\lambda > 0$ and $[u, v] \subset (a, c)$

$$\inf_{u \le x \le v} \mathbb{P}\left\{ e^{\lambda(D-\delta)} < \mathbb{T}_{\lambda}^{x} < e^{\lambda(D+\delta)} \right\} \neq 1 , \quad \lambda \neq \infty .$$

Proof. The proof is similar to that of the corresponding lemma of (1) but even much simpler. Let $x \in [u, v]$ be fixed. Setting

$$s_{\lambda}(y) = \widehat{S}_{\lambda}(y) / \widehat{S}_{\lambda}(c) = \int_{x}^{y} e^{\lambda W(z)} dz / \int_{x}^{c} e^{\lambda W(z)} dz$$

and applying Lemma 1 and 2, we have

$$T_{\lambda}^{\mathbf{x}} = \widehat{S}_{\lambda}(c) \int_{a}^{c} L(s_{\lambda}(a), 1, s_{\lambda}(y)) e^{-\lambda W(y)} dy$$
.

Since

$$\widehat{S}_{\lambda}(c) \leq (c - x) \exp \left\{ \lambda \max_{[x,c]} W \right\}^{3}$$

$$T_{\lambda}^{x} \stackrel{d}{\leq} (c - x)(c - a) \exp \left\{ \lambda \max_{[x,c]} W - \lambda \min_{[a,c]} W \right\} L' \leq (c - a)^{2} L' e^{\lambda D},$$

$$L' = \max_{y \leq 1} L(-\infty, 1, y),$$

we have

$$P\left\{T_{\lambda}^{x} > e^{\lambda(D+\delta)}\right\}$$

$$\leq P\left\{(c - a)^{2}L'e^{\lambda D} > e^{\lambda(D+\delta)}\right\}$$

$$= P\left\{L' > e^{\lambda\delta}/(c - a)^{2}\right\} \rightarrow 0, \lambda \rightarrow \infty.$$

To obtain an estimate from below first we notice that

(1.3)
$$\lim_{\lambda \to \infty} \lambda^{-1} \log C_{\lambda} = D,$$

3)
$$\max W = \max\{W(x), x \in I\}$$
, $\min W = \min\{W(x), x \in I\}$.
I

where

$$C_{\lambda} = |\widehat{S}_{\lambda}(a)| \wedge |\widehat{S}_{\lambda}(c)|$$
,

and the convergence is uniform in $x \in [u, v]$. Next, for given $\delta > 0$ we set

$$\begin{aligned} \mathbf{a}_{1} &= \sup\{\mathbf{x} < \mathbf{b}_{1} : W(\mathbf{x}) = \delta/4\}, \\ \widehat{\mathbf{s}}_{\lambda}(\mathbf{y}) &= \widehat{\mathbf{S}}_{\lambda}(\mathbf{y})/\mathbf{C}_{\lambda}, \\ \mathbf{L}_{\lambda} &= \min\{\mathbf{L}(-1, 1, \mathbf{y}) : \widehat{\mathbf{s}}_{\lambda}(\mathbf{a}_{1}) \le \mathbf{y} \le \widehat{\mathbf{s}}_{\lambda}(\mathbf{b}_{1})\}. \end{aligned}$$

Then applying Lemma 1 and 2 we have

$$\begin{aligned} \mathbf{T}_{\lambda}^{\mathbf{x}} &= \mathbf{C}_{\lambda} \int_{\mathbf{a}}^{\mathbf{c}} \mathbf{L}(\widehat{\mathbf{s}}_{\lambda}(\mathbf{a}), \widehat{\mathbf{s}}_{\lambda}(\mathbf{c}), \widehat{\mathbf{s}}_{\lambda}(\mathbf{y})) e^{-\lambda W(\mathbf{y})} d\mathbf{y} \\ &\geq \mathbf{C}_{\lambda} \int_{\mathbf{a}_{1}}^{\mathbf{b}_{1}} \mathbf{L}(-1, 1, \widehat{\mathbf{s}}_{\lambda}(\mathbf{y})) e^{-\lambda W(\mathbf{y})} d\mathbf{y} \\ &\geq e^{\lambda (\mathbf{D} - \frac{\delta}{4})} (\mathbf{b}_{1} - \mathbf{a}_{1}) \mathbf{L}_{\lambda} \exp\left\{-\lambda \max_{\left[\mathbf{a}_{1}, \mathbf{b}_{1}\right]}^{\mathbf{a}}\right\} \\ &= (\mathbf{b}_{1} - \mathbf{a}_{1}) \mathbf{L}_{\lambda} e^{\lambda (\mathbf{D} - \frac{\delta}{2})} . \end{aligned}$$

Since $\lambda^{-1}\log|\hat{s}_{\lambda}(a_1)|$ and $\lambda^{-1}\log|\hat{s}_{\lambda}(b_1)|$ converges to max W - D, $\begin{bmatrix}x \wedge a_1, x \vee a_1\end{bmatrix}$ max W - D, respectively, which are both negative, we have $\begin{bmatrix}x \wedge b_1, x \vee b_1\end{bmatrix}$

$$\lim_{\lambda \to \infty} \widehat{s}_{\lambda}(a_{1}) = \lim_{\lambda \to \infty} \widehat{s}_{\lambda}(b_{1}) = 0$$

the convergence being uniform in $x \in [u, v]$. Therefore

$$P\left\{T_{\lambda}^{X} < e^{\lambda(D-\delta)}\right\} \leq P\left\{L_{\lambda} < (b_{1} - a_{1})^{-1}e^{-\lambda\delta/2}\right\} + 0 , \lambda \neq \infty$$

uniformly in $x \in [u, v]$, because $\lim_{\lambda \neq \infty} L_{\lambda} = L(-1, 1, 0) > 0$.

§2. The limit distribution of $X(e^{\lambda r}, \lambda W)$

In this section we change the notation slightly. Given $W \in W$ and a valley $V = (a, b_1, b_2, c)$ of W, we set

$$\Omega = C([0, \infty) \rightarrow \mathbb{R}) ,$$

$$\widehat{\Omega} = C([0, \infty) \rightarrow [a, c]) ,$$

and denote by P_{λ}^{x} , $x \in \mathbb{R}$ (resp. \hat{P}_{λ}^{y} , $y \in [a, c]$) the probability measure

on Ω (resp. $\widehat{\Omega})$ induced by the diffusion process with generator

(2.1)
$$\frac{1}{2} e^{\lambda W(x)} \frac{d}{dx} \left(e^{-\lambda W(x)} \frac{d}{dx} \right)$$

(resp. the diffusion process on [a, c] with (local) generator (2.1) and with reflecting barriers at a and c). The latter diffusion has the invariant probability measure m_{λ} given by

$$m_{\lambda}(dy) = e^{-\lambda W(y)} dy / \int_{a}^{c} e^{-\lambda W(z)} dz$$
.

For any interval $[u, v] \subset [a, c]$

$$m_{\lambda}([u, v]) = \frac{\int_{0}^{\infty} e^{-\lambda\xi} K([u, v], \xi) d\xi}{\int_{0}^{\infty} e^{-\lambda\xi} K([a, c], \xi) d\xi}$$

where, for an interval I in ${\rm I\!R}$, $K(I,\,\xi)$ is the local time at ξ for the reflected Brownian medium, i.e.,

(2.2)
$$K(I, \xi) = \lim_{\epsilon \neq 0} \frac{1}{\epsilon} \int_{I} \mathbb{I}_{[\xi, \xi+\epsilon)}(W(s)) ds .$$

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Therefore

(2.3)
$$m_{\lambda}([u, v]) = \frac{\int_{0}^{e^{-\xi}} K([u, v], \lambda^{-1}\xi) d\xi}{\int_{0}^{\infty} e^{-\xi} K([a, c], \lambda^{-1}\xi) d\xi}$$
$$\rightarrow \frac{K([u, v], 0)}{K([a, c], 0)} \equiv m([u, v]), \quad \lambda \neq \infty.$$

Next we set

$$\hat{\mathbf{P}}_{\lambda} = \int_{\mathbf{a}}^{b} \mathbf{m}_{\lambda}(\mathbf{d}\mathbf{y}) \hat{\mathbf{P}}_{\lambda}^{\mathbf{y}} , \quad \mathbb{P}_{\lambda}^{\mathbf{x},\mathbf{y}} = \mathbf{P}_{\lambda}^{\mathbf{x}} \otimes \hat{\mathbf{P}}_{\lambda}^{\mathbf{y}} , \quad \mathbb{P}_{\lambda}^{\mathbf{x}} = \mathbf{P}_{\lambda}^{\mathbf{x}} \otimes \hat{\mathbf{P}}_{\lambda}^{\mathbf{x}} .$$

$$\mathbf{R} = \mathbf{R}(\boldsymbol{\omega}, \, \widehat{\boldsymbol{\omega}}) = \inf\{\mathbf{t} \ge 0 : \boldsymbol{\omega}(\mathbf{t}) = \, \widehat{\boldsymbol{\omega}}(\mathbf{t})\} .$$

Lemma 5. For any $\delta > 0$

$$\lim_{\lambda \to \infty} \mathbb{P}^{0}_{\lambda} \Big\{ \mathbb{R} < e^{\lambda (A + \delta)} \Big\} = 1 .$$

Proof. First we prove that

(2.4)
$$\lim_{\lambda \to \infty} \mathbb{P}_{\lambda}^{\mathbf{X}} \left\{ \mathbb{R} < e^{\lambda(A+\delta)} \right\} = 1 \text{ holds for } \mathbf{x} = \mathbf{b}_{1} \text{ and } \mathbf{b}_{2}.$$

Without loss of generality we may consider the case $x = b_2$. We write b instead of b_2 for simplicity. For any $\delta > 0$ such that $A + \delta < D$ we define $a_1 \in (a, b_1)$, $a_2 \in (a, b_1)$, $c_2 \in (b_2, c)$ by

$$a_{1} = \max \left\{ x < b_{1} : W(x) = A + \frac{\delta}{4} \right\},$$

$$a_{2} = \max \left\{ x < b_{1} : W(x) = A + \frac{\delta}{2} \right\},$$

$$c_{2} = \min \left\{ x > b_{2} : W(x) = A + \frac{\delta}{2} \right\},$$

and set

$$\begin{split} \mathbf{T}_{0} &= \mathbf{T}_{0}(\omega) = \inf \left\{ t \ge 0 : \mathbf{w}(t) = \mathbf{a}_{1} \right\}, \\ \mathbf{T}_{1} &= \mathbf{T}_{1}(\omega) = \inf \left\{ t \ge 0 : \mathbf{w}(t) \notin (\mathbf{a}_{1}, \mathbf{c}_{2}) \right\}, \\ \mathbf{T}_{2} &= \mathbf{T}_{2}(\omega) = \inf \left\{ t \ge 0 : \mathbf{w}(t) \notin (\mathbf{a}_{2}, \mathbf{c}_{2}) \right\}. \end{split}$$

Then we can prove easily that

(2.5)
$$\mathbb{P}_{\lambda}^{b}\left\{\mathbb{T}_{0} < \infty\right\} \ge \mathbb{P}_{\lambda}^{b}\left\{\mathbb{T}_{0} = \mathbb{T}_{1}\right\} = \frac{\mathbb{S}_{\lambda}(\mathbb{C}_{2}) - \mathbb{S}_{\lambda}(\mathbb{D})}{\mathbb{S}_{\lambda}(\mathbb{C}_{2}) - \mathbb{S}_{\lambda}(\mathbb{A}_{1})} \to 1 , \lambda \to \infty ,$$

and hence

$$(2.6) \qquad \mathbb{P}_{\lambda}^{b} \Big\{ \mathbb{R} \leq \mathbb{T}_{0} \Big\} \\ \geq \mathbb{P}_{\lambda}^{b} \Big\{ \widehat{\omega}(0) \in \{a, b\}, \widehat{\omega}(\mathbb{T}_{0}) \in \{a_{1}, c\} \Big\} \\ \geq \mathbb{P}_{\lambda}^{b} \Big\{ \widehat{\omega}(0) \in \{a, b\} \Big\} + \mathbb{P}_{\lambda}^{b} \Big\{ \widehat{\omega}(\mathbb{T}_{0}) \in \{a_{1}, c\} \Big\} - 1 \\ = \mathbb{m}_{\lambda}(\{a, b\}) + \int_{0}^{\infty} \widehat{\mathbb{P}}_{\lambda} \Big\{ \widehat{\omega}(t) \in \{a_{1}, c\} \Big\} \mathbb{P}_{\lambda}^{b} \Big\{ \mathbb{T}_{0} \in dt \Big\} - 1 \\ \rightarrow 1, \lambda \rightarrow \infty,$$

by (2.3) because $m(\{x \in (a, c) : W(x) = 0\}) = 1$. On the other hand Lemma 4 applied to the valley (a_2, b_1, b_2, c_2) whose depth is $A + (\delta/2)$ implies

(2.7)
$$P_{\lambda}^{b} \left\{ T_{1} < e^{\lambda(A+\delta)} \right\} \ge P_{\lambda}^{b} \left\{ T_{2} < e^{\lambda(A+\delta)} \right\} \to 1 , \lambda \to \infty ,$$

and so

$$\begin{split} & \mathbb{P}_{\lambda}^{\mathbf{X}} \Big\{ \mathbb{R} < e^{\lambda(\mathbb{A} + \delta)} \Big\} \\ & \geq \mathbb{P}_{\lambda}^{\mathbf{X}} \Big\{ \mathbb{T}_{0} < e^{\lambda(\mathbb{A} + \delta)} \Big\} - o(1) \qquad (by (2.6)) \\ & \geq \mathbb{P}_{\lambda}^{\mathbf{X}} \Big\{ \mathbb{T}_{1} < e^{\lambda(\mathbb{A} + \delta)}, \ \mathbb{T}_{1} = \mathbb{T}_{0} \Big\} - o(1) \end{split}$$

$$\geq \mathbb{P}_{\lambda}^{\mathbf{x}} \left\{ \mathbb{T}_{1} < e^{\lambda(\mathbf{A} + \delta)} \right\} - o(1) \qquad (by (2.5))$$

$$\rightarrow 1, \quad as \quad \lambda \to \infty \qquad (by (2.7))$$

Next, to consider the case where the diffusion starts at 0 we shall consider three diffusion processes starting at 0, b_1 and b_2 , respectively. By making use of the comparison theorem in one-dimensional diffusion processes (for example, see [3: p.352]) we can construct, on a suitable probability space $(\widetilde{\Omega}_{\lambda}, \widetilde{P}_{\lambda})$, three processes $\widetilde{X}_0(t)$, $\widetilde{X}_1(t)$ and $\widetilde{X}_2(t)$ such that the probability measure on Ω induced by $\widetilde{X}_0(t)$ (resp. $\widetilde{X}_1(t), \widetilde{X}_2(t)$) coincides with P^0_{λ} (resp. $P^{b_1}_{\lambda}$, $P^{b_2}_{\lambda}$) and

(2.8)
$$\widetilde{X}_{1}(t) \leq \widetilde{X}_{0}(t) \leq \widetilde{X}_{2}(t)$$
, $\forall_{t \geq 0}$, \widetilde{P}_{λ} -a.s.

Put

$$\begin{split} \widetilde{\mathbb{P}}_{\lambda} &= \widetilde{\mathbb{P}}_{\lambda} \bigotimes \, \widehat{\mathbb{P}}_{\lambda} , \\ \widetilde{\mathbb{R}}_{\underline{i}} &= \inf \Big\{ t \geq 0 \, : \, \widetilde{X}_{\underline{i}}(t) \, = \, \widehat{\omega}(t) \Big\} , \quad \underline{i} = 0, \, 1, \, 2 \, . \end{split}$$

Since
$$\widetilde{\mathbb{R}}_{0} \leq \widetilde{\mathbb{R}}_{1} \vee \widetilde{\mathbb{R}}_{2}$$
 by (2.8), we have

$$P_{\lambda}^{0} \left\{ \mathbb{R} < e^{\lambda(A+\delta)} \right\} = \widetilde{\mathbb{P}}_{\lambda} \left\{ \widetilde{\mathbb{R}}_{0} < e^{\lambda(A+\delta)} \right\}$$

$$\geq \widetilde{\mathbb{P}}_{\lambda} \left\{ \widetilde{\mathbb{R}}_{1} \vee \widetilde{\mathbb{R}}_{2} < e^{\lambda(A+\delta)} \right\}$$

$$\geq \mathbb{P}_{\lambda}^{b_{1}} \left\{ \mathbb{R} < e^{\lambda(A+\delta)} \right\} + \mathbb{P}^{b_{2}} \left\{ \mathbb{R} < e^{\lambda(A+\delta)} \right\} - 1$$

$$\longrightarrow 1, \quad \lambda \to \infty$$

by (2.4), completing the proof of Lemma 5.

Lemma 6. For any \mathbf{r}_1 , \mathbf{r}_2 with $\mathbb{A}\!<\!\mathbf{r}_1\!<\!\mathbf{r}_2\!<\!\mathbb{D}$ and for any interval (u, v) in \mathbb{R}

$$\lim_{\lambda \to \infty} \mathbb{P}^{0}_{\lambda} \left\{ \omega(e^{\lambda r}) \in [u, v] \right\} = \mathbb{m}([u, v] \cap [b_{1}, b_{2}])$$

uniformly in $r \in [r_1, r_2]$, where m is defined in (2.3).

Proof. Denote by T (resp. \widehat{T}) the exit time of (a, c) for $\omega(t)$ (resp. $\widehat{\omega}(t)$), and by \widetilde{T}_R (resp. \widehat{T}_R) the exit time of (a, c) for $\omega(t)$ (resp. $\widehat{\omega}(t)$) after the collision time R. Since $m_\lambda(U) \rightarrow 1$ as $\lambda \rightarrow \infty$ for any open set U containing $\{x \in (a, c) : W(x) = 0\}$, it follows from Lemma 4 that

$$\widehat{P}_{\lambda}\left\{e^{\lambda(D-\delta)} < \widehat{T} < e^{\lambda(D+\delta)}\right\}$$

$$= \int_{a}^{c} \mathfrak{m}_{\lambda}(\mathrm{d} x) \mathbb{P}_{\lambda}^{x} \left\{ \mathrm{e}^{\lambda(D-\delta)} < T < \mathrm{e}^{\lambda(D+\delta)} \right\}$$
$$\longrightarrow 1, \lambda \to \infty.$$

This combined with Lemma 5 implies

$$\begin{split} \mathbf{p}_{\lambda} &:= \mathbb{P}_{\lambda}^{0} \Big\{ \mathbb{R} < \mathbf{e}^{\lambda \mathbf{r}_{1}} < \mathbf{e}^{\lambda \mathbf{r}_{2}} < \widehat{\mathbf{T}}_{\mathbb{R}} \Big\} \\ &\geq \mathbb{P}_{\lambda}^{0} \Big\{ \mathbb{R} < \mathbf{e}^{\lambda \mathbf{r}_{1}} < \mathbf{e}^{\lambda \mathbf{r}_{2}} < \widehat{\mathbf{T}} \Big\} \quad (:: \widehat{\mathbf{T}} \leq \widehat{\mathbf{T}}_{\mathbb{R}}) \\ &\longrightarrow 1 , \lambda \rightarrow \infty . \end{split}$$

Therefore for $r \in [r_1, r_2]$

$$(2.9) \qquad P_{\lambda}^{0} \left\{ \omega(e^{\lambda r}) \in [u, v] \right\} \\ \geq \mathbb{P}_{\lambda}^{0} \left\{ \mathbb{R} < e^{\lambda r} , \omega(e^{\lambda r}) \in [u, v], e^{\lambda r} < \widetilde{T}_{R} \right\} \\ = \mathbb{P}_{\lambda}^{0} \left\{ \mathbb{R} < e^{\lambda r} , \widehat{\omega}(e^{\lambda r}) \in [u, v], e^{\lambda r} < \widetilde{T}_{R} \right\} \\ \geq \mathbb{P}_{\lambda} + \mathbb{P}_{\lambda}([u, v]) - 1 \\ \rightarrow \mathbb{P}([u, v] \land [b_{1}, b_{2}]), \lambda \rightarrow \infty ;$$

as for the above equality we used the strong Markov property. Similarly we have

$$\lim_{\lambda \to \infty} \mathbb{P}^{0}_{\lambda} \Big\{ \omega(e^{\lambda r}) \in [u, v]^{c} \Big\} \geq \mathbb{M}([u, v]^{c} \land [b_{1}, b_{2}]) ,$$

which combined with (2.9) implies

$$\mathbb{P}^{0}_{\lambda} \Big\{ \omega(e^{\lambda r}) \in [u, v] \Big\} \to \mathbb{m}([u, v] \land [b_{1}, b_{2}]) , \lambda \to \infty .$$

The uniform convergence in $r \in [r_1, r_2]$ is also clear.

§3. Proof of Theorem 1

Let $V = (a, b_1, b_2, c)$ be a valley of W such that A < 1 < D. Such a valley exists with Q-probability 1. In fact, b_1 and b_2 are taken as

> b_1 = the smallest root of W(x) = 0 in (a', 0) b_2 = the largest root of W(x) = 0 in (0, c')

where $a' = \sup \{x < 0 : W(x) = 1\}$ and $c' = \inf \{x > 0 : W(x) = 1\}$. The endpoints a and c can be chosen suitably so that a < a', c > c' and

 $V = (a, b_1, b_2, c)$ is a valley with A < 1 < D. In what follows $V = (a, b_1, b_2, c)$ denotes such a valley of W. We denote by m_W the probability measure on R defined by

(3.1)
$$m_{W}((u, v)) = \frac{K((u', v'), 0)}{K((b_{1}, b_{2}), 0)}$$

where $[u', v'] = [u, v] \land [b_1, b_2]$. Then, in the notation of §1 Lemma 6 reads as follows: For any interval I in \mathbb{R} and for any family $\{r(\lambda), \lambda > 0\}$ satisfying $\lim_{\lambda \to \infty} r(\lambda) = 1$,

(3.2)
$$\lim_{\lambda \to \infty} \mathbb{P} \left\{ \mathbb{X}(e^{\lambda r(\lambda)}, \lambda \mathbb{W}) \in \mathbb{I} \right\} = \mathbb{M}_{\mathbb{W}}(\mathbb{I})$$

for almost all W with respect to Q. Now we define $\mathbb{P} = P \otimes Q$ and $\mu = \int m_W Q(dW)$. Integrating both sides of (3.2) with respect to Q we have

(3.3)
$$\lim_{\lambda \to \infty} \mathbb{P}\left\{ \mathbb{X}(e^{\lambda r(\lambda)}, \lambda W) \in I \right\} = \mu(I) .$$

Next, define W_{λ} as in Lemma 3. Then $\{W_{\lambda}(x), x \in \mathbb{R}\}$ is again a reflected Brownian medium. Therefore (3.3) yields

(3.4)
$$\lim_{\lambda \to \infty} \mathbb{P}\left\{ \mathbb{X}(e^{\lambda r(\lambda)}, \lambda \mathbb{W}_{\lambda}) \in \mathbb{I} \right\} = \mu(\mathbb{I}) .$$

We now apply the scaling relation (1.2) to (3.4); the result is

$$\lim_{\lambda \to \infty} \mathbb{P}\left\{\lambda^{-2} \mathbb{X}(\lambda^{4} e^{\lambda r(\lambda)}, \mathbb{W}) \in \mathbb{I}\right\} = \mu(\mathbb{I}) .$$

Taking $r(\lambda) = 1 - 4\lambda^{-1} \cdot \log \lambda$ in the above, we obtain

$$\lim_{\lambda \to \infty} \mathbb{P}\left\{\lambda^{-2} \mathbb{X}(e^{\lambda}, \mathbb{W}) \in \mathbb{I}\right\} = \mu(\mathbb{I}) .$$

This completes the proof of Theorem 1.

§4. Proof of Theorem 2

The absolute continuity of μ can be proved easily. In fact, if $\mu_{\rm n}$ is the measure in R defined by

$$\mu_{n}(I) = E^{Q} \left\{ \frac{K(I \cap [b_{1}, b_{2}])}{K([b_{1}, b_{2}])} ; K([b_{1}, b_{2}]) > \frac{1}{n} \right\},$$

then μ_n is absolutely continuous because

$$\begin{split} \mu_{n}(I) &\leq n E^{\mathbb{Q}} \Big\{ K(I \cap [b_{1}, b_{2}]) \Big\} \\ &= 2n \int_{I} p(IxI, 0, 0) dx , \end{split}$$

where $p(t, \xi, \eta)$ is the transition density of the Brownian motion with absorbing barriers at ± 1 . Thus μ is absolutely continuous because $\mu_n \uparrow \mu$ as $n \uparrow \infty$.

We proceed to the proof of (3). Let K(I) = K(I, 0) be the local time at 0 for the reflected Brownian medium as defined by (2.2) with $\xi = 0$ and consider the number of times $d_{\xi}(t)$ that the reflected Brownian path $\{W(u) : u \ge 0\}$ crosses down from $\xi > 0$ to 0 before time t. Then as found in [4: p.48]

(4.1)
$$Q\left\{\lim_{\varepsilon \downarrow 0} 2\varepsilon d_{\varepsilon}(t) = K([0, t]), t \ge 0\right\} = 1.$$

Let a', c', b_1 and b_2 be defined as in the beginning of §3.

(4.2)
$$\mathbb{E}^{\mathbb{Q}}\left\{e^{-\alpha K([0,b_{2}])-\beta c'}\right\} = \frac{1}{2\alpha + c(\beta)} \cdot \frac{2\sqrt{2\beta}}{e^{\sqrt{2\beta}} - e^{-\sqrt{2\beta}}}$$

where

$$c(\beta) = \frac{e^{\sqrt{2\beta}} + e^{-\sqrt{2\beta}}}{e^{\sqrt{2\beta}} - e^{-\sqrt{2\beta}}} \cdot \sqrt{2\beta}$$

In Particular, $K([0, b_2])$ is exponentially distributed:

(4.3)
$$\mathbb{E}^{\mathbb{Q}}\left\{e^{-\alpha K([0,b_2])}\right\} = \frac{1}{2\alpha + 1} \cdot$$

Proof. Since $c(\beta) \sim 1$ as $\beta \downarrow 0$, (4.3) follows from (4.2) by letting $\beta \downarrow 0$. To prove (4.2) we first apply (4.1) to write down

$$\begin{array}{ll} (4.4) & \mathbb{E}^{\mathbb{Q}} \left\{ \mathrm{e}^{-\alpha \mathrm{K}([0, \mathbf{b}_{2}]) - \beta \mathrm{c}'} \right\} \\ & = \mathbb{E}^{\mathbb{Q}} \left\{ \mathrm{e}^{-\alpha \mathrm{K}([0, \mathbf{c}']) - \beta \mathrm{c}'} \right\} \\ & = \mathbb{E}^{\mathbb{Q}} \left\{ \mathrm{e}^{-\alpha \mathrm{K}([0, \mathbf{c}']) - \beta \mathrm{c}'} \right\} \\ & = \lim_{\mathcal{E} \downarrow 0} \mathbb{E}^{\mathbb{Q}} \left\{ \mathrm{e}^{-2\alpha \mathcal{E} \mathrm{d}_{\mathcal{E}}(\mathrm{c}') - \beta \mathrm{c}'} \right\} \\ & = \lim_{\mathcal{E} \downarrow 0} \mathbb{E}^{\mathbb{Q}} \left\{ \mathrm{e}^{-2\alpha \mathcal{E} \mathrm{d}_{\mathcal{E}}(\mathrm{c}') - \beta \mathrm{c}'} \right\} \\ & = \lim_{\mathcal{E} \downarrow 0} \sum_{n=0}^{\infty} \mathrm{e}^{-2\alpha \mathcal{E} \mathrm{n}} \mathbb{E}^{\mathbb{Q}} \left\{ \mathrm{e}^{-\beta \mathrm{T}_{\mathcal{E}}} \right\}^{n+1} \mathbb{E}^{\mathbb{Q}}_{\mathcal{E}} \left\{ \mathrm{e}^{-\beta \mathrm{T}_{0}}; \mathbb{T}_{0} < \mathbb{T}_{1} \right\}^{n} \mathbb{E}^{\mathbb{Q}}_{\mathcal{E}} \left\{ \mathrm{e}^{-\beta \mathrm{T}_{1}}; \mathbb{T}_{1} < \mathbb{T}_{0} \right\} , \end{array}$$

where $\mathbb{E}^{\mathbb{Q}}_{\mathcal{E}}$ denotes the expectation with respect to the probability measure of the reflected Brownian motion starting at $\mathcal E$ and

$$T_x = \inf \left\{ u \ge 0 : W(u) = x \right\}$$

If we set

$$A_{\boldsymbol{\varepsilon}} = e^{-2 \boldsymbol{\alpha} \boldsymbol{\varepsilon}} E^{\mathbb{Q}} \left\{ e^{-\boldsymbol{\beta} T_{\boldsymbol{\varepsilon}}} \right\} E^{\mathbb{Q}}_{\boldsymbol{\varepsilon}} \left\{ e^{-\boldsymbol{\beta} T_{0}}; T_{0} < T_{1} \right\},$$
$$B_{\boldsymbol{\varepsilon}} = E^{\mathbb{Q}} \left\{ e^{-\boldsymbol{\beta} T_{\boldsymbol{\varepsilon}}} \right\} E^{\mathbb{Q}}_{\boldsymbol{\varepsilon}} \left\{ e^{-\boldsymbol{\beta} T_{1}}; T_{1} < T_{0} \right\},$$

then (4.4) yields

(4.5)
$$E^{\mathbb{Q}}\left\{e^{-\alpha K([0,b_2])-\beta c'}\right\} = \lim_{\varepsilon \downarrow 0} B_{\varepsilon} \sum_{n=0}^{\infty} A_{\varepsilon}^{n}$$
$$= \lim_{\varepsilon \downarrow 0} \frac{B_{\varepsilon}}{1-A_{\varepsilon}} .$$

Next we make use of the well-known formula

$$\mathbb{E}_{x}\left\{e^{-\alpha T}a; T_{a} < T_{b}\right\} = \frac{e^{\sqrt{2\alpha}(b-x)} - e^{-\sqrt{2\alpha}(b-x)}}{e^{\sqrt{2\alpha}(b-a)} - e^{-\sqrt{2\alpha}(b-a)}}, \quad a \le x \le b,$$

where ${\rm E}_{_{\bf X}}$ denotes the expectation with respect to the probability measure of a standard Brownian motion starting at $\,$ x . We then have

$$(4.6) \qquad \mathbb{E}^{\mathbb{Q}}\left\{e^{-\beta T_{\varepsilon}}\right\} = 2\mathbb{E}_{0}\left\{e^{-\beta T_{\varepsilon}}; T_{\varepsilon} < T_{-\varepsilon}\right\}$$
$$= \frac{2(e^{\varepsilon/2\beta} - e^{-\varepsilon/2\beta})}{e^{2\varepsilon/2\beta} - e^{-2\varepsilon/2\beta}}$$
$$= 1 + 0(\varepsilon^{2}), \quad \varepsilon \downarrow 0;$$

(4.7)
$$E_{\mathcal{E}}^{\mathbb{Q}} \left\{ e^{-\beta T_{0}}; T_{0} < T_{1} \right\} = \frac{e^{\sqrt{2\beta}(1-\epsilon)} - e^{-\sqrt{2\beta}(1-\epsilon)}}{e^{\sqrt{2\beta}} - e^{-\sqrt{2\beta}}}$$

= 1 - $\frac{\sqrt{2\beta}(e^{\sqrt{2\beta}} + e^{-\sqrt{2\beta}})}{e^{\sqrt{2\beta}} - e^{-\sqrt{2\beta}}} \cdot \epsilon + o(\epsilon), \quad \epsilon \downarrow 0 ;$

(4.8)
$$\mathbb{E}_{\mathcal{E}}^{\mathbb{Q}} \left\{ e^{-\beta T_{1}}; T_{1} < T_{0} \right\} = \frac{e^{\sqrt{2\beta} \mathcal{E}} - e^{-\sqrt{2\beta} \mathcal{E}}}{e^{\sqrt{2\beta}} - e^{-\sqrt{2\beta}}}$$
$$\sim \frac{2\sqrt{2\beta}}{e^{\sqrt{2\beta}} - e^{-\sqrt{2\beta}}} \cdot \mathcal{E} , \quad \mathcal{E} \downarrow 0 .$$

From (4.6), (4.7) and (4.8) we obtain

$$\frac{{}^{\mathrm{B}}\varepsilon}{1-\mathrm{A}_{\varepsilon}} \sim \frac{1}{2\,\alpha+\,\mathrm{c}(\beta)} \cdot \frac{2\sqrt{2\beta}}{\mathrm{e}^{\sqrt{2\beta}}-\,\mathrm{e}^{-\sqrt{2\beta}}} , \varepsilon \downarrow 0 ,$$

which combined with (4.5) proves the lemma. Given x > 0 we set

$$K_1 = K([b_1,0]), \quad K_2 = K([0,x]), \quad K_3 = K([x,b_2]).$$

$$\begin{array}{l} \underline{\text{Lemma 8}}, \quad \text{For } x > 0 \quad \text{and } t > 0 \\ (4.9) \qquad & \mathbb{E}^{\mathbb{Q}} \Big\{ \mathbb{K}_{3} e^{-t(\mathbb{K}_{1} + \mathbb{K}_{2} + \mathbb{K}_{3})}; \ x < \mathbb{b}_{2} \Big\} \\ & = \frac{2}{(2t + 1)^{3}} \mathbb{E}^{\mathbb{Q}} \Big\{ (1 - \mathbb{W}(x)) e^{-t\mathbb{K}([0, x])}; \ x < \mathbb{c}' \Big\} . \end{array}$$

Proof. The left hand side of (4.9) equals

$$E^{Q}\left\{e^{-tK_{1}}\right\}E^{Q}\left\{K_{3}e^{-t(K_{2}+K_{3})}; x < b_{2}\right\}$$

Since $E^{\mathbb{Q}}\left\{e^{-tK}\right\} = (2t + 1)^{-1}$ by Lemma 7, for the proof of the lemma it is enough to show

(4.10)
$$E^{\mathbb{Q}}\left\{K_{3}e^{-t(K_{2}+K_{3})}; x < b_{2}\right\}$$

= $\frac{2}{(2t + 1)^{2}}E^{\mathbb{Q}}\left\{(1 - W(x))e^{-tK_{2}}; x < c'\right\}$.

To prove this we introduce the smallest σ -field \mathcal{F}_{x} on W which makes W(s), $0 \le s \le x$, measurable and consider the event Γ that the shifted trajectory $W(\cdot + x)$ hits 0 before it hits 1. Then first using the strong Markov property of the reflected Brownian motion and then (4.3), we have

$$\begin{split} \mathbb{E}^{\mathbb{Q}\left\{K_{3}e^{-tK_{3}} \mathbf{1}_{\Gamma} / \mathcal{F}_{x}\right\}} \\ &= \left\{1 - \mathbb{W}(x)\right\} \mathbb{E}^{\mathbb{Q}\left\{K([0, b_{2}])e^{-tK([0, b_{2}])}\right\}} \\ &= \frac{2}{(2t + 1)^{2}} \left\{1 - \mathbb{W}(x)\right\}, \text{ a.s.} \\ \text{Since } \left\{x < b_{2}\right\} = \left\{x < c^{\dagger}\right\} \cap \Gamma \text{ and } \left\{x < c^{\dagger}\right\} \in \mathcal{F}_{x}, \text{ we have } \\ &= \mathbb{E}^{\mathbb{Q}\left\{K_{3}e^{-t(K_{2}+K_{3})}; x < b_{2}\right\}} \\ &= \mathbb{E}^{\mathbb{Q}\left\{e^{-tK_{2}} \mathbf{1}_{\left\{x < c^{\dagger}\right\}} \mathbb{E}^{\mathbb{Q}\left\{K_{3}e^{-tK_{3}} \mathbf{1}_{\Gamma} / \mathcal{F}_{x}\right\}}\right\}} \end{split}$$

$$= \frac{2}{(2t + 1)^2} \mathbb{E}^{\mathbb{Q}} \left\{ (1 - \mathbb{W}(x)) e^{-t\mathbb{K}_2}; x < c' \right\},$$

proving (4.10) and hence the lemma.

(4.11)

$$\frac{\text{Lemma 9}}{\int_{0}^{\infty} e^{-\lambda x} E^{Q} \left\{ (1 - W(x))e^{-tK([0,x])}; x < c' \right\} dx}$$

$$= \frac{1}{\lambda} \left\{ 1 - \frac{(2t + 1)S}{C + 2tS} \right\},$$

where

$$C = \cosh \sqrt{2\lambda}$$
 , $S = \frac{\sinh \sqrt{2\lambda}}{\sqrt{2\lambda}}$

Proof. Let $\mathcal{G}(\mathbf{x}) = 1 - |\mathbf{x}|$. Consulting with [4: Chapter 5], we see that the left hand side of (4.11) equals $f_{\lambda}(0)$ where f_{λ} is the continuous solution of

(4.12)
$$\begin{cases} \lambda f - \frac{1}{2} f'' = 9 & \text{in} (-1, 0) \lor (0, 1) \\ \frac{1}{2} \{ f'(0+) - f'(0-) \} = 2 t f(0) \\ f(-1) = f(1) = 0 . \end{cases}$$

To solve (4.12) we first find the solution g_{λ} of $\lambda f - \frac{1}{2}f'' = g$ in (-1,1) with boundary condition f(-1) = f(1) = 0 and then express f_{λ} as follows:

$$f_{\lambda}(x) = \begin{cases} g_{\lambda}(x) + c \sinh \sqrt{2\lambda} (1+\dot{x}) & \text{for } x \in (-1, 0) \\ g_{\lambda}(x) + c \sinh \sqrt{2\lambda} (1-x) & \text{for } x \in (0, 1) \end{cases}$$

If we determine c so that the above f_{λ} satisfies the second condition of (4.12), then the f_{λ} is a solution of (4.12). Thus $f_{\lambda}(0)$ can be computed and we obtain (4.11).

Now Theorem 2 can be proved as follows. By Lemma 8 we have

$$\mu((\mathbf{x}, \boldsymbol{\infty})) = \mathbb{E}^{\mathbb{Q}} \left\{ \frac{\mathbb{K}((\mathbf{x}, \mathbf{x}^{\mathbf{v}} \mathbf{b}_{2}))}{\mathbb{K}((\mathbf{b}_{1}, \mathbf{b}_{2}))} \right\}$$

$$= \mathbb{E}^{\mathbb{Q}} \left\{ \frac{\mathbb{K}_{3}}{\mathbb{K}_{1} + \mathbb{K}_{2} + \mathbb{K}_{3}} ; \mathbf{x} < \mathbf{b}_{2} \right\}$$

$$= \int_{0}^{\infty} \mathbb{E}^{\mathbb{Q}} \left\{ \mathbb{K}_{3} e^{-t(\mathbb{K}_{1} + \mathbb{K}_{2} + \mathbb{K}_{3})} ; \mathbf{x} < \mathbf{b}_{2} \right\} dt$$

$$= \int_{0}^{\infty} \frac{2}{(2t + 1)^{3}} E^{\mathbb{Q}} \left\{ (1 - \mathbb{W}(x)) e^{-t\mathbb{K}([0, x])} ; x < c' \right\} dt$$

and hence by Lemma 9

$$\int_{0}^{\infty} e^{-\lambda x} \mu((x, \infty)) dx = \int_{0}^{\infty} \frac{2}{(2t + 1)^{3}} \cdot \frac{1}{\lambda} \left\{ 1 - \frac{(2t + 1)s}{c + 2ts} \right\} dt$$
$$= \frac{1}{2\lambda} - \frac{1}{\lambda} \int_{0}^{\infty} \frac{2}{(2t + 1)^{2}} \cdot \frac{s}{c + 2ts} dt .$$

Thus integration by parts yields

$$\int_{0}^{\infty} e^{-\lambda x} \mu(dx) = \frac{1}{2} - \lambda \int_{0}^{\infty} e^{-\lambda x} \mu((x, \infty)) dx \quad (\text{notice that } \mu((0, \infty)) = \frac{1}{2})$$

$$= \int_{0}^{\infty} \frac{2S}{(2t + 1)^{2}(C + 2tS)} dt$$

$$= \int_{0}^{\infty} \frac{Sdt}{(t + 1)^{2}(C + tS)} ,$$

and this proves (3).

REFERENCES

- T.Brox, A one-dimensional diffusion process in a Wiener medium, to appear in Ann. Probab.
- [2] A.O.Golosov, The limit distributions for random walks in random environments, Soviet Math. Dokl., 28(1983), 18-22.
- [3] N.Ikeda and S.Watanabe, Stochastic Differential Equations and Diffusion Processes, North-Holland, 1981.
- (4) K.Itô and H.P.McKean, Diffusion Processes and Their Sample Paths, Springer-Verlag, 1965.
- [5] K.Kawazu, Y.Tamura and H.Tanaka, One-dimensional diffusions and random walks in random environments, in preparation.
- [6] H.Kesten, The limit distribution of Sinai's random walk in random environment, to appear in Physica.
- [7] S.Schumacher, Diffusions with random coefficients, Contemporary Math. (Particle Systems, Random Media and Large Deviations, ed. by R. Durrett), 41(1985), 351-356.

- (8) Y.G.Sinai, The limiting behavior of a one-dimensional random walk in a random medium, Theory of Probab. and its Appl. 27(1982), 256-268.
- (9) H.Tanaka, Limit distributions for one-dimensional diffusion processes in self-similar random environments, to appear in the Proc. of the workshop on Hydrodynamic behavior and interacting particle systems and applications held at IMA, University of Minnesota, March 1986.

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