ON THE RATE OF CONVERGENCE IN THE INVARIANCE PRINCIPLE FOR WEAKLY DEPENDENT RANDOM VARIABLES

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We consider nonstationary sequences of φ -mixing random variables. By using the Levy–Prokhorov distance, we estimate the rate of convergence in the invariance principle for nonstationary φ -mixing random variables. The obtained results extend and generalize several known facts established for nonstationary φ -mixing random variables.

1. Introduction

Let $\{\xi_{kn}, k = 1, 2, ..., k(n), n = 1, 2, ...\}$ be a sequence of random variables (r.v.) in a probability space $\{\Omega, \Im, P\}$ and let

$$M_a^b(n) = \sigma\{\xi_{kn}, a \le k \le b\}, \quad 1 \le a \le b \le k(n).$$

For any $m \ge 1$, we define (see [11])

$$\begin{aligned} \alpha(m) &= \sup_{k,n} \sup_{A \in M_1^k(n), B \in M_{k+m}^{k(n)}(n)} |P(A \cap B) - P(A)P(B)|, \\ \beta(m) &= E \left\{ \sup_{k,n} \sup_{A \in M_{k+m}^{k(n)}(n)} \left| P(A/M_1^k(n)) - P(A) \right| \right\}, \\ \varphi(m) &= \sup_{k,n} \sup_{A \in M_1^k(n), B \in M_{k+m}^{k(n)}(n)} |P(B/A) - P(B)|, \quad P(A) > 0. \end{aligned}$$

A sequence is said to be strongly mixing (s.m.), absolutely regular (a.r.), or *uniformly strong mixing* (u.s.m.) if $\alpha(m) \to 0$, $\beta(m) \to 0$, or $\varphi(m) \to 0$ as $m \to \infty$, respectively. Let

$$S_{kn} = \sum_{j \le k} \xi_{jn}, \qquad S_n = S_{k(n)n}, \qquad B_{kn}^2 = ES_{kn}^2, \qquad B_n^2 = B_{k(n)n}^2, \qquad S_{0n} = B_{0n}^2 = 0,$$
$$L_{ns} = B_n^{-s} \sum_{j \le k(n)} E |\xi_{jn}|^s, \qquad E\xi_{kn} = 0, \quad \varphi(0) = 1.$$

By $C(\cdot)$ with or without indices, we denote positive constants (generally speaking, different in different formulas) that depend only on the quantities in parentheses; by C we denote an absolute positive constant.

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We now consider the following points:

$$t_{kn} = \frac{\max_{1 \le i \le k} B_{in}^2}{\max_{1 \le i \le k(n)} B_{in}^2}$$

from the interval [0; 1]. Further, we order these points and construct a continuous random polygon $W_n(t)$ on the interval [0; 1] with vertices $\left(t_{kn}; \frac{S_{kn}}{B_n}\right)$. If some t_{kn} are identical, i.e.,

$$B_{k_1n}^2 = B_{k_2n}^2 = \ldots = B_{k_rn}^2, \quad k_i \neq k_j,$$

then we choose any of these points $\left(t_{k_r n}; \frac{S_{k_i n}}{B_n}\right)$.

Consider the space C[0;1] of continuous functions on [0;1] equipped with the norm

$$||x(t)|| = \sup_{0 \le t \le 1} |x(t)|,$$

which generates a σ -algebra \mathfrak{T}_C . If W_n is the distribution of the process $\{W_n(t), t \in [0, 1]\}$ and W is the distribution of the standard Wiener process $\{W(t), t \in [0, 1]\}$, then the weak convergence W_n to W means that

$$\lim_{n \to \infty} P(W_n(t) \in A) = P(W(A))$$

for any Borel set A such that $W(\partial A) = 0$. This fact is usually called the invariance principle (IP). Donsker [8] proved the IP for i.i.d. (independent identically distributed) random variables. At the same time, Yu. Prokhorov [16] proved the IP for triangular arrays $\{\xi_{kn}, k = 1, 2, ..., k(n), n = 1, 2, ...\}$ of independent (in each series) r.v. under Lundeberg's condition:

$$\Lambda_n(\varepsilon) = \frac{1}{B_n^2} \sum_{k=1}^n E\left\{ X_{kn}^2; |X_{kn}| > \varepsilon B_n \right\} \to 0 \quad \text{as} \quad n \to \infty \quad \text{for all} \quad \varepsilon > 0.$$

Under Lundeberg's condition, T. Zuparov and A. Muhamedov [26] and M. Peligrad and S. Utev [15] proved the IP for nonstationary φ -mixing and α -mixing r.v., respectively.

By L(P;Q) we denote the Levy–Prokhorov distance between the distributions P and Q in C[0;1] (see [3, p. 327]):

$$L(P;Q) = \inf \left\{ \varepsilon > 0 \colon P(A) \le Q(A^{\varepsilon}) + \varepsilon \text{ and } Q(A) \le P(A^{\varepsilon}) + \varepsilon \text{ for all } A \in \mathfrak{S}_C \right\},$$

where A^{ε} is a ε -neighborhood of A. Thus, the IP can be rewritten as $L(W_n; W) \to 0$ as $n \to \infty$.

It is known that

$$L(W_n; W) = \max\left\{\varepsilon \colon P\left(\|W_n(\cdot) - W(\cdot)\| > \varepsilon\right)\right\}.$$
(1)

In order to estimate (1), it is sufficient to establish the estimate for $P(||W_n(\cdot) - W(\cdot)|| > \varepsilon)$. The rate of convergence in the IP was studied in detail in the case where the sequences of r.v. are independent. The first

estimation in this case was proposed by Prokhorov [16]. He proved that

$$L(W_n; W) = o\left(L_{n3}^{1/4} \ln^2 L_{n3}\right), \quad n \to \infty.$$

This estimate was improved in the i.i.d. case by Heyde [10], Dudley [7], and other researchers. A. Borovkov [4] proved that

$$L(W_n; W) = C(s)L_{ns}^{1/(s+1)}, \quad 2 < s \le 3.$$
(2)

It should be emphasized that the one probability space method was used in all estimates presented above. R. Dudley [7] and A. Borovkov [4] showed that neither the Prokhorov method, nor the Skorokhod method can be used to get (2) in the case where s > 5. J. Komlos, P. Major, and G. Tusnady (KMT) [13] proposed a method, which allowed them to prove (1) in the i.i.d. case for all s > 2. Modifying the KMT method, A. Sakhanenko [17–21] extended (2) to the general case.

The fact that (2) is the best possible estimate was proved by several authors: Borovkov [4], Sakhanenko [17–21], T. Arak [1], Komlos, Major and Tusnady [14]. I. Berkes and W. Philipp [2] and Borovkov, Sakhanenko [5], Zuparov, and Muhamedov [26, 27] proposed the methods that can be used to obtain estimates for the Levy–Prokhorov distances for different classes of weakly dependent sequences.

Yoshihara [25] obtained the first result:

$$L(W_n; W) = O\left(n^{-1/8} \ln^{1/2} n\right)$$

for a.r. strictly stationary sequence $\{\xi_k, k \in N\}$ satisfying the inequality

$$\sum_{k=1}^{\infty} k \cdot \left(\beta(k)\right)^{\delta/(4+\delta)} < \infty,$$

under the condition of existence of the absolute moment of order $4 + \delta$, $\delta > 0$. Kanagawa [12] obtained the rate of convergence for the u.s.m. and s.m. strictly stationary sequences of r.v..

By the Prokhorov method, the best estimate in the IP was obtained in [9] for the stationary case with s.m. conditions, namely,

(i) if the coefficients $\alpha(k)$ of s.m. exponentially decrease to zero and

$$0 < \sigma = E\xi_1^2 + 2\sum_{i=2}^{\infty} E\xi_1\xi_i < \infty,$$
(3)

then

$$L(W_n; W) = O\left(n^{-\frac{s-2}{2(s-1)}} \ln^{\frac{2s+1}{6}} n\right);$$

(ii) if the coefficients $\alpha(k)$ of s.m. decrease to zero as follows:

$$\alpha(k) \le C n^{-\theta s(s-1)/(s-2)^2}, \quad C > 0, \quad \theta > 1,$$

and condition (3) is satisfied, then

$$L(W_n; W) = O\left(n^{-\frac{(s-2)(\theta-1)}{6(\theta+1)+2(\theta-1)(s-2)}}\sqrt{\ln n}\right).$$

For the u.s.m. case and weak stationary sequences $\{\xi_k, k \in N\}$, S. Utev [23] showed that

$$L(W_n; W) = C(s; g; \sigma) \left(n^{-s/2} \sum_{i=1}^n E |\xi_i|^s \right)^{1/(s+1)}, \quad 2 < s < 5,$$

under conditions (3) for

$$\begin{split} \phi(k) &\leq A \cdot k^{-g(s)}, \quad g(s) > j(u)(j(u)-1), \\ u &= (2+5s)/2(5-s), \quad \text{and} \quad j(u) = 2\min\{k \in N \colon 2k \geq u\}. \end{split}$$

Zuparov and Muhamedov [27] announced the following estimate for nonstationary u.s.m. sequences:

$$L(W_n; W) \le C(s; \theta; K) L_{ns}^{\frac{1}{s+1}}$$

for 2 < s < 6 and $\phi(k) \leq Ak^{-\theta(s)}$; here, $\theta(s) > 2s$.

In the present paper, by using the Levy–Prokhorov distance, Bernstein's method, the Berkes–Philipp approximation theorems [2], Utev's moment inequalities [24], and the results obtained by Sakhanenko [19], we find the best possible rate of convergence for the IP and extend and generalize several known results for nonstationary φ -mixing random variables.

The paper is organized as follows. Our main results are presented in Section 2. In Section 3, we give some auxiliary lemmas. In Section 4, we present the proofs of our results.

2. Main Results

Theorem 2.1. Suppose that, for any numbers θ and s such that

$$\theta > \max(4, s, s(s-2)/4), \quad s > 2,$$

the following conditions are satisfied:

$$\varphi(\tau) \le K\tau^{-\theta}, \quad K > 0,$$

 $E |\xi_{kn}|^s < \infty, \quad k = 1, 2, \dots, k(n), \quad n = 1, 2, \dots$

Then there exist a Wiener process $\{W(t), t \in [0, 1]\}$ and a constant $C(s; \theta; K)$ such that inequality

$$P\left(\|W_n(t) - W(t)\| > x\right) \le C(s;\theta;K) \frac{L_{ns}}{x^s}$$

holds for all x > 0*.*

Corollary. Under the conditions of Theorem 2.1, the following inequality takes place:

$$L(W_n; W) \le C(s; \theta; K) L_{ns}^{\frac{1}{s+1}}.$$

Theorem 2.2. Under the conditions of Theorem 2.1, for $\theta > \max(4, s, 3s(s-2)/4)$, there exist a Wiener process $\{W(t), t \in [0; 1]\}$ and a constant $C(s; \theta; K)$ such that inequality

$$E \|W_n(t) - W(t)\|^s \le C(s;\theta;K)L_{ns}$$

holds.

Remark. In [24], Utev proved that $E ||W_n(t) - W(t)||^s$ converges to zero. The inequality in Theorem 2.2 for a nonstationary sequence of φ -mixing random variables is obtained for the first time.

Concerning the existence of sequences satisfying the conditions of Theorems 2.1 and 2.2, we can make the following remarks:

In Theorem 3.3 from [6], Bradley proved that if $X := (X_k, k \in Z)$ is a Markov chain (not necessarily stationary) and $\varphi(n) < 1/2$ for some $n \ge 1$, then $\varphi(n) \to 0$ at least exponentially rapidly as $n \to \infty$.

By using a strictly stationary sequence of Markov chains

$$X := (X_k, k \in Z),$$

we construct a nonstationary sequence $\xi := (\xi_{kn}, 1 \le k \le n)$ as follows: $\xi_{2k-1n} = -X_{2k-1}, 1 \le 2k - 1 \le n$, and $\xi_{2kn} = X_{2k}, 1 \le 2k \le n$, for every series. As $X := (X_k, k \in Z)$, strictly stationary sequences satisfy the φ -mixing condition exponentially rapidly as $n \to \infty$. Thus, the sequence $\xi := (\xi_{kn}, 1 \le k \le n)$ also satisfies the φ -mixing condition exponentially rapidly as $n \to \infty$. In addition, if $E |X_k|^s$, s > 2, then the nonstationary sequence $\xi := (\xi_{kn}, 1 \le k \le n)$ satisfies the conditions of the main theorems.

3. Auxiliary Lemmas

Lemma 3.1 (see [11]). Let the r.v. ξ and η be measurable with respect to the σ -algebras M_1^k and $M_{k+\tau}^{k(n)}$, respectively, where $k \ge 1$ and $k + \tau \le k(n)$. If $E|\xi|^p < \infty$ and $E|\eta|^q < \infty$ for p > 1 and q > 1 such that $\frac{1}{p} + \frac{1}{q} = 1$, then

$$|E\xi \cdot \eta - E\xi \cdot E\eta| \le 2\varphi^{\frac{1}{p}}(\tau)E^{\frac{1}{p}}|\xi|^p E^{\frac{1}{q}}|\eta|^q.$$

Lemma 3.2 (see [2]). Let $\{(S_k, \sigma_k), k \ge 1\}$ be a sequence of complete separable metric spaces. Also let $\{X_k, k \ge 1\}$ be a sequence of random variables with values in S_k and let $\{B_k, k \ge 1\}$ be a sequence of σ -fields such that X_k is B_k -measurable. Suppose that, for some $\varphi_k \ge 0$,

$$|P(AB) - P(A)P(B)| \le \varphi_k P(A)$$

for all $B \in B_k$, $A \in \bigcup_{j < k} B_j$. Then, without changing the distribution, we can redefine the sequence $\{X_k, k \ge 1\}$ on a richer probability space together with a sequence $\{Y_k, k \ge 1\}$ of independent random variables such that Y_k has the same distribution as X_k and

$$P(\sigma_k(X_k, Y_k) \ge 6\varphi_k) \le 6\varphi_k, \quad k = 1, 2, \dots$$

Lemma 3.3 (see [24]). Let $\{X_k, k \ge 1\}$ be a sequence of random variables satisfying the u.s.m. condition and let $\varphi(p) < \frac{1}{4}$. Then there exists a constant $C(\varphi(p))$ depending only on $\varphi(p)$ and such that, for all $t \ge 1$ and

all $1 \le q \le t$, the following inequality takes place:

$$E \max_{1 \le k \le n} \left| \sum_{j=1}^{k} X_j \right|^t \le (C(\varphi(p)t))^t \left\{ p^t E \max_{1 \le k \le n} |X_k|^t + \max_{1 \le k \le n} \left(E \left| \sum_{j=1}^{k} X_j \right|^q \right)^{\frac{t}{q}} \right\}.$$

Lemma 3.4 (see [19]). Let $\{X_k, k \ge 1\}$ be a sequence of independent random variables such that

$$EX_k = 0$$
 and $\sum_{k=1}^n EX_k^2 = 1.$

Suppose that

$$t_0 = 0,$$
 $t_k = \sum_{i=1}^k EX_i^2,$ $k = 1, 2, \dots, n,$

and

$$L_{ns} = \sum_{i=1}^{n} E|X|^s.$$

Let S(t) be a continuous random polygon with vertices $\left(t_k, S(t_k) = \sum_{j=1}^k X_j\right)$. Then, for any numbers $s \ge 2$ and $b \ge 1$, there exists a Wiener process $\{W(t), t \in [0,1]\}$ such that the inequality

$$P\Big(\|S(t) - W(t)\| \ge C_1 s b x\Big) \le \left(\frac{L_{ns}}{bx}\right)^b + P\left(\max_{1 \le i \le n} |X_i| > x\right)$$

is true for all x > 0.

We introduce the following notation:

$$\xi_{jn}(x) = \xi_{jn}I\{|\xi_{jn}| \le CxB_n\} - E\xi_{jn}I\{|\xi_{jn}| \le CxB_n\}, \quad \bar{\xi}_{jn}(x) = \xi_{jn} - \xi_{jn}(x),$$

where x > 0 is an arbitrary real number,

$$S_{kn}(b) = \sum_{j=b+1}^{b+k} \xi_{jn}, \quad S_{kn}(b,x) = \sum_{j=b+1}^{b+k} \xi_{jn}(x), \quad \bar{S}_{kn}(b,x) = \sum_{j=b+1}^{b+k} \bar{\xi}_{jn}(x), \quad S_{n}(x) = S_{k(n)n}(0,x),$$

$$B_{kn}^{2}(b) = ES_{kn}^{2}(b), \quad B_{kn}^{2}(b,x) = ES_{kn}^{2}(b,x), \quad B_{n}^{2}(x) = ES_{n}^{2}(x), \quad \varphi_{t} = \sum_{i=0}^{k(n)+1} \varphi^{1/t}(i),$$

$$L_{ns} = B_{n}^{-s} \sum_{j \le k(n)} E|\xi_{jn}|^{s}, \qquad L_{nsx}(a,b) = B_{n}^{-s} \sum_{j=a+1}^{b} E|\xi_{jn}(x)|^{s}, \quad s > 2,$$

$$\bar{\varphi}_{t} = \sum_{i=0}^{k(n)+1} (i+1)\varphi^{1/t}(i).$$

We now define the positive integers m_i by using the following algorithm:

$$m_0 = 0,$$

$$m_{i+1} = \min\left\{m: m_i < m < n: E\left(\sum_{k=m_i+1}^{m+1} \xi_{kn}(x)\right)^2 > h(n)\right\} \text{ for } i = 1, 2, \dots, M-1,$$

where M-1 is the last number for which we can define m_{M-1} , i.e.,

$$E\left(\sum_{j=m_{M-1}+1}^{k(n)} \xi_{jn}(x)\right)^2 < h(n),$$

where h(n) is a sequence of positive numbers.

By η_j and $\eta_j(x)$, respectively, we denote

$$\eta_j = \sum_{i=m_{j-1}+1}^{m_j} \xi_{in}$$
 and $\eta_j(x) = \sum_{i=m_{j-1}+1}^{m_j} \xi_{in}(x).$

The positive integers l_i are described by using the outlined algorithm:

$$l_0 = 0,$$

$$l_{i+1} = \min\left\{l: \ l_i < l < M: \ E\left(\sum_{k=l_i+1}^{l+1} \eta_k(x)\right)^2 > T(n)\right\} \quad \text{for} \quad i = 1, 2, \dots, N-1,$$

where M - 1 is the last number for which we can define l_{N-1} , i.e.,

$$E\left(\sum_{j=l_{N-1}+1}^{M} \eta_j(x)\right)^2 < T(n),$$

where T(n) is a sequence of positive numbers. The sequences T(n) and h(n) are selected in what follows. By ψ_j and $\psi_j(x)$, respectively, we denote

$$\psi_j = \sum_{i=l_{j-1}+1}^{l_j-1} \eta_i$$
 and $\psi_j(x) = \sum_{i=l_{j-1}+1}^{l_j-1} \eta_i(x).$

Lemma 3.5. The following inequalities are true:

$$\left|B_{kn}^{2}(b) - B_{kn}^{2}(b,x)\right| \le C(\varphi_{s})B_{n}^{2}x^{2-s}L_{ns}(b),\tag{4}$$

$$\max_{1 \le k \le N} \left| \sum_{j=1}^{k} (D\psi_j - D\psi_j(x)) \right| \le C(\varphi_s) B_n^2 x^{2-s} L_{ns},$$
(5)

$$\max_{1 \le k \le N} \left| B_{m_k}^2 - \sum_{j=1}^k D\psi_j(x) \right| \le C(\varphi_2) N \cdot h(n), \tag{6}$$

$$E\psi_j^2(x) \le T(n) + \theta \cdot h(n), \quad |\theta| \le C(\varphi_2),$$
(7)

$$M \le C\left(\bar{\varphi}_2\right) \frac{B_n^2(x)}{h(n)}, \qquad N \le C\left(\bar{\varphi}_2\right) \frac{B_n^2(x)}{T(n)}.$$
(8)

Proof. It is obvious that

$$|B_{kn}^{2}(b) - B_{kn}^{2}(b, x)| = \left| E\left(\sum_{j=b+1}^{b+k} \left(\xi_{jn}(x) + \bar{\xi}_{jn}(x)\right)\right)^{2} - E\left(\sum_{j=b+1}^{b+k} \xi_{jn}(x)\right)^{2} \right|$$
$$\leq \left| \sum_{b+1 \le i \ne j \le b+k} E\xi_{in}(x)\bar{\xi}_{jn}(x) \right| + \left| \sum_{b+1 \le i \ne j \le b+k} E\bar{\xi}_{in}(x)\xi_{jn}(x) \right|$$
$$+ \left| \sum_{b+1 \le i \ne j \le b+k} E\bar{\xi}_{in}(x)\bar{\xi}_{jn}(x) \right|.$$

We now estimate the first term on the right-hand side of the inequality. The other terms can be estimated similarly. By virtue of Lemma 3.1 and the Hölder inequality, we find

$$\sum_{b+1 \le i \ne j \le b+k} E\xi_{in}(x)\bar{\xi}_{jn}(x) \left| \le \sum_{b+1 \le i \ne j \le b+k} \varphi^{1/s}(|j-i|)E^{1/s}|\xi_{in}(x)|^s E^{(s-1)/s} \left|\bar{\xi}_{jn}(x)\right|^{s(s-1)} \right| \le C \left(\sum_{i=0}^{k(n)} \varphi^{1/s}(i)\right) B_n^2 x^{2-s} L_{ks}(b) \le C(\varphi_s) B_n^2 x^{2-s} L_{ks}(b).$$

Inequality (4) is proved. Inequality (5) can be obtained in a similar way.

We now prove inequality (6). To do this, we estimate the difference

$$\left| B_n^2(x) - \sum_{j=1}^N D\psi_j(x) \right| \quad \text{for} \quad k = N.$$

The other cases are proved similarly. It is clear that

$$B_n^2(x) = E\left(\sum_{j=1}^N (\psi_j(x) + \eta_{l_j}(x))\right)^2.$$

By Lemma 3.1, we get

$$\begin{aligned} \left| B_n^2(x) - \sum_{j=1}^N E\psi_j^2(x) \right| &= \left| E\left(\sum_{j=1}^N (\psi_j(x) + \eta_{l_j}(x)) \right)^2 - \sum_{j=1}^N E\psi_j^2(x) \right| \\ &\leq \left| 2 \sum_{1 \le j \le l \le N} E(\psi_j(x) + \eta_{l_j}(x))(\psi_k(x) + \eta_{l_k}(x)) \right| \\ &\leq 2 \left| \sum_{j=1}^N E(\psi_j(x) + \eta_{l_j}(x)) \left(\sum_{l=j+1}^N E(\psi_k(x) + \eta_{l_k}(x)) \right) \right| \\ &\leq 2 \left| \sum_{j=1}^N E\left(\sum_{i=1}^{l_j} \eta_i(x) \right) \left(\sum_{l=l_j+1}^{l_M} \eta_i(x) \right) \right| \\ &\leq 2 \left| \sum_{i=1}^{k(n)} (i+1)\varphi^{1/2}(i)N \cdot h(n) \right| \\ &\leq C(\bar{\varphi}_2)N \cdot h(n). \end{aligned}$$

Proof of inequality (7). By the definitions of random variables $\psi_j(x)$ and $\eta_{ij}(x)$, we obtain

$$E\eta_{m_j+1n}^2(x) \le h(n)$$

and

$$\begin{split} E\psi_{j}^{2}(x) &\leq T(n) < E\left(\psi_{j}(x) + \eta_{l_{j}}(x)\right)^{2} \\ &\leq E\psi_{j}^{2}(x) + 2E\psi_{j}(x)\eta_{l_{j}}(x) + E\eta_{l_{j}}^{2}(x) \\ &\leq T(n) + 2E\left(\sum_{i=l_{j-1}+1}^{l_{j}}\eta_{i}(x)\right)\eta_{l_{j}}(x) + E\eta_{l_{j}}^{2}(x) \\ &\leq T(n) + 2\sum_{i=1}^{N}\varphi^{1/2}(i)E^{1/2}\eta_{l_{i}}^{2}(x)E^{1/2}\eta_{l_{j}+1}^{2}(x) + E\eta_{l_{j}+1}^{2}(x) \\ &\leq T(n) + C(\varphi_{2})h(n). \end{split}$$

Relations (4) and (5) imply that

$$B_n^2(x) \ge \sum_{i=1}^N D\psi_j(x) - C(\varphi_2)N \cdot h(n)$$

$$\geq \sum_{i=1}^{N-1} D\psi_j(x) - C(\varphi_2)N \cdot h(n)$$
$$\geq (N-1) \cdot T(n) - C(\varphi_2)N \cdot h(n).$$

Hence, we get the second inequality in (8). Since h(n) = o(T(n)), the first inequality in (8) is estimated similarly. Therefore, Lemma 3.5 is proved.

4. Proofs of Theorems

Proof of Theorem 2.1. We denote by $W_{nx}(t)$ a random polygon with vertices $\left(t_{kn}; \frac{S_k(x)}{B_n}\right)$. A polygon with vertices $\left(t_{m_k n}; \frac{S_{m_k}(x)}{B_n}\right)$ is denoted by $\overline{W}_{nx}(t)$. Let \overline{W} and $\widehat{W}_{nx}(t)$ be random polygons with vertices

$$\left(t_{m_kn}; \frac{\sum_{j=1}^k \psi_j(x)}{B_n}\right) \quad \text{and} \quad \left(t_{m_kn}; \frac{\sum_{j=1}^k \widehat{\psi}_j(x)}{B_n}\right),$$

respectively, where $\widehat{\psi}_j(x)$, j = 1, 2, ..., N, are independent r.v. whose marginal distributions coincide with the distributions of r.v. $\psi_j(x)$. A polygon with vertices

$$\left(\frac{\sqrt{\sum_{j=1}^{k} D\psi_j(x)}}{\sqrt{\sum_{j=1}^{N} D\psi_j(x)}}; \frac{\sum_{j=1}^{k} \widehat{\psi}_j(x)}{\sqrt{\sum_{j=1}^{N} D\psi_j(x)}}\right)$$

is denoted by $\widetilde{W}_{nx}(t)$.

It is obvious that

$$P\left(\|W_{n}(t) - W(t)\| > x\right)$$

$$\leq P\left(\|W_{n}(t) - W_{nx}(t)\| > \frac{x}{6}\right) + P\left(\left\|\overline{W}_{nx}(t) - \overline{W}_{nx}(t)\right\| > \frac{x}{6}\right)$$

$$+ P\left(\left\|W_{nx}(t) - \overline{W}_{nx}(t)\right\| > \frac{x}{6}\right) + P\left(\left\|\overline{W}_{nx}(t) - \widehat{W}_{nx}(t)\right\| > \frac{x}{6}\right)$$

$$+ P\left(\left\|\widehat{W}_{nx}(t) - \widetilde{W}_{nx}(t)\right\| > \frac{x}{6}\right) + P\left(\left\|\widetilde{W}_{nx}(t) - W(t)\right\| > \frac{x}{6}\right) = \sum_{i=1}^{6} P_{i}.$$
(9)

To prove Theorem 2.1, we now estimate each term on the right-hand side of (9). Without loss of generality, we can assume that $L_{ns} < 1$. Let

$$T(n) = C(s, \theta, K) B_n^2 x^{\frac{2(t-s)}{t-2}} L_{ns}^{\frac{2}{t-2}}, \quad t > s.$$

Then

$$N \leq C(s,\theta,K) \frac{B_n^2(x)}{T(n)} \ll C(s,\theta,K) x^{-\frac{2(t-s)}{t-2}} L_{ns}^{-\frac{2}{t-2}}.$$

Estimate P_1 . It is clear that

$$P_1 = P\left(\|W_n(t) - W_{nx}(t)\| > \frac{x}{6}\right) \le P\left(\max_{k \le k(n)} |\xi_{kn}| > C_1 B_n x\right) \le C \frac{L_{ns}}{x^s}.$$

Estimate P_2 . By virtue of the Chebyshev inequality and Lemmas 3.3 and 3.5, for q = 2 and t > s, we get

$$P_{2} = P\left(\left\|W_{nx}(t) - \overline{W}_{nx}(t)\right\| > \frac{x}{6}\right) \leq \sum_{j \leq N} P\left(\max_{m_{j-1} \leq k \leq m_{j}} |S_{kn}(x) - S_{m_{j-1}n}(x)| > C\frac{xB_{n}}{12}\right)$$
$$\leq C\frac{1}{x^{t}B_{n}^{t}}\sum_{j \leq N} E\max_{m_{j-1} \leq k \leq m_{j}} |S_{kn}(x) - S_{m_{j-1}n}(x)|^{t}$$
$$\leq C(t, \theta, K) \left[\frac{L_{nt}(x)}{x^{t}} + \frac{1}{x^{t}} \left(\frac{T(n)}{B_{n}^{2}}\right)^{\frac{t-2}{2}}\right]$$
$$\leq C(s, \theta, K) \frac{L_{ns}}{x^{s}}.$$

Estimate P_3 . It is obvious that

$$P_{3} = P\left(\left\|\overline{W}_{nx}(t) - \overline{\overline{W}}_{nx}(t)\right\| > \frac{x}{6}\right) \le P\left(\max_{k \le N} \left|\sum_{j \le k} \frac{\eta_{m_{j}}(x)}{B_{n}}\right| > \frac{x}{6}\right).$$

We now estimate P_3 . By analogy with P_2 , we obtain

$$P_3 = P\left(\left\|\overline{W}_{nx}(t) - \overline{\overline{W}}_{nx}(t)\right\| > \frac{x}{6}\right) \le C(s,\theta,K)\frac{L_{ns}}{x^s}.$$

Estimate P_4 . It is clear that

$$P\left(\left\|\overline{\overline{W}}_{nx}(t) - \widehat{W}_{nx}(t)\right\| > \frac{x}{6}\right) \le P\left(\max_{k \le N} \left|\sum_{j \le k} \left(\frac{\psi_j(x)}{B_n} - \frac{\widehat{\psi}_j(x)}{B_n}\right)\right| > \frac{x}{6}\right).$$

By using the Berkes–Philipp approximation theorem (see Lemma 3.2) and Lemmas 3.3 and 3.4, we get

$$P_4 \le \sum_{j \le N} P\left(\left| \frac{\psi_j(x)}{B_n} - \frac{\widehat{\psi}_j(x)}{B_n} \right| > \frac{x}{6N} \right)$$

$$\leq \sum_{j \leq N} P\left(\left| \frac{\psi_j(x)}{B_n} - \frac{\widehat{\psi}_j(x)}{B_n} \right| > 6\varphi(p) \right)$$

$$\leq 6N\varphi(p) \quad \text{for} \quad \frac{x}{6N\varphi(p)} > 6 \quad \text{or} \quad 36N\varphi(p) \leq x,$$

where

$$p = \min_{j \le N} (m_j - m_{j-1}).$$

To obtain the estimate

$$P_4 \le C(s, \theta, K) \frac{L_{ns}(x)}{x^s},$$

we find p from the condition

$$N\varphi(p) \le Cx, \qquad N\varphi(p) \le C\frac{L_{ns}}{x^s}.$$

In view of Lemma 3.5, this yields

$$N\varphi(p) \le nKp^{-\theta} \le C(s,\theta,K)x^{-\frac{2(t-s)}{t-2}}L_{ns}^{-\frac{2}{t-2}}p^{-\theta} \le C(s,\theta,K)\min\left(x,\frac{L_{ns}}{x^s}\right).$$

Hence,

$$p \ge C(s,\theta,K) \left(\max\left(x^{-\frac{3t-2(s+1)}{t-2}} L_{ns}^{-\frac{2}{t-2}}; x^{\frac{t(s-2)}{t-2}} L_{ns}^{-\frac{t}{t-2}} \right) \right)^{\frac{1}{\theta}}.$$

Estimate P_5 . It is clear that

$$P\left(\left\|\widehat{W}_{nx}(t) - \widetilde{W}_{nx}(t)\right\| > \frac{x}{5}\right)$$

$$\leq P\left(\max_{k \leq N} \left| \left(1 - \frac{B_n}{\sqrt{\sum_{j \leq N} D\widehat{\psi}_j(x)}}\right) \sum_{j \leq k} \left(\frac{\widehat{\psi}_j}{B_n}\right) \right| > \frac{x}{5}\right)$$

$$\leq P\left(\max_{k \leq N} \left| \sum_{j \leq k} \left(\frac{\widehat{\psi}_j(x)}{\sqrt{\sum_{j \leq N} D\widehat{\psi}_j(x)}}\right) \right| > \frac{xB_n\sqrt{\sum_{j \leq N} D\widehat{\psi}_j(x)}}{5\left(B_n - \sqrt{\sum_{j \leq N} D\widehat{\psi}_j(x)}\right)}\right)$$

$$\leq C \left| \frac{B_n - \sqrt{\sum_{j \leq N} D\widehat{\psi}_j(x)}}{xB_n} \right|^t E\left(\max_{k \leq N} \left| \sum_{j \leq k} \left(\frac{\widehat{\psi}_j(x)}{\sqrt{\sum_{j \leq N} D\widehat{\psi}_j(x)}}\right) \right|^t\right).$$

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Thus, by Lemma 3.3, we obtain

$$E\left(\max_{k\leq N}\left|\sum_{j\leq k}\left(\frac{\widehat{\psi}_{j}(x)}{\sqrt{\sum_{j\leq N}D\widehat{\psi}_{j}(x)}}\right)\right|^{t}\right)\leq C(t,\theta,K).$$
(10)

Since

$$\frac{B_n - \sqrt{\sum_{j \le N} D\widehat{\psi}_j(x)}}{B_n} = \frac{B_n^2 - \sum_{j \le N} D\widehat{\psi}_j(x)}{B_n \left(B_n + \sqrt{\sum_{j \le N} D\widehat{\psi}_j(x)}\right)}$$

and

$$D\widehat{\psi}_j(x) = D\psi_j(x),$$

it follows from Lemma 3.5 that

$$\sum_{j \le N} D\psi_j(x) = B_n^2 (1 + o(1)).$$

As a result, it suffices to estimate $B_n^2 - \sum_{j \leq N} D \hat{\psi}_j(x)$. Let

$$h(n) = T(n)x^{\frac{t-s}{t}}L_{ns}^{\frac{1}{t}}$$

Thus, Lemma 3.5 implies that

$$\left| \frac{B_n^2 - \sum_{j \le N} D\psi_j(x)}{x B_n^2} \right| \le C(\varphi_2) \left(\frac{Nh(n) + B_n^2 x^{2-s} L_{ns}}{x B_n^2} \right) = C(\varphi_2) \left(\frac{h(n)}{x T(n)} + x^{1-s} L_{ns} \right)$$
$$\le C(t, \varphi_2) \left(x^{-\frac{s}{t}} L_{ns}^{\frac{1}{t}} + x^{1-s} L_{ns} \right).$$
(11)

This yields

$$P_{5} = P\left(\left\|\widehat{W}_{nx}(t) - \widetilde{W}_{nx}(t)\right\| > \frac{x}{6}\right)$$

$$\leq C(t,\varphi_{2})\left(x^{-\frac{s}{t}}L_{ns}^{\frac{1}{t}} + x^{1-s}L_{ns}\right)^{t}$$

$$\leq C(t,\varphi_{2})\left(\frac{L_{ns}}{x^{s}} + \left(x\frac{L_{ns}}{x^{s}}\right)^{t}\right).$$
(12)

It is clear that if $0 < x \le 1$, then

$$P_5 \le C(t,\varphi_2) \frac{L_{ns}}{x^s}.$$

Now let $x \ge 1$. Thus, to estimate $P_5 \le C(t, \varphi_2) \frac{L_{ns}}{x^s}$, the second term of inequality (12) should satisfy the condition

$$\left(x\frac{L_{ns}}{x^s}\right)^t \le \frac{L_{ns}}{x^s}$$

This inequality holds for $x \ge L_{ns}^{\frac{t-1}{s(t-1)-t}}$. Hence, inequality $P_4 \le C(t,\varphi_2) \frac{L_{ns}}{x^s}$ is true for all x > 0.

Estimate P_6 . By using Lemma 3.4, we obtain

$$P_6 = P\left(\left\|\widetilde{W}_{nx}(t) - W(t)\right\| > \frac{x}{6}\right) \le C\left(\frac{1}{x}\right)^t \left(\sum_{j \le N} E\left|\frac{\widehat{\psi}_j(x)}{\sqrt{\sum_{j \le N} D\widehat{\psi}_j(x)}}\right|^t\right).$$

We now estimate

$$\sum_{j \le N} E \left| \widehat{\psi}_j(x) \right|^t.$$

Since $\hat{\psi}_j(x)$ are independent r.v. whose marginal distributions coincide with the distributions of r.v. $\psi_j(x)$, by Lemmas 3.3 and 3.5, we find

$$\sum_{j \le N} E |\psi_j(x)|^t \le \sum_{j \le N} \left(\sum_{i=l_{j-1}}^{l_j} E |\eta_i(x)|^t + (D\psi_j(x))^{t/2} \right)$$
$$\le C(t) \left(\sum_{i=1}^{k(n)} E |\xi_{in}(x)|^t + N(T(n))^{t/2} \right).$$
(13)

Hence, it follows from Lemma 3.5 and the definition of T(n) that

$$P_{6} = P\left(\left\|\widetilde{W}_{nx}(t) - W(t)\right\| > \frac{x}{5}\right)$$

$$\leq C(t,\varphi)\left(\frac{1}{x^{t}}L_{nt} + \frac{1}{x^{t}}\left(\frac{T(n)}{B_{n}^{2}}\right)^{\frac{t-2}{2}}\right) \leq C(t,\varphi)\frac{L_{ns}}{x^{s}}.$$
(14)

We now demonstrate the possibility of splitting of the above-mentioned isolated groups, namely, as $n \to \infty$, the conditions

$$B_n^2$$
, $T(n)$, $h(n) \to \infty$, $T(n) = o(B_n^2)$, $h(n) = o(T(n))$, and $L_{ns} \to 0$

should be satisfied, and explain the necessity of curtailing in order to prove Theorem 2.1. These conditions are clear in the stationary case. In this case, the following asymptotic relations are true, i.e.,

$$L_{ns} \approx n^{-\frac{s-2}{2}}$$
 for $s > 2$, $T(n) \approx n^{\frac{t-s}{t-2}}$ for some $t, t > s$,

$$\begin{split} h(n) &\approx n^{\frac{2t^2 - (3s - 2)t + 2s - 4}{2t(t - 2)}} \quad \text{for some} \quad t, \quad t > t_0 = \frac{3s - 2 + \sqrt{9s^2 - 28s + 36}}{4} > s, \\ p &\gg n^{\frac{t(s - 2)}{2\theta(t - 2)}}, \qquad N \ll n^{\frac{t(s - 2)}{s(t - 2)}}, \qquad \text{and} \qquad \theta > \max\left(4, s, \frac{s(s - 2)}{4}\right). \end{split}$$

To obtain the required estimate for P_2 and P_4 , it is necessary to have a moment of t, which is larger than s. This is why, curtailing is necessary.

Theorem 2.1 is proved.

As indicated above, the Levy–Prokhorov distance between the distributions W_n and W is determined in (1). Selecting $\varepsilon = x = L_{ns}^{\frac{1}{s+1}}$ in relation (1) and Theorem 2.1, respectively, we obtain the proof of the corollary.

Proof of Theorem 2.2. The method used to prove Theorem 2.2 remains the same as in Theorem 2.1. Here, we only list the places where it is necessary to make certain changes.

As in the proof of Theorem 2.1, the following inequality is true:

$$E \|W_{n}(t) - W(t)\|^{s} \leq E \|W_{n}(t) - W_{nx}(t)\|^{s} + E \|W_{nx}(t) - \overline{W}_{nx}(t)\|^{s}$$
$$+ E \|\overline{W}_{nx}(t) - \overline{W}_{nx}(t)\|^{s} + E \|\overline{W}_{nx}(t) - \widehat{W}_{nx}(t)\|^{s}$$
$$+ E \|\widehat{W}_{nx}(t) - \widetilde{W}_{nx}(t)\|^{s} + E \|\widetilde{W}_{nx}(t) - W(t)\|^{s} = \sum_{i=1}^{6} E_{i}.$$
(15)

Thus, in order to prove Theorem 2.2, we estimate each term on the right-hand side of (15) and take $x = L_{ns}^{1/s}$. Hence, we get

$$T(n) = B_n^2 L_{ns}^{\frac{2t}{s(t-2)}}, \qquad h(n) = T(n) L_{ns}^{1/s} = B_n^2 L_{ns}^{\frac{3t-2}{s(t-2)}},$$
$$N = \frac{B_n^2}{T(n)} = L_{ns}^{-\frac{2t}{s(t-2)}}, \qquad \frac{h(n)}{T(n)} = L_{ns}^{\frac{1}{s}}.$$

Estimate E_1 . It is clear that

$$E_1 = E \|W_n(t) - W_{nx}(t)\|^s \le E \left(\max_{k \le k(n)} |\xi_{kn}|^s / B_n^s\right) \le L_{ns}.$$

Estimate E_2 . Based on the moment inequality, Lemmas 3.3 (for q = 2 and t > s) and 3.5, and the definition of T(n), we get the following inequality:

$$E_{2} = E \left\| W_{nx}(t) - \overline{W}_{nx}(t) \right\|^{s} \leq E^{s/t} \left\| W_{nx}(t) - \overline{W}_{nx}(t) \right\|^{t}$$
$$\leq \left(\sum_{j \leq N} E \left(\max_{m_{j-1} \leq k \leq m_{j}} \left| S_{kn}(x) - S_{m_{j-1}n}(x) \right|^{t} / B_{n}^{t} \right) \right)^{s/t}$$

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and

$$\leq C \left(\sum_{j \leq N} E \left(\frac{1}{B_n^t} \max_{m_{j-1} \leq k \leq m_j} \left| S_{kn}(x) - S_{m_{j-1}n}(x) \right|^t \right) \right)^{s/t}$$

$$\leq C(t, \theta, K) \left(L_{nt}(x) + \left(\frac{T(n)}{B_n^2} \right)^{\frac{t-2}{2}} \right)^{s/t}$$

$$\leq C(s, \theta, K) L_{ns}. \tag{16}$$

Estimate E_3 . It is obvious that

$$E_{3} = E \left\| \overline{W}_{nx}(t) - \overline{W}_{nx}(t) \right\|^{s} \le E \max_{k \le N} \left| \sum_{j \le k} \frac{\eta_{m_{j}}(x)}{B_{n}} \right|^{s}.$$

We now estimate E_3 . By analogy with E_2 , we obtain

$$E_3 = E \left\| \overline{W}_{nx}(t) - \overline{\overline{W}}_{nx}(t) \right\|^s \le C(s, \theta, K) L_{ns}.$$

Estimate E_4 . By Lemmas 3.2, 3.3, and 3.5, following the paper [24], we can estimate E_4 as follows:

$$E_{4} \leq E\left(\max_{k\leq N}\left|\sum_{j\leq k}\left(\frac{\psi_{j}(x)}{B_{n}} - \frac{\widehat{\psi}_{j}(x)}{B_{n}}\right)\right|^{s}\right)$$

$$\leq N^{s}\max_{j\leq N}E\left|\frac{\psi_{j}(x)}{B_{n}} - \frac{\widehat{\psi}_{j}(x)}{B_{n}}\right|^{s}$$

$$\leq N^{s}\left((6\varphi(p))^{s} + \max_{j\leq N}\left(E\left|\frac{\psi_{j}(x)}{B_{n}} - \frac{\widehat{\psi}_{j}(x)}{B_{n}}\right|^{s}, 6\varphi(p) < \left|\frac{\psi_{j}(x)}{B_{n}} - \frac{\widehat{\psi}_{j}(x)}{B_{n}}\right| \leq 1\right)\right)$$

$$+ N^{s}\max_{j\leq N}E\left|\frac{\psi_{j}(x)}{B_{n}} - \frac{\widehat{\psi}_{j}(x)}{B_{n}}\right|^{t}$$

$$\leq CN^{s}\left(\varphi^{s}(p) + \max_{j\leq N}P\left(\left|\frac{\psi_{j}(x)}{B_{n}} - \frac{\widehat{\psi}_{j}(x)}{B_{n}}\right| \geq 6\varphi(p)\right) + \left(\frac{T(n)}{B_{n}^{2}}\right)^{t/2}\right) \leq L_{ns}.$$

In this case, the mixing coefficients decrease as $N^s \varphi(p) \leq L_{ns}$. In turn,

$$N^{s}\varphi(p) \le L_{ns}^{-\frac{2t}{t-2}}p^{-\theta} \le L_{ns} \Rightarrow p \ge L_{ns}^{-\frac{3t-2}{\theta(t-2)}}$$

for $\theta > \max\left(4, s, \frac{3s(s-2)}{4}\right)$.

Estimate E_5 . It is obvious that

$$E \left\| \widehat{W}_{nx}(t) - \widetilde{W}_{nx}(t) \right\|^{s} \leq C \left(\frac{B_{n} - \sqrt{\sum_{j \leq N} D\widehat{\psi}_{j}(x)}}{B_{n}} \right)^{s} E \left(\max_{k \leq N} \left| \sum_{j \leq k} \left(\frac{\widehat{\psi}_{j}(x)}{\sqrt{\sum_{j \leq N} D\widehat{\psi}_{j}(x)}} \right) \right|^{s} \right).$$

By Lemma 3.5 and inequalities (10), (11), we get

$$E\left\|\widehat{W}_{nx}(t) - \widetilde{W}_{nx}(t)\right\|^{s} \le C(s,\varphi_{2}) \left\|\frac{B_{n} - \sqrt{\sum_{j \le N} D\widehat{\psi}_{j}(x)}}{B_{n}}\right\|^{s} \le \left(\frac{h(n)}{T(n)} + x^{2-s}L_{ns}\right)^{s} \le L_{ns}.$$

Estimate E_6 . Due to moment inequality and similar estimates for (13), (14), and (16), by Lemmas 3.3 and 3.4, we obtain

$$E \left\| \widetilde{W}_{nx}(t) - W(t) \right\|^{s} \leq E^{s/t} \left\| \widetilde{W}_{nx}(t) - W(t) \right\|^{t}$$
$$\leq \left(\sum_{j \leq N} E \left| \frac{\widehat{\psi}_{j}(x)}{\sqrt{\sum_{j \leq N} D\widehat{\psi}_{j}(x)}} \right|^{t} \right)^{s/t}$$
$$\leq C(t, K, \theta) \left(L_{nt}(x) + \left(\frac{T(n)}{B_{n}^{2}} \right)^{s/t} \leq C(t, K, \theta) L_{ns}.$$

Theorem 2.2 is proved.

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REFERENCES

- 1. T. V. Arak, "An estimate of A. A. Borovkov," Theory Probab. Appl., 20, No. 2, 380-381 (1976).
- 2. I. Berkes and W. Philipp, "Approximation theorems for independent and weakly dependent random vectors," *Ann. Probab.*, **7**, No. 1, 29–54 (1979).
- 3. P. Billingsley, Convergence of Probability Measures, Wiley, New York (1968).
- 4. A. A. Borovkov, "On the convergence rate in the invariance principle," Theory Probab. Appl., 29, No. 3, 550–553 (1985).
- A. A. Borovkov and A. I. Sakhanenko, "On the estimates of the rate of convergence in the invariance principle for Banach spaces," *Theory Probab. Appl.*, 25, No. 4, 734–744 (1981).
- 6. R. C. Bradley, "Basic properties of strong mixing conditions. A survey and some open questions," Probab. Surv., 2, 107-144 (2005).
- 7. R. M. Dudley, "Distance of probability measures and random variables," Ann. Math. Statist., 39, 1563–1572 (1968).
- 8. M. Donsker, "An invariance principle for certain probability limit theorems," Mem. Amer. Math. Soc., 6, 250-268 (1951).

- V. V. Gorodetsky, "On the rate of convergence in the invariance principle for strongly mixing sequences," *Theory Probab. Appl.*, 28, No. 4, 780–785 (1983).
- 10. C. C. Heyde, "Some properties of metrics on a study on convergence to normality," Z. Wahrscheinlichkeitstheorie Verw. Gebiete, 11, No. 3, 181–192 (1969).
- 11. I. A. Ibragimov and V. Linnik, Independent and Stationary Sequences of Random Variables, Wolters-Noordhoff, Groningen (1971).
- 12. S. Kanagawa, "Rates of convergence of the invariance principle for weakly dependent random variables," *Yokohama Math. J.*, **30**, No. 1-2, 103–119 (1982).
- J. Komlos, P. Major, and G. Z. Tusnady, "An approximation of partial sums of independent RV's and the sample DF. I," Z. Wahrscheinlichkeitstheorie Verw. Gebiete, 32, No. 2, 111–131 (1975).
- 14. J. Komlos, P. Major, and G. Z. Tusnady, "An approximation of partial sums of independent RV's and the sample DF. II," Z. Wahrscheinlichkeitstheorie Verw. Gebiete, **34**, No. 1, 33–58 (1976).
- 15. M. Peligrad and S. Utev, "A new maximal inequality and invariance principle for stationary sequences," Ann. Probab., 33, No. 2, 798-815 (2005).
- 16. Yu. V. Prokhorov, "Convergence of random processes and limit theorems in probability theory," *Theory Probab. Appl.*, **1**, No. 2, 157–214 (1956).
- 17. A. I. Sakhanenko, "Estimates for the rate of convergence in the invariance principle," Dokl. Akad. Nauk SSSR, 219, 1076–1078 (1974).
- A. I. Sakhanenko, "Estimates in the invariance principle," *Trudy Inst. Mat. SO RAN* [in Russian], Vol. 5, Nauka, Novosibirsk (1985), pp. 27–44.
- A. I. Sakhanenko, "On the accuracy of normal approximation in the invariance principle," *Trudy Inst. Mat. SO RAN* [in Russian], Vol. 19, Nauka, Novosibirsk (1989), pp. 40–66.
- 20. A. I. Sakhanenko, "Estimates in the invariance principle in terms of truncated power moments," *Sib. Math. J.*, **47**, No. 6, 1113–1127 (2006).
- 21. A. I. Sakhanenko, "A general estimate in the invariance principle," Sib. Math. J., 52, No. 4, 696–710 (2011).
- 22. A. V. Skorokhod, Research on the Theory of Stochastic Processes, Kiev University Press, Kiev (1961).
- S. A. Utev, "Inequalities for sums of weakly dependent random variables and estimates of rate of convergence in the invariance principle," *Limit Theorems for Sums of Random Variables, Tr. Inst. Mat.* [in Russian], 3 (1984), pp. 50–77.
- 24. S. A. Utev, "Sums of φ-mixing random variables," *Asymptotic Analysis of Distributions of Random Processes* [in Russian], Nauka, Novosibirsk (1989), pp. 78–100.
- 25. K. Yoshihara, "Convergence rates of the invariance principle for absolutely regular sequence," *Yokohama Math. J.*, **27**, No. 1, 49–55 (1979).
- 26. T. M. Zuparov and A. K. Muhamedov, "An invariance principle for processes with uniformly strongly mixing," *Proc. Funct. Random Processes and Statistical Inference*, Fan, Tashkent (1989), pp. 27–36.
- T. M. Zuparov and A. K. Muhamedov, "On the rate of convergence of the invariance principle for φ-mixing processes," Proc. Rep. VI USSR–Japan Symp. Probab. Theory and Math. Statistics, Kiev, August 5–10 (1991), p. 65.