

A New Method to Prove Strassen Type Laws of Invariance Principle. II

M. Csörgő and P. Révész

1. Introduction

Let X_1, X_2, \dots be a sequence of i.i.d.r.v.'s with

$$P(X_i < t) = \begin{cases} 0 & \text{if } t < 0 \\ t & \text{if } 0 \leq t \leq 1 \\ 1 & \text{if } t > 1 \end{cases}$$

and let $F_n(s)$ be the empirical distribution function based on the sample X_1, X_2, \dots, X_n . The linear interpolation between $nF_n(s)$ and $(n+1)F_{n+1}(s)$ will be denoted by $tF_t(s)$ and put

$$\hat{\xi}(s, t) = t(F_t(s) - s) \quad (0 \leq t < \infty; 0 \leq s \leq 1).$$

A separable Gaussian process $K(s, t)$ defined on $[0, 1] \times [0, \infty)$ will be called a Kiefer-process (of first order) if

$$E(K(s_1, t_1) K(s_2, t_2)) = \min(t_1, t_2) [\min(s_1, s_2) - s_1 s_2],$$

$$E(K(s, t)) = 0.$$

Let us mention that a Kiefer process can be generated by the Wiener process $W(s, t)$ of two variables as follows:

$$W(s, t) - s W(1, t) = K(s, t) \quad (0 \leq t < \infty, 0 \leq s \leq 1),$$

where $W(s, t)$ has zero expectation and covariance function $\min(s_1, s_2) \min(t_1, t_2)$. In [2] the following is proved

Theorem A ([2]). *One can define a probability space (Ω, \mathcal{L}, P) and processes $\tilde{\xi}(s, t)$ and $K(s, t)$ (on Ω) such that*

- (i) $\tilde{\xi}(s, t)$ has the same joint law as $\hat{\xi}(s, t)$,
- (ii) $K(s, t)$ is a Kiefer process,
- (iii) $\sup_{0 \leq s \leq 1} |\tilde{\xi}(s, t) - K(s, t)| = O(t^{\frac{1}{2}} (\log t)^{\frac{3}{2}}) \quad (t \rightarrow \infty)$ with probability 1.

From now on let X_1, X_2, \dots be a sequence of i.i.d.r.v.'s uniformly distributed on the unit cube of the d -dimensional Euclidean space, i.e. the common density

function $f(s_1, s_2, \dots, s_d)$ of X_1, X_2, \dots is

$$f(s_1, s_2, \dots, s_d) = \begin{cases} 1 & \text{if } 0 \leq s_i \leq 1 \quad (i=1, 2, \dots, d) \\ 0 & \text{otherwise} \end{cases}$$

and let $F_n(s) = F_n(s_1, s_2, \dots, s_d)$ be the empirical distribution function based on the sample X_1, X_2, \dots, X_n . The linear interpolation between $nF_n(s)$ and $(n+1)F_n(s)$ will be denoted by $tF_t(s)$ and put

$$\hat{\xi}(s_1, s_2, \dots, s_d; t) = \hat{\xi}(s; t) = t(F_t(s_1, s_2, \dots, s_d) - s_1 s_2 \dots s_d).$$

We give the following:

Definition. The separable Gaussian process

$$K(s, t) = K(s_1, s_2, \dots, s_d; t) \quad (0 \leq s_i \leq 1; i=1, 2, \dots, d; 0 \leq t < \infty)$$

will be called a Kiefer process (of d -th order) if

$$\begin{aligned} & E(K(s_{11}, s_{12}, \dots, s_{1d}; t_1) K(s_{21}, s_{22}, \dots, s_{2d}; t_2)) \\ &= \min(t_1, t_2) [\min(s_{11}, s_{21}) \min(s_{12}, s_{22}), \dots, \min(s_{1d}, s_{2d}) \\ &\quad - s_{11} s_{12} \dots s_{1d} s_{21} s_{22} \dots s_{2d}], \\ & E(K(s, t)) = 0. \end{aligned}$$

A Kiefer process (of d -th order) can be generated by the Wiener process $W(s_1, s_2, \dots, s_d; t)$ of $d+1$ variables as follows:

$$\begin{aligned} W(s_1, s_2, \dots, s_d; t) - s_1 s_2 \dots s_d W(1, 1, \dots, 1; t) &= K(s_1, s_2, \dots, s_d; t), \\ (0 \leq t < \infty, 0 \leq s_i \leq 1; i=1, 2, \dots, d), \end{aligned}$$

where $W(s_1, \dots, s_d; t)$ has zero expectation and covariance function

$$\min(t_1, t_2) \min(s_{11}, s_{21}) \min(s_{12}, s_{22}) \dots \min(s_{1d}, s_{2d}).$$

Now we can formulate our

Theorem. Suppose that the r.v.'s X_1, X_2, \dots are defined on a probability space (Ω, \mathcal{L}, P) which is rich enough to define a sequence $W_1(s), W_2(s), \dots$ of independent Wiener processes with zero expectation and covariance function

$$\min(s_{11}, s_{21}) \min(s_{12}, s_{22}) \dots \min(s_{1d}, s_{2d})$$

and a sequence Π_1, Π_2, \dots of independent r.v.'s such that

$$(i) \quad P(\Pi_n = k) = \frac{n^k}{k!} e^{-n},$$

(ii) the sequences $\{X_n\}, \{W_n\}, \{\Pi_n\}$ are also independent.

Then one can define a Kiefer process $K(s, t)$ on Ω such that

$$\sup_{0 \leq s_i \leq 1} |K(s, t) - \hat{\xi}(s, t)| = O\left(t^{\frac{d+1}{2(d+2)}} (\log t)^2\right) \quad (t \rightarrow \infty)$$

$(i = 1, 2, \dots, d)$

with probability 1.

A main tool of our proof will be Lemma 8 which is practically the same result as that of Brillinger ([3]). Hence one can say that our proof shows that Kiefer's result can be obtained as a consequence of a Brillinger type theorem.

For the sake of simplicity the proof of our Theorem will be prepared only in case $d = 2$. The general case can be treated in a quite similar way.

2. Lemmas

Lemma 1. *Let Π be a r.v. with distribution*

$$P(\Pi = k) = \frac{\lambda^k}{k!} e^{-\lambda} \quad (k = 0, 1, 2, \dots; \lambda > 1).$$

Then for any constant $A > 1$ there exists a polynomial $B(x)$ of second order (depending only on A) such that for any x ($|x| \leq A \sqrt{\log \lambda}$) we have

$$F_\lambda(x) = P\left(\frac{\Pi - \lambda}{\sqrt{\lambda}} \leq x\right) = \Phi(x) + \frac{\exp\left(-\frac{x^2}{2}\right)}{\sqrt{\lambda}} f(x, \lambda) \tag{1}$$

where $|f(x, \lambda)| \leq |B(x)|$.

Consequence. Suppose $|x_\lambda| \leq A \sqrt{\log \lambda}$. Then

$$F_\lambda(x_\lambda) \sim \Phi(x_\lambda) \quad \text{and} \quad 1 - F_\lambda(x_\lambda) \sim 1 - \Phi(x_\lambda).$$

Proof of Lemma 1. Put $[\lambda + x \sqrt{\lambda}] = v$, then it is well-known

$$\begin{aligned} F_\lambda(x) &= \int_\lambda^\infty \frac{t^v}{v!} e^{-t} dt = \exp\left(-\frac{\theta_v}{12v}\right) \sqrt{\frac{v}{2\pi}} \int_{-\infty}^{1-\lambda/v} ((1-t) e^t)^v dt \\ &= \exp\left(-\frac{\theta_v}{12v}\right) \sqrt{\frac{v}{2v}} \left[\int_{-\infty}^{-2A \sqrt{\frac{\log \lambda}{\lambda}}} ((1-t) e^t)^v dt + \int_{-2A \sqrt{\frac{\log \lambda}{\lambda}}}^{1-\lambda/v} ((1-t) e^t)^v dt \right], \end{aligned} \tag{2}$$

where $0 < \theta_v < 1$.

The first member of the right hand side clearly can be estimated by

$$\exp\left(-\frac{\theta_v}{12v}\right) \sqrt{\frac{v}{2\pi}} \int_{-\infty}^{-2A \sqrt{\frac{\log \lambda}{\lambda}}} ((1-t) e^t)^v dt = O\left(\frac{1}{\lambda^{4A^2/3}}\right). \tag{3}$$

The second integral can be evaluated, making use of the simple formula $(1-t)e^t = \exp\left(-\frac{t^2}{2} + g(t)\right)$ where $|g(t)| \leq |t|^3$ if $|t| \leq 1$, as follows

$$\begin{aligned} \sqrt{\frac{v}{2\pi}} \int_{-2A\sqrt{\frac{\log \lambda}{\lambda}}}^{1-\lambda/v} ((1-t)e^t)^v dt &= \sqrt{\frac{v}{2\pi}} \int_{-2A\sqrt{\frac{\log \lambda}{\lambda}}}^{1-\lambda/v} \exp\left(-\frac{t^2}{2} v + g(t)v\right) dt \\ &= \frac{1}{\sqrt{2\pi}} \int_{-2A\sqrt{\frac{\log \lambda}{\lambda}}\sqrt{v}}^{\frac{v-\lambda}{\sqrt{v}}} \exp\left(-\frac{s^2}{2} + g\left(\frac{s}{\sqrt{v}}\right)v\right) ds \quad (4) \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\frac{v-\lambda}{\sqrt{v}}} \exp\left(-\frac{s^2}{2} + g\left(\frac{s}{\sqrt{v}}\right)v\right) ds + h(\lambda) \end{aligned}$$

where $h(\lambda) = O\left(\frac{1}{\lambda^{4A^2/3}}\right)$.

Now a very simple calculation shows:

$$\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\frac{v-\lambda}{\sqrt{v}}} \exp\left(-\frac{s^2}{2} + g\left(\frac{s}{\sqrt{v}}\right)v\right) ds = \Phi(x) + \exp\left(-\frac{x^2}{2}\right) \frac{\chi(x, \lambda)}{\sqrt{\lambda}} \quad (5)$$

where $|\chi(x, \lambda)| \leq \Pi_2(x)$ and $\Pi_2(x)$ is a polynomial of second order. (2), (3), (4) and (5) imply (1).

Lemma 2. Let $f_\lambda(t) = \Phi^{-1}(F_\lambda(t))$. Then

$$|f_\lambda(t) - t| = O\left(\frac{\log \lambda}{\sqrt{\lambda}}\right) \quad (\lambda \rightarrow \infty)$$

uniformly in t provided that $|t| \leq A\sqrt{\log \lambda}$, where the capital O depends only on A .

Proof is practically the same as that of Lemma 3 of [1], so it will be omitted.

Consider the lattice points $\left(\frac{i}{r}, \frac{j}{r}\right)$ ($i=0, 1, 2, \dots, r; j=0, 1, 2, \dots, r$) of the unit square and let $A_{ij} = \left[\frac{i}{r}, \frac{(i+1)}{r}\right) \times \left[\frac{j}{r}, \frac{(j+1)}{r}\right)$ ($i, j=0, 1, 2, \dots, r-1$). Let α_{ij} be the number of the elements of the sample X_1, X_2, \dots, X_n lying in the square A_{ij} . Further let II be a r.v. of Poisson distribution with parameter n , and independent of the $\{X_i\}$. Finally let β_{ij} be the number of elements of the sample X_1, X_2, \dots, X_n lying in A_{ij} . Introduce the notations

$$\mathfrak{A}_{IJ} = \sum_{\substack{i \leq I \\ j \leq J}} \frac{\alpha_{ij} - n/r^2}{\sqrt{n}},$$

$$\mathfrak{B}_{IJ} = \sum_{\substack{i \leq I \\ j \leq J}} \frac{\beta_{ij} - \Pi/r^2}{\sqrt{n}}$$

($1 \leq I, J \leq r$).

Now we can formulate our

Lemma 3. *We have*

$$(i) \quad P \left\{ \sup_{1 \leq I, J \leq r} |\mathfrak{A}_{IJ} - \mathfrak{B}_{IJ}| \geq \frac{K(\log n)^{\frac{3}{2}}}{n^{\frac{1}{2}}} \right\} = O \left(\frac{1}{n^2} \right)$$

if K is a big enough positive constant and $r^2 = o(n)$,

(ii) the r.v.'s β_{ij} are independent obeying the Poisson law of parameter n/r^2 .

Proof. Our second statement is well-known, so we have only to prove the first one. Introduce the notations:

$$|\alpha_{ij} - \beta_{ij}| = \gamma_{ij},$$

$$C_{IJ} = |\mathfrak{A}_{IJ} - \mathfrak{B}_{IJ}| = \left| \sum_{\substack{i \leq I \\ j \leq J}} \frac{\gamma_{ij} - \frac{|n - \Pi|}{r^2}}{\sqrt{n}} \right|.$$

Then we have

$$\begin{aligned} P \left(C_{IJ} \geq \frac{K(\log n)^{\frac{3}{2}}}{n^{\frac{1}{2}}} \right) &= \sum_{k=0}^{\infty} P \left(C_{IJ} \geq \frac{K(\log n)^{\frac{3}{2}}}{n^{\frac{1}{2}}} \mid \Pi = k \right) P(\Pi = k) \\ &\leq \sum_{\substack{|k-n| \\ \sqrt{n} \geq K\sqrt{\log n}}} P(\Pi = k) + \sum_{\substack{|k-n| \\ \sqrt{n} < K\sqrt{\log n}}} P \left(C_{IJ} \geq \frac{K(\log n)^{\frac{3}{2}}}{n^{\frac{1}{2}}} \mid \Pi = k \right) \\ &\leq P \left(\left| \frac{\Pi - n}{\sqrt{n}} \right| \geq K\sqrt{\log n} \right) + \max_{|j| \leq K\sqrt{\log n}} P \left(C_{IJ} \geq \frac{K(\log n)^{\frac{3}{2}}}{n^{\frac{1}{2}}} \mid \Pi - n = j \right) \\ &= O \left(\frac{1}{n^{K^2/2}} \right) + O \left(\frac{1}{n^{K/2}} \right). \end{aligned}$$

Since

$$P \left\{ \sup_{1 \leq I, J \leq r} C_{IJ} \geq \frac{K(\log n)^{\frac{3}{2}}}{n^{\frac{1}{2}}} \right\} \leq r^2 \sup_{1 \leq I, J \leq r} P \left(C_{IJ} \geq \frac{K(\log n)^{\frac{3}{2}}}{n^{\frac{1}{2}}} \right)$$

we have our statement.

The following is well-known:

Lemma 4. *Making use of the notations of Lemma 3 let $r = [n^\alpha]$ ($0 < \alpha < \frac{1}{2}$), $G_n(x, y) = \sqrt{n}(F_n(x, y) - xy)$ and let $B(x, y)$ be a Brownian bridge with zero expectation and covariance function $\min(x_1, x_2) \min(y_1, y_2) - x_1 x_2 y_1 y_2$. Then for any $A > 0$ there exists a $B = B(A) > 0$ such that*

$$P \left(\sup_{i,j} \sup_{\substack{(x_1, y_1) \in A_{ij} \\ (x_2, y_2) \in A_{ij}}} |B(x_1, y_1) - B(x_2, y_2)| \geq B \frac{\log r}{\sqrt{r}} \right) = O \left(\frac{1}{r^A} \right)$$

and

$$P \left(\sup_{i,j} \sup_{\substack{(x_1, y_1) \in A_{ij} \\ (x_2, y_2) \in A_{ij}}} |G_n(x_1, y_1) - G_n(x_2, y_2)| \geq B \frac{\log r}{\sqrt{r}} \right) = O \left(\frac{1}{r^A} \right).$$

Our second statement easily follows, for example, from Theorem 2 of [4]. As to our Brownian bridge on the unit square $B(x, y)$, it can be generated by the Wiener process $W(x, y)$ of two variables as follows:

$$B(x, y) = W(x, y) - x y W(1, 1), \quad (0 \leq x, y \leq 1),$$

where $W(x, y)$ has zero expectation and covariance function $\min(x_1, x_2) \min(y_1, y_2)$.

Our next lemma can be easily proved using well-known technics of Gaussian processes.

Lemma 5. *Let $K(s_1, s_2; t)$ be a Kiefer process. Then for any $A > 0$ there exists a $B = B(A) > 0$ such that*

$$P \left\{ \sup_{\substack{0 \leq t \leq T \\ 0 \leq s_1, s_2 \leq 1}} |K(s_1, s_2; t)| \geq B \sqrt{T \log T} \right\} \leq \frac{1}{T^A}$$

if T is large enough.

Lemma 6. *Let r be an integer and let $\{\Omega, \mathcal{S}, P\}$ be a probability space. Suppose that on Ω there exist a double array $\{N_{ij}\}$ ($i, j = 1, 2, \dots, r$) of independent r.v.'s of standard normal law and a double array $W_{ij}(s_1, s_2)$ ($i, j = 1, 2, \dots, r$) of independent Wiener processes such that the arrays $\{N_{ij}\}$ and $\{W_{ij}\}$ are also independent. Then there exists a Wiener process $W(s_1, s_2)$ ($0 \leq s_1, s_2 \leq 1$) on Ω such that*

$$W(i/r, j/r) = \frac{1}{r} \sum_{\substack{\alpha \leq i \\ \beta \leq j}} N_{\alpha\beta}. \tag{6}$$

Proof. Let

$$W_{ij}^{(1)}(s_1, s_2) = W_{ij}(s_1, s_2) - s_1 s_2 W_{ij}(1, 1) + s_1 s_2 N_{ij}, \quad (0 \leq s_1, s_2 \leq 1),$$

$$W_{ij}^{(2)}(s_1, s_2) = \frac{1}{r} W_{ij}^{(1)}(r s_1, r s_2), \quad (0 \leq s_1, s_2 \leq 1/r),$$

$$W_{ij}^{(3)}(s_1, s_2) = W_{ij}^{(2)}\left(s_1 - \frac{i-1}{r}, s_2 - \frac{j-1}{r}\right), \left(\frac{i-1}{r} \leq s_1 \leq \frac{i}{r}; \frac{j-1}{r} \leq s_2 \leq \frac{j}{r}\right),$$

$$W_j(s_1, s_2) = W_{1j}(1/r, s_2) + W_{2j}(2/r, s_2) + \dots + W_{i-1,j}\left(\frac{i-1}{r}, s_2\right) + W_{ij}(s_1, s_2)$$

$$\text{if } \frac{i-1}{r} \leq s_1 \leq \frac{i}{r}, \frac{j-1}{r} \leq s_2 \leq \frac{j}{r}, \tag{7}$$

$$W(s_1, s_2) = W_1(s_1, 1/r) + W_2(s_1, 2/r) + \dots + W_{i-1}\left(s_1, \frac{i-1}{r}\right) + W_i(s_1, s_2)$$

$$\left(0 \leq s_1 \leq 1; \frac{i-1}{r} \leq s_2 \leq \frac{i}{r}\right).$$

It is quite clear that $W(s_1, s_2)$ of (7) is obeying condition (6). We only have to check that $W(s_1, s_2)$ is really a Wiener process, and this is rather simple. The Wiener processes of this lemma are, of course, defined as the one generating $B(x, y)$ of Lemma 4.

Lemma 7. Let $0 = t_0 < t_1 < t_2 < \dots$ be a sequence of real numbers and let $\{\Omega, \mathcal{S}, P\}$ be a probability space. Suppose that there exist a sequence $\{B_i(s_1, s_2)\}$ of independent Brownian bridges and a sequence $\{K_i(s_1, s_2; t)\}$ of independent Kiefer processes (both of them defined on Ω) such the sequences $\{B_i\}$ and $\{K_i\}$ are mutually independent. Then there exists a Kiefer process $K(s_1, s_2, t)$ such that

$$K(s_1, s_2, t) = \sqrt{t_1} B_2(s_1, s_2) + \sqrt{t_2 - t_1} B_2(s_1, s_2) + \dots + \sqrt{t_i - t_{i-1}} B_i(s_1, s_2). \quad (8)$$

Proof. Let

$$K_i^{(1)}(s_1, s_2; t) = K_i(s_1, s_2; t - t_{i-1}) - \frac{t - t_{i-1}}{t_i - t_{i-1}} K_i(s_1, s_2; t_i - t_{i-1}) + \frac{t - t_{i-1}}{\sqrt{t_i - t_{i-1}}} B_i(s_1, s_2) \quad (t_{i-1} \leq t \leq t_i)$$

and let

$$K(s_1, s_2; t) = \sqrt{t_1} B_1(s_1, s_2) + \sqrt{t_2 - t_1} B_2(s_1, s_2) + \dots + \sqrt{t_{i-1} - t_{i-2}} B_{i-1}(s_1, s_2) + K_i^{(1)}(s_1, s_2; t) \quad t_{i-1} \leq t \leq t_i. \quad (9)$$

Now condition (8) clearly holds and it is easy to see that $K(s_1, s_2; t)$ (defined by (9)) is a Kiefer process. Here the Brownian bridges $\{B_i(s_1, s_2)\}$ are defined as that of Lemma 4.

Lemma 8. Suppose that the conditions of the Theorem hold. Then for each n one can construct a Brownian bridge $B(s_1, s_2) = B_n(s_1, s_2)$ such that

$$P \left\{ \sup_{0 \leq s_1, s_2 \leq 1} |G_n(s_1, s_2) - B(s_1, s_2)| \cdot \frac{n^{\frac{1}{2}}}{(\log n)^{\frac{1}{2}}} \geq C \right\} = O \left(\frac{1}{n^2} \right) \quad (10)$$

where $G_n(x, y) = \sqrt{n}(F_n(x, y) - xy)$, and C is large enough.

Remark. We get the d -dimensional version of this lemma if we replace $n^{\frac{1}{2}}$ by $n^{\frac{1}{2} \frac{(d+1)}{(d+1)}}$.

Proof. Let $r = n^{\frac{1}{d}}$ and define the process $B(x, y)$ as follows: let

$$N_{ij} = f_n \cdot \frac{\beta_{ij} - n/r^2}{\sqrt{n/r^2}}$$

where f_n resp. β_{ij} were defined in Lemmas 2. resp. 3. Then by Lemma 5 there exists a Wiener process $W(x, y)$ such that

$$W \left(\frac{i}{r}, \frac{j}{r} \right) = \frac{1}{r} \sum_{\substack{0 \leq \alpha \leq i \\ 0 \leq \beta \leq j}} N_{\alpha\beta}$$

and let $B(x, y) = W(x, y) - xy W(1, 1)$.

We have to show that B obeys (10).

In fact by Lemma 2

$$\left| N_{ij} - \frac{\beta_{ij} - n/r^2}{\sqrt{n/r^2}} \right| = O \left(\frac{\log n}{\sqrt{n/r^2}} \right) \quad (i, j = 1, 2, \dots, r)$$

provided that $|(\beta_{ij} - n/r^2)/\sqrt{n/r^2}| \leq A \sqrt{\log n}$.

¹ In the d -dimensional case $r = n^{1/d+1}$.

Since

$$P \left\{ \sup_{i,j} \left| \frac{\beta_{ij} - n/r^2}{\sqrt{n/r^2}} \right| > A \sqrt{\log n} \right\} \leq 1/n^2$$

if A is large enough, we have

$$P \left\{ \sup_{i,j} \left| N_{ij} - \frac{\beta_{ij} - n/r^2}{\sqrt{n/r^2}} \right| > C \frac{\log n}{\sqrt{n/r^2}} \right\} \leq 1/n^2 \tag{11}$$

if C is large enough.

Let

$$\varepsilon_{ij} = N_{ij} - \frac{\beta_{ij} - n/r^2}{\sqrt{n/r^2}}$$

and

$$\varepsilon_{ij}^* = \begin{cases} \varepsilon_{ij} & \text{if } |\varepsilon_{ij}| \leq C \frac{\log n}{\sqrt{n/r^2}} \\ 0 & \text{otherwise.} \end{cases}$$

Then

(i) the r.v.'s ε_{ij}^* are independent,

(ii) $|E\varepsilon_{ij}^*| = O\left(\frac{1}{n}\right)$;

hence

$$P \left\{ \sup_{I,J} \left| \sum_{\substack{i \leq I \\ j \leq J}} (\varepsilon_{ij}^* - E(\varepsilon_{ij}^*)) \right| \frac{\sqrt{n}}{r \log n} \geq Ar \sqrt{\log r} \right\} \leq 1/n^2,$$

and also

$$P \left\{ \sup_{I,J} \left| \sum_{\substack{i \leq I \\ j \leq J}} \varepsilon_{ij}^* \right| \frac{\sqrt{n}}{r \log n} \geq Ar \sqrt{\log r} \right\} \leq 1/n^2$$

if A is large enough, which, by (11), implies:

$$P \left\{ \sup_{I,J} \left| \sum_{\substack{i \leq I \\ j \leq J}} \varepsilon_{ij} \right| \geq Ar^2 \frac{1}{\sqrt{n}} (\log n)^{\frac{3}{2}} \right\} = O\left(\frac{1}{n^2}\right),$$

i.e.

$$P \left\{ \sup_{I,J} \left| \frac{1}{r} \sum_{\substack{i \leq I \\ j \leq J}} N_{ij} - \sum_{\substack{i \leq I \\ j \leq J}} \frac{\beta_{ij} - n/r^2}{\sqrt{n}} \right| \geq A \frac{r}{\sqrt{n}} (\log n)^{\frac{3}{2}} \right\} = O\left(\frac{1}{n^2}\right). \tag{12}$$

Especially if $I = J = r$ we have

$$P \left\{ \left| W(1, 1) - \frac{\Pi - n}{\sqrt{n}} \right| \geq A \frac{r}{\sqrt{n}} (\log n)^{\frac{3}{2}} \right\} = O\left(\frac{1}{n^2}\right). \tag{13}$$

(12) and (13) together imply

$$P \left\{ \sup_{I,J} \left| B \left(\frac{I}{r}, \frac{J}{r} \right) - \mathfrak{B}_{IJ} \right| \geq 2A \frac{r}{\sqrt{n}} (\log n)^{\frac{3}{2}} \right\} = O\left(\frac{1}{n^2}\right).$$

Now making use of Lemmas 3 and 4 one has Lemma 8.

3. Proof of the Theorem

Consider the sequence $0 = n_0 < n_1 < n_2 < \dots$ of integers where $n_k = k^4$ and let $n_k - n_{k-1} = m_k$. Denote by $H_k(x, y)$ the empirical distribution function based on the sample

$$X_{n_{k-1}+1}, \dots, X_{n_k} \quad \text{and let} \quad \sqrt{m_k} \{H_k(x, y) - xy\} = \tilde{H}_k(x, y);$$

further let $B_k(x, y)$ be a Brownian bridge for which

$$P \left\{ \sup_{x,y} |B_k(x, y) - \tilde{H}_k(x, y)| \frac{m_k^{\frac{1}{2}}}{(\log m_k)^{\frac{1}{2}}} \geq C \right\} = O \left(\frac{1}{m_k^2} \right).$$

By Lemma 7 there exists a Kiefer process $K(s_1, s_2, t)$ for which

$$K(s_1, s_2; n_i) = \sum_{j=1}^i \sqrt{m_j} B_j(s_1, s_2).$$

It will be shown that this Kiefer process is obeying statement of our Theorem. Since

$$\sum_{k=1}^K \sqrt{m_k} H_k(x, y) = n_K (F_{n_K}(x, y) - xy),$$

one can get by Lemma 8:

$$P \left\{ \sup_{x,y} |n_K (F_{n_K}(x, y) - xy) - K(x, y; n_K)| \geq \left(A \log K \sum_{k=1}^K m_k^{\frac{1}{2}} (\log m_k)^3 \right)^{\frac{1}{2}} \right\} = O \left(\frac{1}{K^2} \right)$$

hence our Theorem follows from Lemma 5 and the Borel-Cantelli theorem.

Acknowledgements. The authors are indebted to G. Tusnádi for his valuable remarks; especially the idea to use the Poisson law (see Lemma 3) is due to him. A similar idea is used by M. J. Wichura ([5]). The fundamental idea of the first part of this paper ([1]) is very closely related to a paper of P. Bártfai ([6]).

References

1. Csörgő, M., Révész, P.: A new method to prove Strassen type laws of invariance principle, I. *Z. Wahrscheinlichkeitstheorie verw. Geb.* **31**, 255-259 (1975)
2. Kiefer, J.: Skorohod Embedding of Multivariate R.V.'s and the Sample D.F.Z. *Wahrscheinlichkeitstheorie verw. Gebiete* **24**, 1-35 (1972)
3. Brillinger, D.R.: An Asymptotic representation of the sample *df*. *Bull. Amer. Math. Soc.* **75**, 545-547 (1969)
4. Révész, P.: Testing of density functions. *Period. Math. Hungar.* **1**, 35-44 (1971)
5. Wichura, M.J.: Some Strassen-type laws of the iterated logarithm for multiparameter stochastic processes with independent increments. *Ann. Probability*, **1**, 272-296 (1973)
6. Bártfai, P.: Über die Entfernung der Irrfahrtswege. *Studia Sci. Math. Hungar.* **5**, 41-49 (1970)

M. Csörgő
 Department of Mathematics
 Carleton University
 Colonel By Drive
 Ottawa
 Canada

P. Révész
 Mathematical Institute of the
 Hungarian Academy of Sciences
 Reáltanoda u. 13-15
 Budapest V.
 Hungary