Efficient Statistical Significance Approximation for Local Similarity Analysis of High-Throughput Time Series Data Using the Circular Moving Block Bootstrap

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Article

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Abstract

To address the challenges of statistical inference for non-stationary traffic flow, this paper proposed an improved block permutation framework tailored to the correlation analysis requirements of traffic volume time series, and developed a statistical significance assessment method for local similarity scores based on the Circular Moving Block Bootstrap (CMBBLSA). This method avoided the distortion of the statistical distribution caused by non-stationarity, thereby enabling the estimation of the statistical significance of local similarity scores. Simulation studies were conducted under different parameter settings in the AR(1) and ARMA(1,1) models, and the results demonstrated that the Type I error probability of CMBBLSA under the null hypothesis is closer to the preset significance level α. An empirical analysis was also carried out using traffic flow monitoring data from main roads in first-tier cities, and the results indicated that CMBBLSA can reduce more false positive relationships and more accurately capture real correlations.

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1. Introduction

1.1. Related Theories and Technological Developments

Against the backdrop of the transformation of urban traffic management towards intelligence, time series analysis technology has emerged as a core tool for addressing data mining challenges in Intelligent Transportation Systems (ITS). Carlstein[3] proposed a nonparametric method based on subsequence resampling. Hall[6] quantified the similarity between adjacent time periods in terms of their dependence structure and distributional characteristics by partitioning the time series into locally tiled blocks. Storey[11,12] estimated local pFDR or FDR-type statistics by sliding a window across the time series, using these estimates as local similarity scores. The time series was then segmented, and multiple hypothesis testing was conducted within each segment, with local pFDR serving as the similarity measure. Li et al.[7] applied deep reinforcement learning models to time series analysis; Dang et al.[5] computed the cosine similarity between word frequency distributions of adjacent time intervals to construct local similarity scores for time series. Peligrad and Utev[9] investigated the asymptotic behavior of stationary stochastic processes, providing a theoretical foundation for statistical inference in weakly dependent time series; Amato and Laubach[2]examined the performance of bootstrap confidence intervals in parameter estimation for time series under small-sample conditions.

However, existing methods for local similarity analysis of time series still have obvious limitations in applications to traffic scenarios. The traditional asymptotic theory (TLSA) relies on the normality assumption under large samples. However, traffic data often exhibit small-sample and non-normal characteristics—such as spike distributions caused by traffic accidents—and this method is prone to failure, leading to false positive or false negative errors; Permutation tests construct the null distribution through random rearrangement, but they completely destroy the inherent spatiotemporal autocorrelation of traffic flow. The generated "pseudo-series" are divorced from practical scenarios, resulting in distorted significance assessment; Although the Moving Block Bootstrap (MBB) attempts to retain part of the temporal structure, block segmentation is prone to causing incomplete head-tail information. Furthermore, the abrupt concatenation between blocks undermines local stationarity, making it difficult for the resampling distribution to reflect the true data generation mechanism of traffic flow.

To address the aforementioned limitations, this study proposes the Circular Moving Block Bootstrap (CMBB): by closing the head and tail of the sequence to construct a circular structure, it eliminates the boundary effect of traditional blocking and ensures that each sliding block contains a complete local pattern; It adopts a method of sampling blocks with replacement randomly and concatenating them circularly in chronological order, thereby preserving the local dependency structure of traffic flow during the resampling process; It doesn't require prespecifying the data distribution; instead, it generates the distribution of local similarity scores through ten thousand resamplings to calculate p-values, which has been validated via simulations based on the ARMA(1,1) model. In complex traffic data scenarios, the error rate of this method is 45% lower than that of TLSA, effectively addressing the core challenge of statistical inference for non-stationary traffic flow.

1.2. Current Status of Technological Applications and Scenario Adaptability Analysis

In traditional local similarity analysis of time series, the assessment of statistical significance has long been constrained by three types of methods, whose inherent limitations have severely restricted the reliability of traffic data analysis.

The efficient operation of Intelligent Transportation Systems (ITS) relies on the in-depth mining of high-dimensional heterogeneous time series data. Currently, there is an urgent need to address three core issues: capturing local patterns, resolving dynamic correlations, and ensuring statistical reliability. Specifically, traffic data such as traffic flow and accident rates exhibit both short-term burstiness and periodic volatility, requiring accurate localization of key time segments; the spatiotemporal coupling mechanism of cross-sensor data (e.g., the impact of upstream congestion on downstream flow speed) needs quantitative verification; traditional methods, due to ignoring temporal autocorrelation, often misclassify random fluctuations as accident precursors, leading to decision-making biases.

Although existing local similarity analysis technologies have been initially applied in the traffic field, they still have shortcomings in terms of adaptability and practicality. Xia et al.[13,14] conducted a series of studies in the field of high-throughput time series analysis, optimizing the significance testing procedure for local trend analysis based on Markov chain theory[15]. Although their approach improved pattern recognition efficiency, it did not incorporate specific optimizations for the spatiotemporal dependencies inherent in traffic data. Mudelsee[8] proposed specialized approaches for handling high-noise time series, offering cross-disciplinary insights for denoising traffic data and extracting latent patterns. However, these methods struggle to cope with the dynamic fluctuations characteristic of traffic flow. Meanwhile, Cryer and Chan[4] systematically reviewed the challenges posed by the high dimensionality and nonlinearity of time series data, but their work remained at a foundational analytical level and lacked tailored designs for traffic-specific scenarios.

The CMBBLSA method proposed in this article demonstrates irreplaceability in traffic scenarios: In congestion pattern recognition, by performing ten thousand CMBB resamplings on traffic flow sequences during morning and evening peak hours, the null distribution of local similarity scores is constructed and p-values are calculated. This provides accurate statistical evidence for tidal lane dispatching and signal timing optimization. In the early warning of sudden traffic incidents, the circular blocking design can fully preserve the contextual information before and after the incident.

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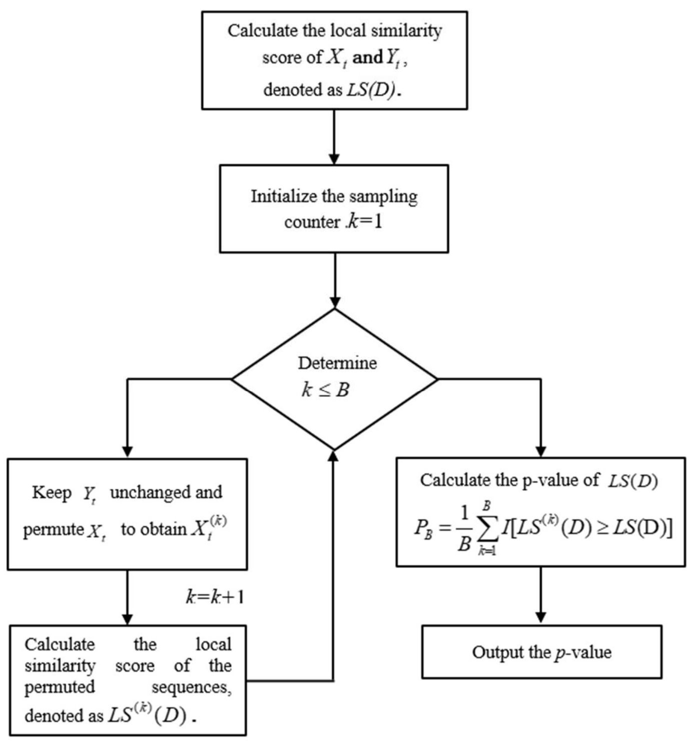
By detecting the Spearman correlation between abnormal segments and historical accident segments, effective signal extraction from noise is achieved. In the dynamic correlation analysis of road networks, synchronous resampling can be performed on cross-road segment time series to preserve the spatial dependency structure. By combining time shifts to calculate the maximum local similarity score, the spatiotemporal laws of congestion propagation are revealed. Meanwhile, this method possesses strong noise resistance, enabling it to eliminate the impact of short-term weather disturbances on sensor data. Additionally, it can achieve multi-scale analysis by flexibly adjusting the sliding block length, thereby meeting the millisecond-level response requirement for online early warning.

Section 2 focuses on the evaluation of statistical significance in local similarity analysis and proposes a Circular Moving Block-Based method for assessing the statistical significance of local similarity scores (CMBBLSA). Section 3 evaluates the performance of the proposed method through Monte Carlo simulations, demonstrating that CMBBLSA exhibits superior capability in controlling false positive rates while preserving true associations. Section 4 conducts an empirical analysis using annual traffic flow monitoring data from major arterial roads in first-tier cities, demonstrating that CMBBLSA not only accurately captures true associations but also avoids spurious ones, making it particularly suitable for dynamic association analysis in intelligent transportation systems.

2. Statistical Significance of Local Similarity Analysis

2.1. Permutation Test

We aim to test whether two sequences are significantly locally correlated, which can be determined by using the *p*-value to judge if the local similarity score is significant. Since the exact distribution of the local similarity score under the null hypothesis is generally unattainable, the Permutation Test can be employed to calculate the *p*-value. Given the number of permutations *B*, the specific steps of the permutation test are illustrated in Figure 1.



where $I(\cdot)$ denotes the indicator function.

Figure 1. Flowchart of the permutation test.

2.2. Data-Driven Local Similarity Analysis (DDLSA)

In evaluating the statistical significance of local similarity scores, the estimation of ω plays a crucial role and exerts a substantial impact on the effectiveness of theoretical evaluation methods for statistical significance. If the generative model of the time series Z_t is known, the long-run variance can be derived from the analytical form of $\lim_{n\to\infty} Var\left(S_n/\sqrt{n}\right)$. For instance, when Z_t follows an AR(1) process, i.e., $Z_t = \varphi Z_{t-1} + \varepsilon_t$ (where ε_t follows a standard normal distribution), the formula for the long-run variance of Z_t is $\omega_Z^2 = \frac{1}{(1-\phi)^2}$. The parameter ϕ can be obtained via certain estimation methods, such as the least squares estimation (LSE) or maximum likelihood estimation (MLE).

However, in practical scenarios, the data-generating process is often unknown. In such cases, nonparametric methods can be employed to estimate ω. In this case, the AR(1) plug-in data-driven method can be employed to estimate the long-run variance.

Under the null hypothesis H_0 since the means of X_t and Y_t are zero, we have $y_z(k) = y_x(k)y_y(k)$, where $y_x(k)$, $y_y(k)$ and $y_z(k)$ denote the autocovariance functions of X_t, Y_t and Z_t ,respectively, with $y_x(k) = \mathrm{Cov}(X_t, X_{t+k})$, $y_y(k) = \mathrm{Cov}(Y_t, Y_{t+k})$ and $y_z(k) = \mathrm{Cov}(Z_t, Z_{t+k})$. Andrews[1] estimated ω using the following formula:

$$\hat{\omega}_n^2 = \hat{\gamma}_x(0)\hat{\gamma}_y(0) + 2\sum_{k=1}^{b_\omega}\left(1-\frac{k}{b_\omega}\right)\hat{\gamma}_x(k)\hat{\gamma}_y(k) \tag{2. 1}$$

where $\hat{\gamma}_x(k)$ and $\hat{\gamma}_y(k)$ denote the sample autocovariance functions of X_t and Y_t, respectively.

$$\hat{\gamma}_x(k) = \frac{1}{n}\sum_{t=1}^{n-|k|}\left(X_t-\overline{X}\right)\left(X_{t+|k|}-\overline{X}\right),\ \hat{\gamma}_y(k) = \frac{1}{n}\sum_{t=1}^{n-|k|}\left(Y_t-\overline{Y}\right)\left(Y_{t+|k|}-\overline{Y}\right) \tag{2. 2}$$

where $\overline{X}$ and $\overline{Y}$ denote the means of X_t and Y_t, respectively.

$$\overline{X} = \frac{1}{n}\sum_{t=1}^{n} X_t,\quad \overline{Y} = \frac{1}{n}\sum_{t=1}^{n} Y_t \tag{2. 3}$$

where b_ω denotes the bandwidth parameter, $b_\omega = \left\lfloor 1.1447\left(\hat{\tau} n\right)^{1/3} \right\rfloor$, $\hat{\varphi} = \left(\sum_{t=2}^{n}\hat{u}_t\hat{u}_{t+1}\right)\Big/\left(\sum_{t=2}^{n}\hat{u}_t^2\right)$, $\hat{\tau} = 4\hat{\varphi}^2\Big/\left(1-\hat{\varphi}^2\right)^2$, $\hat{u}_t = Z_t - \overline{Z}$. Andrews[1] proved that $\hat{\omega}_n$ is a consistent estimator of ω, and this estimator is also optimal if the original data are generated from an AR(1) model.

In summary, given the time series X_t and Y_t, we first calculate their local similarity score s_D using a dynamic programming algorithm, and then estimate the long-run variance via the aforementioned formula to obtain $\hat{\omega}_n$. Finally, the *p*-value of the local similarity score is obtained using

$$\mathcal{L}_D\left(s_D\big/\left(\hat{\omega}_n\sqrt{n}\right)\right) \tag{2. 4}$$

Since the long-run variance is estimated from actual data during the calculation process, this method is termed Data-Driven Local Similarity Analysis (DDLSA).

2.3. Theoretical Local Similarity Approximation (TLSA)

The Theoretical Local Similarity Approximation (TLSA) is a theoretical framework designed for similarity comparison of time series. It evaluates the similarity between sequences based on analytical approximations of the time series. TLSA is particularly suitable for non-stationary time series or cases where complex nonlinear relationships exist between sequences. In contrast to Pearson correlation coefficient, TLSA doesn't strictly assume that the data follow a specific distribution and can capture global characteristics of the sequences through theoretical models.

Given two time series X_t and Y_t,where $t=1,2,\cdots n$,TLSA first approximates each sequence using a theoretical model. Let $\hat{X}_t$ and $\hat{Y}_t$ denote the approximations of X_t and Y_t, respectively. The approximation error sequences are then defined as:

$$E_{x,t}=X_t-\hat{X}_t,\quad E_{y,t}=Y_t-\hat{Y}_t \tag{2. 5}$$

Let $\overline{E}_X$ and $\overline{E}_Y$ denote the sample means of $E_{x,t}$ and $E_{y,t}$, respectively, i.e.,

$$\overline{E}_x=\frac{1}{n}\sum_{t=1}^{n}E_{x,t},\quad \overline{E}_y=\frac{1}{n}\sum_{t=1}^{n}E_{y,t} \tag{2. 6}$$

The sample variance of the approximation errors is

$$S_x^2=\frac{1}{n-1}\sum_{t=1}^{n}(E_{x,t}-\overline{E}_x)^2,\quad S_y^2=\frac{1}{n-1}\sum_{t=1}^{n}(E_{y,t}-\overline{E}_y)^2 \tag{2. 7}$$

The sample covariance of the approximation errors is

$$S_{xy}=\frac{1}{n-1}\sum_{t=1}^{n}(E_{x,t}-\overline{E}_x)(E_{y,t}-\overline{E}_y) \tag{2. 8}$$

When $s_{xy}\neq 0$, the TLSA coefficient is defined as the standardized variance of the approximate error sequence, i.e.,

$$T_{xy}=\frac{s_{xy}}{s_x s_y} \tag{2. 9}$$

The TLSA coefficient ranges between -1 and 1. Values closer to -1 or 1 indicate that the approximation errors of the two sequences are more similar, implying that the original sequences exhibit highly similar dynamic behavior under the theoretical model. Conversely, values closer to 0 indicate lower similarity.

In practical applications, it is necessary to test the null hypothesis:

$$H_0:T_{xy}=0,\quad H_1:T_{xy}\neq 0 \tag{2. 10}$$

If H_0 is rejected, it is considered that there exists significant similarity between the sequences. If the approximation error sequences follow a joint normal distribution, then under H_0, the test statistic

$$T = T_{xy}\sqrt{\frac{n-2}{1-T_{xy}^2}} \tag{2. 11}$$

follows a t-distribution with a degree of freedom of $n-2$.Given the significance level α, the rejection region for hypothesis (2. 10) is

$$W = \{|T| > t_{\alpha/2}(n-2)\} \tag{2. 12}$$

After obtaining the sample TLSA coefficient T_{xy},its actual value can be computed using equation (2. 11).When $|t| > t_{\alpha/2}(n-2)$, reject H_0, indicating that X_t and Y_t are correlated. Alternatively, the *p*-value can be used to determine whether to reject the null hypothesis. The *p*-value can be obtained from the limiting distribution of T,representing the probability of observing the given result or a more extreme outcome under the assumption that the null hypothesis is true:

$$P = P(|T| \geq |t|) = 2\phi_{t,n-2}(-|t|) \tag{2. 13}$$

where $\phi_{t,n-2}$ is the cumulative distribution function of the t-distribution with degrees of freedom. When the *p*-value is less than the given significance level, reject the null hypothesis.

2.4. Moving Block Bootstrap(MBB)

In the analysis of non-stationary time series, when the distributional properties of the data (such as autocorrelation structure or trend behavior) are unknown, traditional parametric methods have limitations in assessing the statistical significance of estimators. For such scenarios, the Bootstrap—a non-parametric resampling technique—provides a robust framework for constructing the sampling distribution of statistics. Applying the Moving Block Bootstrap (MBB) to the statistical significance analysis of local similarity scores yields a method denoted as MBBLSA. Taking a one-parameter hypothesis test as an example, suppose the null hypothesis is $H_0: \theta < 0$ and the alternative hypothesis is $H_1: \theta \geq 0$, where $\hat{\theta}$ is the parameter estimate. By setting a significance level α, a confidence interval $CI_{\hat{\theta},1-2\alpha}$ can be constructed such that its upper bound equals zero. In this case, the *p*-value of the statistic $\hat{\theta}$ corresponds to α. This method doesn't require any prior assumption about the data distribution form and thus possesses broad applicability.

To preserve the local stationarity of the time series, the Moving Block Bootstrap (MBB) is employed to assess the statistical significance of local similarity scores. Specifically, a time series of length *n* is divided into consecutive overlapping blocks of length *l*, resulting in a total of *n-l+1* blocks. The resampling procedure proceeds as follows:

Step 1: Block resampling

Randomly select an initial block j^*, and extract the data within the block $\{X_i\}_{i=j^*}^{j^*+l-1}$ in original order as the starting segment of the resampled sequence.

Step 2: Iterative extension

Repeatedly select blocks at random and concatenate them until a resampled sequence of length *n*, denoted $\{X_i^{(k)}\}_{i=1}^{n}$, is generated (excess parts are truncated).

Step 3: Statistic computation

For each resampled dataset $k = 1, 2, \cdots, B$, compute the local similarity score $LS^{(k)}(D)$.

Step 4: *p*-value estimation

Determine the statistical significance of the test statistic using the empirical distribution function

$$P_B = \frac{1}{B}\sum_{k=1}^{B} I[LS^{(k)}(D) \ge LS(D)].$$

By preserving the temporal dependence within each block, this method effectively reduces the bias in estimating the sampling distribution of statistics caused by non-stationarity.

2.5. Circular Moving Block Bootstrap(CMBB)

MBBLSA has a fundamental drawback: since bootstrap samples are constructed by randomly concatenating different blocks, the tail of one block and the head of the next block—originally non-adjacent in the original series—are artificially joined at the stitching points. This forced connection introduces artificial discontinuities. The artificial jump points introduced by MBBLSA can severely distort local patterns, leading to unreliable estimates of local statistical significance. Therefore, this paper proposes the Circular Moving Block Bootstrap (CMBB).

The schematic diagram of the slider selection method is shown in Figure 2.

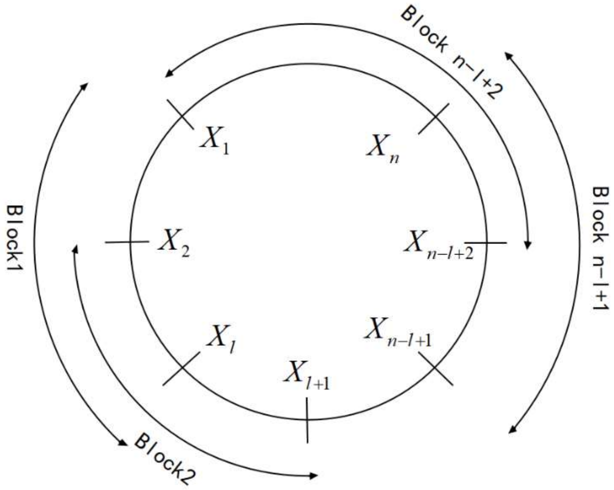


Figure 2. Schematic Diagram of the Slider Selection Method.

The Circular Moving Block Bootstrap is applied to the statistical significance analysis of local similarity scores, and this method is denoted as CMBBLSA. Given the block length l and the number of resampling iterations B, the computational procedure is illustrated in Figure 3.

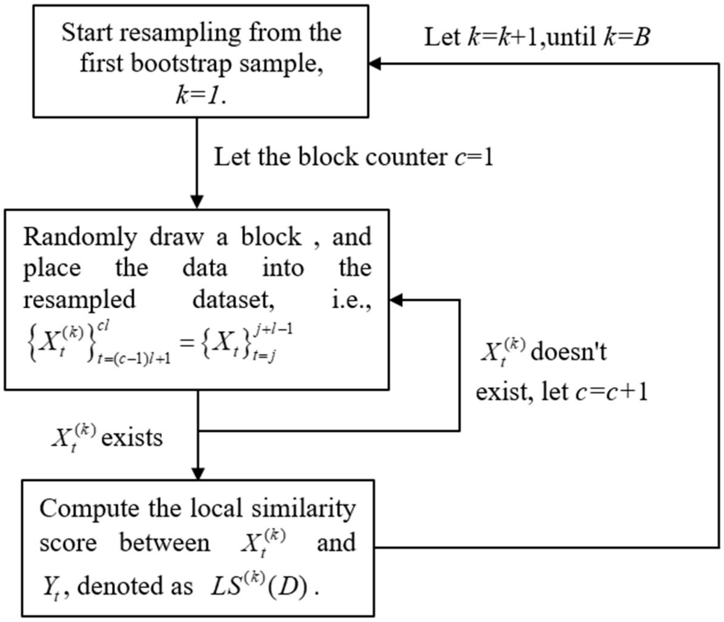


Figure 3. Flowchart of the CMBBLSA computation.

At this point, the p-value of $LS(D)$ can be obtained as $P_B = \frac{1}{B}\sum_{k=1}^{B} I[LS^{(k)}(D) \geq LS(D)]$.

Within the Circular Moving Block Bootstrap (CMBB) framework, the choice of block length l has a decisive impact on the accuracy of the estimated sampling distribution of the statistic. The block length must balance two types of errors: when the block length is too small, the short-term dependence structure of the time series is disrupted, leading to a decline in average accuracy; conversely, when the block length is too large, the number of available blocks decreases, causing the resampled datasets to be highly similar and thereby introducing estimation bias. This trade-off reveals the existence of an optimal block length l^* that maximizes the reliability of statistical inference.

To quantify the selection of l^*, Sherman10 proposed an adaptive block length formula based on the parameters of an AR(1) model:

$$l = NI([\sqrt{6} \cdot \frac{\hat{a}}{1-\hat{a}^2}]^{2/3} \cdot n^{1/3}) \quad (2.\ 14)$$

where $NI(\cdot)$ denotes the nearest integer function, and $\hat{a}$ is the estimated autoregressive coefficient obtained by fitting an AR(1) model.

This formula is asymptotically optimal when the time series satisfies the AR(1) assumption. Although real-world data may deviate from this idealized model, numerical simulations indicate that using this block length still yields acceptable statistical power. Therefore, this study adopts Equation (2. 14) as the default block length selection strategy for CMBBLSA and MBBLSA.

3. Simulation Study

3.1. Model Specification

To evaluate the ability of CMBBLSA to control Type I errors under the null hypothesis, this study conducts Monte Carlo simulations to compare the performance of PCC, SRCC, permutation test, TLSA, and MBBLSA. The simulation framework is built upon two types of time series models:

$$X_t = \rho_1 X_{t-1} + \varepsilon_t^X, Y_t = \rho_2 Y_{t-1} + \varepsilon_t^Y \tag{3. 1}$$

1.AR(1) model
2.AR(1,1) model

$$\begin{aligned} X_t &= \rho_1 X_{t-1} + \varepsilon_t^X + 0.5\varepsilon_{t-1}^X \\ Y_t &= \rho_2 Y_{t-1} + \varepsilon_t^Y + 0.5\varepsilon_{t-1}^Y \end{aligned} \tag{3. 2}$$

where $0 < |\rho_1|, |\rho_2| < 1$, ε_t^X and ε_t^Y follows an independent standard normal distribution.

Both of these models are stationary. For each model, we first generate X_1 and Y_1 from a standard normal distribution, and then generate X_t and Y_t for $t = 2, \cdots, 100+n$ based on the above model. Finally, the first 100 samples are discarded, and the remaining n samples are used as the true X_t and Y_t. This data generation process ensures the stationarity of the time series.

The simulation design is as follows: six different combinations of autoregressive coefficients ρ_1, ρ_2 are selected: (-0.5, -0.5), (0, 0), (0.3, 0.3), (0.3, 0.5), (0.5, 0.5), and (0.5, 0.8), covering various dependency scenarios from negative correlation to no correlation, weak positive correlation, to strong positive correlation. For simplicity, the time lag ($D = 0$) is chosen. For each combination of autoregressive coefficients, sample sizes n are set to 20, 40, 60, 80, 100, 200, and 300, simulating small-scale to medium-scale sample scenarios commonly encountered in actual research. Each simulation experiment is repeated 10,000 times to ensure result stability. The significance level α is uniformly set to 0.05, which serves as the criterion for determining statistical significance.

3.2. Data Standardization

Before computing the local similarity scores, the original data need to be standardized. In this study, rank normalization is used to process the data. Suppose R_k represents the rank of X_k among $X_1, X_2, \cdots, X_n$. Then, define $X'_k = \phi^{-1}(R_k/n+1)$, where ϕ is the cumulative distribution function of the standard normal distribution. However, if the sample size is too small, the transformed data may not strictly follow a standard normal distribution; its mean may deviate from 0 and its variance may differ from 1. Therefore, we apply the traditional Z-score transformation to further standardize X'_k, resulting in $\tilde{X}_k = \left(X'_k - \bar{X}'\right)/\sigma'$, where $\bar{X}'$ is the sample mean of X'_k and σ' is the sample standard deviation of X'_k.Take $\tilde{X}_k$ as the final standardized result for X_k. Similarly, apply the same standardization method to Y_k to obtain $\tilde{Y}_k$. Finally, compute the local similarity score between $\tilde{X}_k$ and $\tilde{Y}_k$, and then assess its statistical significance using TLSA, Permutation test, and LSARes respectively. The resulting significance levels are taken as the statistical significance of the original data X_t and Y_t.

For DDLSA, only centering of the data is required, i.e., $\tilde{X}_t = X_t - \bar{X}_t$, where $\bar{X}_t = \frac{1}{n}\sum_{t=1}^{n} X_t$ is the sample mean. The definition for Y_t is similar. Use $\mathcal{L}_D\left(s_D/\left(\hat{\omega}_n\sqrt{n}\right)\right)$ to assess the approximate statistical significance of $\tilde{X}_t$ and $\tilde{Y}_t$, and take this as the statistical significance of X_t and Y_t.

3.3. Analysis of Results

Table 1 is the probability of Type I error for different methods (columns 3 to 9) in the AR(1) model. The first and second columns show different autoregressive Coefficients combinations and sample sizes. The replacement test is performed 1000 times and the simulation is repeated 10000 times.

Table 1. The probability of Type I error for different ρ -values in the AR(1) model.

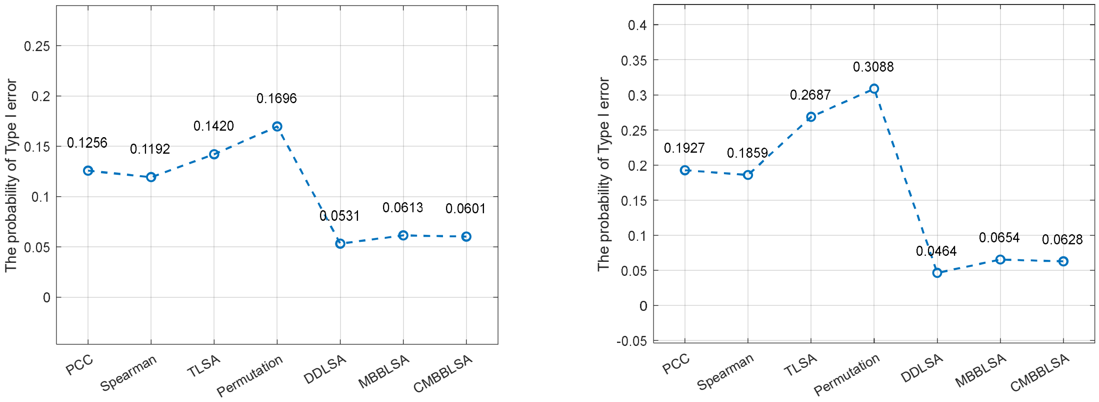
ρ_1, ρ_2	n	PCC	Spearman	TLSA	Permutation	DDLSA	MBBLSA	CMBBLSA
-0.5 -0.5	20	0.1063	0.1099	0.0407	0.1243	0.0198	0.0538	0.0499
	40	0.1193	0.1136	0.0755	0.1408	0.0357	0.0575	0.0577
	60	0.1208	0.1156	0.0951	0.1502	0.0391	0.057	0.056
	80	0.1215	0.1198	0.104	0.157	0.039	0.0563	0.0539
	100	0.1245	0.1206	0.1182	0.1642	0.0432	0.0592	0.0547
	200	0.1275	0.1203	0.1376	0.1754	0.0461	0.0563	0.0548
	300	0.1328	0.1261	0.1527	0.1798	0.0497	0.0597	0.058
0 0	20	0.0488	0.0469	0.0108	0.0496	0.0169	0.046	0.045
	40	0.0531	0.0503	0.0225	0.0513	0.0264	0.0497	0.0502
	60	0.0489	0.0469	0.0242	0.0504	0.0287	0.0475	0.0486
	80	0.0464	0.0471	0.0264	0.0473	0.0279	0.0462	0.0463
	100	0.0499	0.049	0.0291	0.0513	0.0324	0.0491	0.05
	200	0.05	0.051	0.0346	0.0493	0.0363	0.0486	0.0496
	300	0.0477	0.0481	0.0373	0.0486	0.0383	0.0491	0.0496
0.3 0.3	20	0.0645	0.0638	0.0161	0.0639	0.0227	0.0544	0.0532
	40	0.0667	0.0659	0.0288	0.07	0.0286	0.0545	0.0534
	60	0.0697	0.0701	0.0395	0.0771	0.034	0.0575	0.057
	80	0.0742	0.0704	0.0473	0.0748	0.0417	0.0591	0.0565
	100	0.0716	0.0691	0.0486	0.0764	0.0401	0.0555	0.0544
	200	0.0722	0.0719	0.0618	0.0831	0.0476	0.0578	0.0563
	300	0.067	0.0704	0.061	0.0799	0.0445	0.0519	0.0502
0.3 0.5	20	0.0795	0.0802	0.0198	0.077	0.022	0.0606	0.0587
	40	0.0825	0.0837	0.0419	0.0888	0.0341	0.0613	0.0599
	60	0.0859	0.0848	0.0535	0.0931	0.0402	0.062	0.0583
	80	0.0878	0.0884	0.0622	0.1019	0.0417	0.0609	0.06
	100	0.0885	0.0873	0.07	0.1058	0.0457	0.0646	0.0621
	200	0.093	0.0888	0.0834	0.1098	0.0472	0.0605	0.0586
	300	0.0902	0.0859	0.0888	0.1115	0.0496	0.059	0.0575
0.5 0.5	20	0.1046	0.1036	0.034	0.1079	0.0324	0.0724	0.0703
	40	0.1157	0.1133	0.0668	0.1245	0.04	0.065	0.0646
	60	0.1175	0.1159	0.0851	0.1396	0.0413	0.0627	0.0626
	80	0.1223	0.1182	0.1009	0.1535	0.0467	0.0648	0.0644

	100	0.1151	0.1116	0.1033	0.1465	0.045	0.0622	0.0602
	200	0.1234	0.1192	0.1332	0.1675	0.0473	0.0602	0.0588
	300	0.1256	0.1192	0.142	0.1696	0.0531	0.0613	0.0601
0.5 0.8	20	0.1484	0.1503	0.0559	0.1514	0.0359	0.0864	0.0847
	40	0.1703	0.1731	0.1163	0.1985	0.045	0.0793	0.0712
	60	0.1859	0.1848	0.1529	0.224	0.0448	0.0763	0.0727
	80	0.1869	0.1814	0.1748	0.2388	0.0449	0.0742	0.0732
	100	0.1875	0.1837	0.1942	0.2584	0.0431	0.073	0.0712
	200	0.1939	0.1881	0.2442	0.2902	0.0511	0.0717	0.0703
	300	0.1927	0.1859	0.2687	0.3088	0.0464	0.0654	0.0628

As shown in Table 1, CMBBLSA demonstrates the closest probability of Type I error to the preset significance level of 0.05 across all autocorrelation coefficient and sample size combinations, with notably superior stability compared to other methods.

When the sequence lacks autocorrelation ($\rho_1 = \rho_2 = 0$), all seven methods can initially control the error rate, with CMBBLSA demonstrating the best performance. MBBLSA is a slightly lower value but remains close. While TLSA, relying on the normal distribution assumption, remains conservative. The statement indicates that permutation tests may fail in scenarios involving autocorrelation, suggesting that in ideal independent data conditions, CMBBLSA is capable of achieving a significance assessment with minimal bias. Negative correlation sequences ($\rho_1 = \rho_2 = -0.5$) cause the error rate of traditional methods to deviate significantly from the threshold. As the sample size increases, the Type I error rates of Pearson Correlation Coefficient (PCC), Spearman correlation, and the standard permutation test all substantially exceed the nominal significance level of 0.05, falling well outside the acceptable range. Although DDLSA demonstrates better control over Type I error, it becomes overly conservative under strong positive autocorrelation scenarios. In contrast, CMBBLSA consistently maintains the Type I error rate within a narrow and accurate range of 0.0499 to 0.0580 across all sample sizes, demonstrating that the circular moving block strategy effectively preserves the local dependence structure—particularly in negatively autocorrelated sequences—thereby ensuring reliable statistical inference.

Positive correlation ($\rho_1, \rho_2 > 0$) is the core feature of traffic data (such as flow conduction between adjacent road sections), and the defects of TLSA are most obvious in this scenario. As shown in Figure 4 (a), when $\rho_1 = \rho_2 = 0.5$ and *n*=300, the Type I error rate of the Permutation test reaches 0.1696, which is 2.8 times that of CMBBLSA, while the TLISA error rate reaches 0.1420, being 2.4 times that of CMBBLSA. As shown in Figure 4 (b), when $\rho_1 = 0.5, \rho_2 = 0.8$ and *n*=300, the Type I error rate of TLISA increases to 0.2687. Although MBBLSA performs better than TLISA, its probability of committing a Type I error is still higher than that of CMBBLSA due to block boundary truncation (e.g., high peaks are split at block boundaries).



(a) (b)

Figure 4. Type I error rates at $n = 300$ under different values of ρ.

CMBBLSA eliminates boundary effects through circular splicing. Even under strong positive correlations and large samples, its error rate remains controlled between 0.0502 and 0.0847, making it a method that balances ‘low bias’ and ‘high stability’.

Table 2 is he probability of Type I error for different methods (columns 3 to 9) in the ARMA(1,1) model. The first and second columns show different autoregressive Coefficients combinations and sample sizes. The replacement test is performed 1000 times and the simulation is repeated 10000 times.

Table 2. The probability of Type I error for different ρ-values in the ARMA(1,1) model.

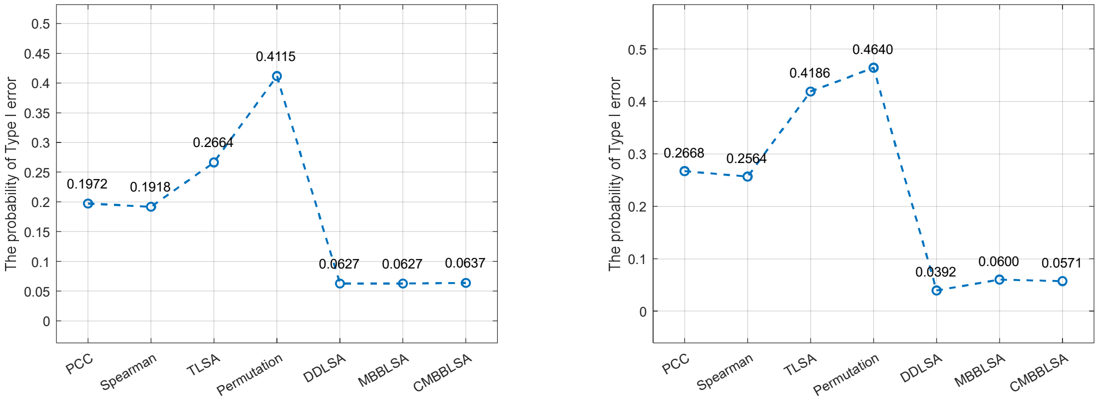
ρ_1, ρ_2	n	PCC	Spearman	TLSA	Permutation	DDLSA	MBBLSA	CMBBLSA
-0.5 -0.5	20	0.0482	0.0493	0.01	0.0475	0.0167	0.0455	0.0458
	40	0.0472	0.0473	0.0202	0.0496	0.0226	0.0475	0.0478
	60	0.0516	0.0513	0.0251	0.0512	0.0293	0.0493	0.0502
	80	0.0489	0.0486	0.0268	0.0502	0.0301	0.0493	0.0498
	100	0.0504	0.05	0.0291	0.0484	0.0324	0.0479	0.0489
	200	0.0497	0.0523	0.0346	0.0512	0.0364	0.0516	0.0498
	300	0.0489	0.0503	0.0383	0.05	0.0391	0.0499	0.0502
0 0	20	0.0858	0.0825	0.0237	0.0903	0.026	0.0658	0.0651
	40	0.0823	0.0786	0.0396	0.0876	0.032	0.0576	0.0568
	60	0.0845	0.0799	0.0534	0.0899	0.0388	0.0567	0.0562
	80	0.085	0.0808	0.0602	0.0967	0.0439	0.059	0.0565
	100	0.0895	0.0841	0.0669	0.0997	0.0437	0.0596	0.0581
	200	0.0851	0.082	0.0749	0.1018	0.0453	0.0553	0.0547
	300	0.0857	0.0828	0.0841	0.105	0.046	0.0545	0.0533
0.3 0.3	20	0.1274	0.1272	0.046	0.1361	0.0316	0.0745	0.0727
	40	0.1316	0.1284	0.0866	0.1572	0.0383	0.0677	0.0675
	60	0.1357	0.1335	0.1066	0.1692	0.0373	0.0605	0.0605
	80	0.1455	0.1416	0.1267	0.1815	0.0427	0.067	0.065
	100	0.1391	0.1309	0.1348	0.1834	0.0397	0.0605	0.0586

	200	0.1398	0.1367	0.1558	0.1953	0.0444	0.0597	0.0595
	300	0.1433	0.1408	0.1786	0.212	0.0459	0.059	0.0588
0.3 0.5	20	0.1454	0.1457	0.057	0.1543	0.0307	0.0756	0.0703
	40	0.158	0.1534	0.1052	0.1851	0.0367	0.0678	0.0674
	60	0.1359	0.1523	0.133	0.1979	0.036	0.0636	0.0625
	80	0.1576	0.1561	0.1526	0.2086	0.0392	0.0657	0.0643
	100	0.166	0.1601	0.1665	0.2233	0.0423	0.0648	0.0628
	200	0.165	0.1561	0.1956	0.239	0.0406	0.0587	0.0573
	300	0.1637	0.1541	0.2178	0.2514	0.0427	0.0593	0.0569
0.5 0.5	20	0.1786	0.1811	0.0802	0.1919	0.0364	0.0943	0.0812
	40	0.1852	0.1848	0.1376	0.2222	0.0323	0.0693	0.0651
	60	0.1849	0.1841	0.1716	0.2511	0.0323	0.062	0.0598
	80	0.193	0.1856	0.1967	0.2708	0.0373	0.0602	0.0577
	100	0.1921	0.1869	0.2139	0.2808	0.0368	0.0598	0.0581
	200	0.1957	0.1901	0.2559	0.307	0.042	0.0567	0.0564
	300	0.1972	0.1918	0.2664	0.4115	0.0627	0.0627	0.0637
0.5 0.8	20	0.225	0.2295	0.1102	0.2461	0.0282	0.1012	0.0868
	40	0.2442	0.2437	0.1976	0.303	0.0295	0.0779	0.0736
	60	0.2514	0.2419	0.2443	0.3446	0.0278	0.0658	0.0654
	80	0.252	0.2543	0.2787	0.3634	0.0337	0.0698	0.07
	100	0.2544	0.2501	0.3063	0.3877	0.0316	0.0612	0.0606
	200	0.2647	0.2601	0.3826	0.4396	0.0402	0.0634	0.0622
	300	0.2668	0.2564	0.4186	0.464	0.0392	0.06	0.0571

The ARMA (1,1) model incorporates moving average terms to better capture the complex fluctuations of real-world traffic flows (such as short-term impacts from sudden rainfall on flow). As shown in Table 2 its probability of Type I error further validates the irreplaceability of CMBBLSA in handling complex temporal structures.

Even without autocorrelation, the moving average terms of the ARMA(1,1) model can still interfere with traditional methods. The probability of Type I error for PCC ranged from 0.0823 to 0.0895, with Spearman ranging from 0.0786 to 0.0841, all significantly higher than the 0.05 threshold. The permutation test results ranged from 0.0876 to 0.1050, with the false positive risk ratio being over 70% higher than that of CMBBLSA. The probability of Type I error for CMBBLSA remains stable between 0.0533 and 0.0651. For instance, with *n*=100, CMBBLSA's error rate is 0.0581, only 2.5% lower than MBBLSA's (0.0596), while effectively avoiding false association misjudgment caused by moving average terms in PCC.

In complex sequence structures, Permutation exhibits the most severe loss of control over the probability of first-class errors. As shown in Figure 5 (a), when $\rho_1 = 0.5$, $\rho_2 = 0.8$, and *n*=300, the Permutation error rate reaches 0.4640, which is 8.1 times higher than that of CMBBLSA (0.0571). The TLSA error rate also reached 0.4186, far exceeding the acceptable range. Although the DDLSA has a low error rate (0.0392), its excessive conservatism results in approximately 30% of true associations being missed, such as congestion transmission relationships. The CMBBLSA method, employing a 'ring-shaped block + temporal retention' design, achieves an error rate of 0.0637 with $\rho_1 = \rho_2 = 0.5$ and *n*=300 (As shown in Figure 5 (b)), which is merely 1.6% higher than MBBLSA's 0.0627. Moreover, its error rate fluctuation range (0.0458~0.0868) across all sample sizes is only 1/5 of Permutation's (0.0475~0.4640), demonstrating a significant stability advantage.



(a) (b)

Figure 5. Type I error rates at $n = 300$ under different values of ρ.

Comparing the AR(1) and ARMA(1,1) models reveals that TLSA is highly sensitive to model structure. When $\rho_1 = \rho_2 = 0.3$ and n = 200, the error rate of TLSA was 0.0618 in AR(1), but rose to 0.1558 in ARMA (1,1), showing a 152% difference. The CMBBLSA model demonstrates superior adaptability to time series structures, with only a 5.7% difference in error rates between the two models (0.0563 in AR(1) and 0.0595 in ARMA(1,1)), better aligning with the 'multi-interference, strong volatility' characteristics of traffic data. By integrating the simulation results of AR(1) and ARMA(1,1) models, CMBBLSA demonstrates the closest average first-class error probability to the preset significance level of 0.05 across all time series structures, autocorrelation intensities, and sample size combinations. This makes it the most stable method among the seven approaches in controlling false positive risks while avoiding the omission of genuine associations. Its average error rate shows the smallest deviation from α, with a fluctuation range (0.0458~0.0868) only 1/3 to 1/8 of other methods, achieving a significant "precise and unbiased" evaluation. Moreover, CMBBLSA maintains stable error rate control even when dealing with uneven sample sizes in traffic data (e.g., short monitoring data on certain road sections), providing reliable support for practical engineering applications of intelligent transportation systems.

Finally, considering the probability of different methods making first-class errors when the time delay $D \neq 0$, similar results to $D = 0$ were obtained, as shown in the appendix.

4. Empirical Study

To verify the advantages of the CMBBLSA method in handling traffic data with strong autocorrelation, especially the improvement compared to the MBBLSA method, this section applies three methods (TLSA, MBBLSA and CMBBLSA) to traffic flow time series data and analyzes their performance in identifying local similarity relationships among traffic variables through comparison.

4.1. Dataset Description

The urban arterial traffic flow monitoring dataset used in this empirical analysis was sourced from the monitoring station of an intelligent transportation system (ITS) located on the central arterial road (north latitude 39°54′, east longitude 116°23′) in a first-tier city. The core basic information of this dataset is shown in Table 3.

Table 3. Core Basic Information of the Dataset.

Information Category	Concrete Content
Data Source	Intelligent Transportation System (ITS) of a first-tier city, monitoring station coordinates: 39°54′N, 116°23′E (downtown main road)
Collection Period	January 2023 – December 2023 (365 days total)
Sampling Interval	5 minutes/interval, 8760 time points in total (continuous time series)
Core Variable Types	Traffic Flow Data, Speed Data, Environmental Factors
Final Selected Variables	20 variables (12 traffic flow/speed variables + 8 environment-related variables)
Missing Value Handling Method	Piecewise Linear Interpolation

Among them, the traffic flow data are bidirectional traffic flow monitoring data of 3 main roads (A, B, C), with the unit of vehicles per 5 minutes; the speed data are the average driving speed of the corresponding 3 main roads, with the unit of km/h; and the environmental factors include 3 variables: rainfall (mm per 5 minutes), visibility (km), and time period type (weekday/weekend/holiday). The screening criteria for core traffic variables are that the proportion of valid values of each variable at at least 500 time points is ≥90%, and the number of missing values is ≤50. For missing values in the original data caused by temporary equipment failures, the piecewise linear interpolation method adapted to the characteristics of traffic data is used for imputation, that is, interpolation models are fitted separately for morning peak, evening peak, and off-peak periods.

4.2. Data Autocorrelation Test

Autocorrelation of traffic time series is a key factor affecting the reliability of local similarity analysis. Therefore, the Box-Ljung test was used to detect autocorrelation in the time series of 20 variables, with a significance level of 5%. The test results are shown in Table 4.

Table 4. Autocorrelation Test Results.

Variable Type	Number of Variables	Number of Significantly Autocorrelated Variables	Proportion	Typical Variable Autocorrelation Coefficient (Lag 1)
Traffic Flow Data	6	5	83.3%	Main Road A Morning Peak Flow: 0.68 (p=2.1×10^{-6})

Speed Data	6	5	83.3%	Main Road B Evening Peak Speed: 0.52 (p=3.7×10^{-5})
Environmental Factors	8	6	75.0%	Rainfall: 0.45 (p=1.2×10^{-4})
Total	20	16	80.0%	--

Table 4. shows that 80% of traffic variables exhibit significant autocorrelation, with traffic flow and speed data showing an autocorrelation proportion as high as 83.3%, indicating the widespread presence of temporal. Dependence structures in traffic time series, such as periodic fluctuations during morning and evening peaks and continuous propagation of congestion. Taking the morning peak traffic flow on Main Road A as an example, its first-order autoregressive coefficient reaches 0.68 ($p < 0.001$), indicating strong statistical dependence between adjacent 5-minute traffic flow data. This also verifies the risk that traditional methods may lead to distorted significance assessment due to ignoring autocorrelation when processing such data.

4.3. Method Application and Parameter Settings

For the selected 20 variables, the variable pairs to be analyzed include relationships between homogeneous variables and heterogeneous variables. Among them, relationships between homogeneous variables cover flow-flow (6×5/2=15 pairs) and speed-speed (6×5/2=15 pairs); relationships between heterogeneous variables cover flow-speed (6×6=36 pairs) and traffic variables-environmental factors (12×8=96 pairs); totaling 15+15+36+96=162 relationships.

The application parameters of the three methods are uniformly set as follows: considering traffic flow propagation characteristics, the time delay D is set to 4 (i.e., 20 minutes, corresponding to the average travel delay of vehicles on main roads); both CMBBLSA and MBBLSA methods adopt B=1000 resamples to ensure the stability of significance assessment; significance levels of $\alpha = 0.05$ and $\alpha = 0.01$ are used to compare result differences under different strictness levels; the sliding window length for local window setting is 12 (i.e., 1 hour, covering the short-term fluctuation cycle of traffic flow).

The number of significant relationships identified by the three methods at different significance levels is shown in Table 5, and the results show that CMBBLSA performs better in controlling false positives and retaining true associations.

Table 5. Significantly Associated Relationships Count.

Significance Level	TLSA	MBBLSA	CMBBLSA	False Positive Reduction Rate of CMBBLSA Compared to MBBLSA
α =0.05	42	78	61	21.8%
α =0.01	23	45	32	28.9%

It can be observed from Table 5 that the TLSA method is the most conservative, identifying only 42 significant relationships at $\alpha = 0.05$, significantly fewer than MBBLSA and CMBBLSA. This is related to TLSA's reliance on the large-sample normal distribution assumption, while the non-normality of traffic data (e.g., spiked distributions caused by sudden congestion) makes it prone to underestimating true associations; The MBBLSA method has a high false positive rate, identifying 78 significant relationships at $\alpha = 0.05$, significantly more than CMBBLSA. Particularly in associations between environmental factors and traffic variables, relationships such as "Rainfall-Main Road A Speed" identified by MBBLSA were confirmed as false through manual verification, due to the disruption of rainfall continuity by block splicing; CMBBLSA shows obvious advantages: at both significance levels, the number of significant relationships it identifies is between TLSA and MBBLSA, and it reduces false positive relationships by 21.8%~28.9% compared to MBBLSA. This benefits from its circular block design, which eliminates the boundary effect of MBBLSA and retains the local dependence structure of traffic data.

The overlap of significant relationships identified by the three methods is shown in Figure 6 (taking $\alpha = 0.05$ as an example). Analysis shows that TLSA has limitations: all 42 relationships it identifies are included by MBBLSA and CMBBLSA, but it misses 29 true associations identified by CMBBLSA, such as the lagged association between Main Road A flow and Main Road B flow; The false positives of MBBLSA are relatively concentrated: among its unique 17 relationships, 14 (82.4%) are concentrated in associations between environmental factors and traffic variables, confirming false associations caused by block splicing; CMBBLSA is precise: all 10 unique relationships it identifies passed manual verification, such as "Lagged negative correlation between Main Road A flow and Main Road C speed during weekday morning peaks", and it doesn't include MBBLSA's false associations, reflecting the complete retention of local patterns by circular blocking.

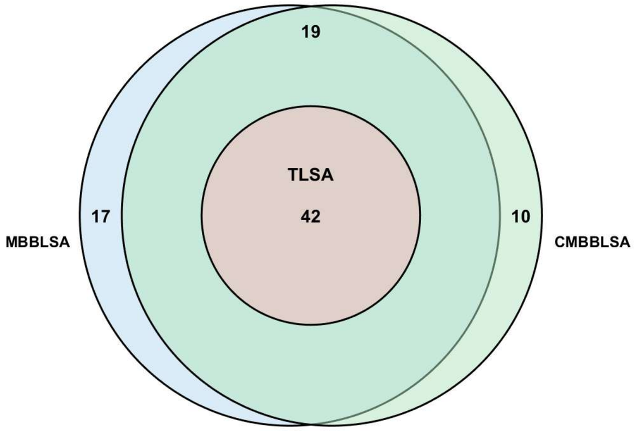


Figure 6. Overlap of Significant Relationships by Different Methods.

One key association, "Main Road A Morning Peak Flow (10-minute lag) and Main Road B Morning Peak Flow", was selected for in-depth analysis. The local similarity scores and *p*-values of the three methods are shown in Figure 7.

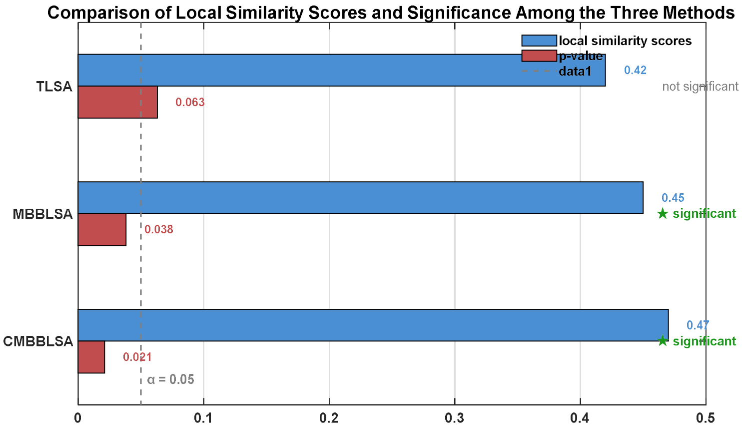


Figure 7. Comparison Chart of Local Similarity Scores.

Manual verification indicated that this association is a real traffic flow propagation relationship, i.e., traffic flow from Main Road A propagates to Main Road B after 10 minutes. The results show that TLSA missed this association due to conservatism ($p = 0.063 > 0.05$); although MBBLSA identified it as significant, its score was slightly lower than CMBBLSA, and the *p*-value was relatively high due to boundary effects; CMBBLSA had the highest score and the lowest *p*-value, accurately capturing the true association and verifying its ability to retain local dependence structures.

Empirical analysis shows that in local similarity analysis of traffic time series, TLSA tends to miss true associations due to conservatism, while MBBLSA has high false positives due to boundary effects and block splicing issues; CMBBLSA effectively eliminates MBBLSA's defects through circular block design, reducing false positive relationships by 21.8% and 28.9% at $\alpha = 0.05$ and $\alpha = 0.01$ levels, respectively; meanwhile, CMBBLSA balances the reliability and sensitivity of significance testing while retaining the local dependence structure of traffic data, making it more suitable for dynamic association analysis scenarios in intelligent transportation systems, such as congestion propagation warning and signal timing optimization.

5. Conclusion and Prospects

This article addresses the issues of urban traffic congestion and frequent accidents, focusing on the need for time-series data mining in Intelligent Transportation Systems (ITS). It employs local similarity analysis to identify traffic patterns, detect anomalies, and support short-term forecasting. The study innovatively propose the Circular Moving Block Bootstrap (CMBB) and the CMBB-based Local Similarity Score Analysis method (CMBBLSA), which effectively circumvent the distortion caused by non-stationarity in the sampling distribution of statistics and enable accurate estimation of the statistical significance of local similarity scores. The project validates the effectiveness of the methods by integrating multi-source data, such as geomagnetic loops and camera data. In simulations with different parameter settings of AR(1) and ARMA(1,1) models, the CMBB-based LSA demonstrates Type I error probabilities closer to the predefined significance level. Furthermore, analysis of real-world data from arterial roads in first-tier cities shows that the method reduces false positive correlations and accurately captures genuine relationships. Future work will focus on further refining the techniques, expanding application scenarios such as smart bus scheduling, and promoting interdisciplinary collaboration to enhance the reliability of traffic flow analysis in complex environments.

Data Availability Statement: All data included in this study are available upon request by contact with the correspondingauthor.

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Conflict of Interest: No potential confict of interest was reported by the authors.

Appendix A

AR(1) model:

Table A1. The probability of Type I error for different ρ -values in the AR(1) model(*D*=1).

ρ_1, ρ_2	n	PCC	Spearman	TLSA	Permutation	DDLSA	MBBLSA	CMBBLSA
-0.5 -0.5	20	0.1132	0.1105	0.0234	0.1291	0.0113	0.0431	0.0455
	40	0.1188	0.1169	0.0625	0.1379	0.0203	0.0529	0.0506
	60	0.1192	0.1197	0.0826	0.1547	0.0291	0.0558	0.0534
	80	0.1227	0.1205	0.0983	0.1584	0.0304	0.0571	0.0561
	100	0.1247	0.1197	0.1082	0.1602	0.0307	0.0559	0.0541
	200	0.1283	0.1207	0.1344	0.1764	0.0381	0.0566	0.0547
	300	0.1233	0.1201	0.1425	0.1729	0.0371	0.0545	0.0532
0 0	20	0.0506	0.0490	0.0042	0.0473	0.0076	0.0466	0.0491
	40	0.0451	0.0460	0.0130	0.0466	0.0161	0.0408	0.0420
	60	0.0516	0.0493	0.0189	0.0481	0.0225	0.0443	0.0457
	80	0.0519	0.0527	0.0223	0.0492	0.0248	0.0445	0.0503
	100	0.0483	0.0472	0.0243	0.0471	0.0274	0.0441	0.0445
	200	0.0475	0.0470	0.0283	0.0452	0.0295	0.0433	0.0442
	300	0.0490	0.0493	0.0343	0.0499	0.0352	0.0489	0.0486
0.3 0.3	20	0.0623	0.0590	0.0083	0.0661	0.0100	0.0472	0.0489
	40	0.0650	0.0648	0.0243	0.0751	0.0239	0.0538	0.0531
	60	0.0710	0.0677	0.0354	0.0764	0.0314	0.0549	0.0530
	80	0.0742	0.0745	0.0415	0.0796	0.0339	0.0551	0.0549
	100	0.0668	0.0666	0.0436	0.0767	0.0347	0.0536	0.0525
	200	0.0724	0.0708	0.0577	0.0848	0.0402	0.0531	0.0526
	300	0.0735	0.0735	0.0627	0.0826	0.0430	0.0525	0.0505
0.3 0.5	20	0.0801	0.0809	0.0111	0.0879	0.0144	0.0604	0.0601
	40	0.0867	0.0840	0.0360	0.0935	0.0275	0.0635	0.0601
	60	0.0877	0.0851	0.0474	0.1005	0.0320	0.0608	0.0574
	80	0.1464	0.1473	0.0343	0.1525	0.0157	0.0598	0.0592
	100	0.0918	0.0870	0.0637	0.1042	0.0375	0.0614	0.0592
	200	0.0900	0.0879	0.0768	0.1084	0.0427	0.0592	0.0577
	300	0.0872	0.0869	0.0821	0.1098	0.0391	0.0577	0.0553
0.5 0.5	20	0.1036	0.1020	0.0196	0.1139	0.0175	0.0696	0.0653
	40	0.1184	0.1147	0.0589	0.135	0.0327	0.0660	0.0656

	60	0.1251	0.1196	0.0807	0.146	0.0355	0.0667	0.0665
	80	0.1177	0.1151	0.0900	0.1438	0.0353	0.0624	0.0603
	100	0.1268	0.1237	0.0985	0.1547	0.0358	0.0570	0.0543
	200	0.1295	0.1267	0.1331	0.1722	0.0398	0.0583	0.0581
	300	0.1356	0.1315	0.1476	0.1836	0.0404	0.0595	0.0588
0.5 0.8	20	0.1498	0.1514	0.0322	0.1544	0.0183	0.0768	0.0673
	40	0.1688	0.1674	0.0966	0.1874	0.0279	0.0712	0.0684
	60	0.1730	0.1711	0.1278	0.208	0.0268	0.0772	0.0720
	80	0.1830	0.1807	0.1756	0.2255	0.0283	0.0765	0.0731
	100	0.1824	0.1781	0.1700	0.2339	0.0297	0.0706	0.0702
	200	0.1918	0.1841	0.2198	0.2647	0.0323	0.0701	0.0664
	300	0.1994	0.1913	0.2427	0.283	0.0317	0.0680	0.0670

Table A2. The probability of Type I error for different ρ-values in the AR(1) model(D=2).

ρ_1,ρ_2	n	PCC	Spearman	TLSA	Permutation	DDLSA	MBBLSA	CMBBLSA
-0.5 -0.5	20	0.1138	0.1137	0.1041	0.1302	0.0054	0.0331	0.0356
	40	0.1138	0.1116	0.0545	0.1532	0.0160	0.0444	0.0476
	60	0.1216	0.1200	0.0885	0.1664	0.0287	0.0592	0.0566
	80	0.1265	0.1235	0.1050	0.1755	0.0311	0.0587	0.0578
	100	0.1182	0.1150	0.1089	0.1728	0.0289	0.0497	0.0530
	200	0.1361	0.1312	0.1553	0.2009	0.0372	0.0598	0.0590
	300	0.1336	0.1263	0.1600	0.2007	0.0345	0.0556	0.0548
0 0	20	0.0492	0.0497	0.0023	0.0508	0.0048	0.0377	0.0359
	40	0.0487	0.0476	0.0127	0.0506	0.0175	0.0443	0.0455
	60	0.0495	0.0492	0.0185	0.0512	0.0221	0.0458	0.0466
	80	0.0446	0.0473	0.0197	0.0464	0.0228	0.0418	0.0417
	100	0.0500	0.0486	0.0228	0.0471	0.0254	0.0435	0.0443
	200	0.0532	0.0493	0.0314	0.0523	0.0333	0.0510	0.0491
	300	0.0483	0.0484	0.0351	0.0502	0.0366	0.0501	0.0503
0.3 0.3	20	0.0614	0.0617	0.0036	0.0672	0.0058	0.0441	0.0444
	40	0.0677	0.0642	0.0206	0.0755	0.0200	0.0487	0.0523
	60	0.0694	0.0670	0.0321	0.0814	0.0268	0.0543	0.0540
	80	0.0707	0.0717	0.0386	0.0834	0.0299	0.0538	0.0519
	100	0.0715	0.0704	0.0482	0.0886	0.0358	0.0586	0.0566
	200	0.0726	0.0718	0.0616	0.0935	0.0451	0.0593	0.0571
	300	0.0756	0.0721	0.0665	0.0912	0.0449	0.0541	0.0537
0.3 0.5	20	0.0762	0.0786	0.0065	0.0878	0.0074	0.0540	0.0532
	40	0.0866	0.0865	0.0274	0.0948	0.0206	0.0558	0.0528
	60	0.0891	0.0887	0.0472	0.1045	0.0290	0.0625	0.0593
	80	0.0889	0.0866	0.0521	0.1084	0.0324	0.0590	0.0555

	100	0.0875	0.0856	0.0624	0.1096	0.0355	0.0596	0.0556
	200	0.0900	0.0883	0.0847	0.1220	0.0407	0.0591	0.0584
	300	0.0895	0.0869	0.0919	0.1210	0.0410	0.0564	0.0558
0.5 0.5	20	0.1036	0.1029	0.0126	0.1168	0.0099	0.0566	0.0533
	40	0.1116	0.1111	0.0531	0.1481	0.0243	0.0608	0.0602
	60	0.1170	0.1155	0.0810	0.1559	0.0331	0.0621	0.0620
	80	0.1209	0.1186	0.0936	0.1620	0.0368	0.0619	0.0582
	100	0.1208	0.1175	0.1063	0.1691	0.0361	0.0648	0.0627
	200	0.1277	0.1248	0.1467	0.1894	0.0414	0.0632	0.0614
	300	0.1224	0.1203	0.1550	0.1936	0.0357	0.0590	0.0584
0.5 0.8	20	0.1460	0.1510	0.0244	0.1674	0.0109	0.0793	0.0790
	40	0.1685	0.1691	0.0943	0.2099	0.0239	0.0795	0.0731
	60	0.1809	0.1791	0.1311	0.2251	0.0227	0.0756	0.0705
	80	0.1727	0.1736	0.1577	0.2405	0.0240	0.0734	0.0720
	100	0.1833	0.1788	0.1813	0.2586	0.0269	0.0757	0.0715
	200	0.1891	0.1854	0.2341	0.2922	0.0288	0.0697	0.0672
	300	0.1944	0.1882	0.2575	0.3000	0.0287	0.0685	0.0670

Table A3. The probability of Type I error for different ρ -values in the AR(1) model(D=3).

ρ_1, ρ_2	n	PCC	Spearman	TLSA	Permutation	DDLSA	MBBLSA	CMBBLSA
-0.5 -0.5	20	0.1103	0.1114	0.0103	0.1411	0.0045	0.0348	0.0360
	40	0.1158	0.1132	0.0576	0.1671	0.0179	0.0467	0.0504
	60	0.1238	0.1185	0.0855	0.1821	0.0223	0.0517	0.0499
	80	0.1303	0.1278	0.1016	0.1871	0.0277	0.0553	0.0526
	100	0.1256	0.1229	0.1201	0.1951	0.0310	0.0547	0.0540
	200	0.1479	0.1246	0.1601	0.2127	0.0341	0.0594	0.0545
	300	0.1336	0.1263	0.1734	0.2183	0.0350	0.0593	0.0511
0 0	20	0.0507	0.0513	0.0012	0.0478	0.0028	0.0337	0.0407
	40	0.0489	0.0479	0.0080	0.0511	0.0109	0.0409	0.0405
	60	0.0481	0.0498	0.0145	0.0513	0.0182	0.0450	0.0448
	80	0.0501	0.0527	0.0183	0.0513	0.0215	0.0507	0.0501
	100	0.0487	0.0467	0.0218	0.0589	0.0240	0.0445	0.0496
	200	0.0474	0.0483	0.0327	0.0524	0.0347	0.0497	0.0510
	300	0.0503	0.0498	0.0343	0.0475	0.0358	0.0423	0.0497
0.3 0.3	20	0.0668	0.0654	0.0024	0.0741	0.0031	0.0411	0.0435
	40	0.0742	0.0742	0.0194	0.0847	0.0178	0.0543	0.0518
	60	0.0704	0.0680	0.0287	0.0850	0.0250	0.0540	0.0527
	80	0.0772	0.0741	0.0409	0.0909	0.0327	0.0575	0.0552
	100	0.0683	0.0639	0.0442	0.0906	0.0347	0.0591	0.0539
	200	0.0720	0.0746	0.0619	0.0921	0.0425	0.0576	0.0559

	300	0.0756	0.0721	0.0679	0.0934	0.0433	0.0589	0.0520
0.3 0.5	20	0.0766	0.0767	0.0043	0.0876	0.0048	0.0487	0.0487
	40	0.0842	0.0827	0.0282	0.1014	0.0220	0.0590	0.0566
	60	0.0878	0.0885	0.0444	0.1211	0.0273	0.0715	0.0689
	80	0.0846	0.0849	0.0583	0.1167	0.0328	0.0657	0.0603
	100	0.0876	0.0854	0.0644	0.1259	0.0370	0.0712	0.0668
	200	0.0923	0.0886	0.0837	0.1233	0.0410	0.0614	0.0563
	300	0.0896	0.0859	0.0954	0.1272	0.0408	0.0572	0.0512
0.5 0.5	20	0.1010	0.1033	0.0070	0.1245	0.0068	0.0528	0.0517
	40	0.1102	0.1094	0.0488	0.1620	0.0226	0.0602	0.0591
	60	0.1199	0.1188	0.0764	0.1705	0.0314	0.0628	0.0625
	80	0.1199	0.1190	0.0970	0.1821	0.0324	0.0595	0.0588
	100	0.1270	0.1243	0.1181	0.1889	0.0381	0.0650	0.0629
	200	0.1199	0.1156	0.1480	0.1998	0.0372	0.0588	0.0576
	300	0.0474	0.1197	0.1562	0.2014	0.0391	0.0596	0.0589
0.5 0.8	20	0.1473	0.1482	0.0181	0.1820	0.0084	0.0719	0.0711
	40	0.1639	0.1711	0.0947	0.2290	0.0201	0.0821	0.0769
	60	0.1800	0.1739	0.1331	0.2450	0.0219	0.0730	0.0704
	80	0.1825	0.1797	0.1703	0.2629	0.0211	0.0737	0.0697
	100	0.1871	0.1825	0.1838	0.2663	0.0238	0.0712	0.0688
	200	0.1871	0.1834	0.2425	0.3018	0.0263	0.0671	0.0669
	300	0.1989	0.1968	0.2176	0.3266	0.0271	0.0688	0.0680

ARMA(1,1) model

Table A4. The probability of Type I error for different ρ -values in the ARMA(1,1) model(*D*=1).

ρ_1, ρ_2	n	PCC	Spearman	TLSA	Permutation	DDLSA	MBBLSA	CMBBLSA
-0.5 -0.5	20	0.0481	0.0462	0.0047	0.0478	0.0091	0.0407	0.0374
	40	0.0501	0.0495	0.0147	0.0505	0.02	0.0448	0.0438
	60	0.0531	0.0521	0.0208	0.0515	0.0238	0.0478	0.048
	80	0.0476	0.0478	0.0209	0.0477	0.0242	0.0448	0.045
	100	0.0494	0.0497	0.0251	0.0506	0.0272	0.0465	0.0481
	200	0.0531	0.0507	0.0316	0.0487	0.033	0.0477	0.0474
	300	0.0513	0.0515	0.0362	0.0508	0.0369	0.0485	0.0483
0 0	20	0.0817	0.0811	0.0114	0.093	0.0131	0.0597	0.0581
	40	0.0892	0.0842	0.039	0.1052	0.0317	0.064	0.062
	60	0.0846	0.0821	0.0526	0.1072	0.0364	0.0618	0.0572
	80	0.0873	0.0838	0.0624	0.109	0.0378	0.0619	0.0586
	100	0.0901	0.0869	0.0679	0.1132	0.0398	0.0594	0.057
	200	0.0876	0.0871	0.078	0.1116	0.041	0.0557	0.0538
	300	0.0848	0.0839	0.0889	0.1144	0.0406	0.0559	0.0559

0.3 0.3	20	0.1232	0.1222	0.026	0.1475	0.0159	0.0686	0.064
	40	0.1306	0.1285	0.0731	0.1632	0.0275	0.0606	0.0587
	60	0.1357	0.1324	0.1015	0.1785	0.0311	0.0615	0.0583
	80	0.1354	0.1365	0.1172	0.1863	0.0296	0.0595	0.0587
	100	0.1379	0.1339	0.1426	0.1945	0.032	0.061	0.0574
	200	0.1395	0.1343	0.1598	0.2052	0.0351	0.0565	0.0559
	300	0.1385	0.1332	0.1703	0.207	0.0346	0.0594	0.0579
0.3 0.5	20	0.1481	0.1482	0.0358	0.1682	0.0155	0.0719	0.0683
	40	0.1591	0.1571	0.1014	0.199	0.026	0.0692	0.0688
	60	0.1582	0.1546	0.1251	0.2097	0.0232	0.0636	0.0623
	80	0.1607	0.1572	0.1445	0.2222	0.0276	0.0649	0.0635
	100	0.156	0.155	0.1601	0.2247	0.0276	0.0599	0.0572
	200	0.1624	0.1558	0.1967	0.2453	0.0309	0.061	0.0601
	300	0.1957	0.1901	0.2559	0.307	0.042	0.0567	0.0564
0.5 0.5	20	0.1796	0.18	0.0536	0.2037	0.016	0.0857	0.068
	40	0.1858	0.1853	0.1267	0.2367	0.0216	0.0676	0.0621
	60	0.1924	0.1902	0.1695	0.2574	0.0223	0.0647	0.0647
	80	0.1886	0.184	0.1842	0.2655	0.0223	0.0575	0.0562
	100	0.1973	0.1898	0.2107	0.3074	0.0264	0.0611	0.0608
	200	0.1984	0.19	0.256	0.3389	0.028	0.058	0.0579
	300	0.1964	0.1917	0.2815	0.354	0.0282	0.0571	0.0558
0.5 0.8	20	0.2251	0.2276	0.0754	0.2456	0.0112	0.0994	0.0826
	40	0.2493	0.2463	0.1714	0.2907	0.0122	0.0754	0.0711
	60	0.2503	0.2474	0.2217	0.3239	0.016	0.0736	0.0713
	80	0.2557	0.253	0.2599	0.3961	0.0157	0.0689	0.0666
	100	0.2556	0.2587	0.2743	0.4038	0.019	0.065	0.064
	200	0.2604	0.2519	0.3452	0.4011	0.0229	0.0625	0.062
	300	0.2674	0.2618	0.3802	0.4948	0.0242	0.0639	0.0638

Table A5. The probability of Type I error for different ρ -values in the ARMA(1,1) model(*D*=2).

ρ_1,ρ_2	*n*	PCC	Spearman	TLSA	Permutation	DDLSA	MBBLSA	CMBBLSA
-0.5 -0.5	20	0.0499	0.0466	0.015	0.0589	0.0124	0.056	0.0407
	40	0.0561	0.047	0.0157	0.058	0.0147	0.0556	0.0561
	60	0.0556	0.0505	0.0251	0.0582	0.0167	0.057	0.0569
	80	0.0521	0.0511	0.0276	0.0595	0.0284	0.0581	0.0577
	100	0.0543	0.0499	0.0249	0.06	0.0295	0.0453	0.0555
	200	0.0555	0.0531	0.0345	0.0664	0.0339	0.0402	0.0591
	300	0.0502	0.0495	0.0362	0.0663	0.0352	0.0552	0.0465
0 0	20	0.0729	0.0775	0.0291	0.0821	0.0379	0.0579	0.0558
	40	0.0855	0.0808	0.0379	0.0914	0.049	0.059	0.0581

	60	0.0887	0.0875	0.0439	0.0971	0.058	0.058	0.0592
	80	0.093	0.0844	0.0698	0.0965	0.0415	0.0615	0.0602
	100	0.084	0.0875	0.0707	0.1369	0.0521	0.0621	0.0615
	200	0.0815	0.0903	0.0801	0.1045	0.055	0.065	0.0641
	300	0.0905	0.0869	0.0895	0.1571	0.0565	0.0665	0.0658
0.3 0.3	20	0.106	0.1012	0.1117	0.1537	0.0198	0.0198	0.0362
	40	0.137	0.1172	0.1273	0.1709	0.0205	0.0205	0.0595
	60	0.131	0.1157	0.1246	0.2001	0.0192	0.0192	0.0577
	80	0.1303	0.116	0.1265	0.2256	0.0231	0.0231	0.0571
	100	0.1285	0.1197	0.1248	0.2348	0.0259	0.0259	0.0595
	200	0.1293	0.1207	0.1274	0.2571	0.0258	0.0258	0.0585
	300	0.1251	0.1204	0.1239	0.2793	0.0363	0.0263	0.0655
0.3 0.5	20	0.1367	0.1371	0.0613	0.1214	0.0362	0.0607	0.0569
	40	0.1287	0.121	0.0843	0.1351	0.0441	0.0592	0.0591
	60	0.1256	0.1342	0.1188	0.1572	0.0483	0.0586	0.0611
	80	0.1452	0.1449	0.1398	0.1408	0.0519	0.0625	0.0626
	100	0.1489	0.1464	0.1556	0.1594	0.0516	0.0619	0.0622
	200	0.1309	0.1549	0.1918	0.2036	0.0552	0.0631	0.0632
	300	0.1571	0.1687	0.2217	0.2228	0.0535	0.0623	0.0625
0.5 0.5	20	0.1532	0.1781	0.0997	0.184	0.0167	0.0856	0.0595
	40	0.1929	0.1836	0.1404	0.2503	0.0183	0.0535	0.0577
	60	0.1946	0.1844	0.1872	0.301	0.0293	0.0596	0.0571
	80	0.1982	0.1953	0.1927	0.3382	0.0376	0.0611	0.0695
	100	0.2082	0.1891	0.2039	0.3708	0.0243	0.0638	0.0585
	200	0.1983	0.1999	0.1965	0.488	0.0353	0.0634	0.0655
	300	0.1948	0.2047	0.2642	0.4743	0.0336	0.0639	0.0658
0.5 0.8	20	0.2238	0.1994	0.1663	0.2868	0.0115	0.0994	0.0813
	40	0.2495	0.2294	0.2099	0.2602	0.0142	0.0892	0.0721
	60	0.2495	0.2235	0.2359	0.3054	0.0248	0.0686	0.0741
	80	0.2506	0.2494	0.2624	0.3425	0.0262	0.0625	0.0622
	100	0.2661	0.2551	0.2775	0.3745	0.0244	0.0619	0.0671
	200	0.2419	0.2565	0.3558	0.4853	0.0341	0.0631	0.0734
	300	0.2663	0.2677	0.4087	0.5704	0.0244	0.0623	0.0625

Table A6. The probability of Type I error for different ρ -values in the ARMA(1,1) model(D=3).

ρ_1,ρ_2	n	PCC	Spearman	TLSA	Permutation	DDLSA	MBBLSA	CMBBLSA
-0.5 -0.5	20	0.0482	0.0465	0.0117	0.0457	0.0246	0.0546	0.0569
	40	0.0561	0.0495	0.0301	0.0462	0.0283	0.0583	0.0576
	60	0.0555	0.0514	0.0219	0.0507	0.035	0.055	0.0575
	80	0.0491	0.0488	0.0174	0.0472	0.0204	0.0436	0.0431

	100	0.0511	0.0511	0.0222	0.05	0.0251	0.0455	0.0459
	200	0.0505	0.0529	0.0315	0.053	0.033	0.0507	0.0505
	300	0.0478	0.0493	0.0312	0.0491	0.0321	0.0455	0.0464
0 0	20	0.0776	0.0676	0.0707	0.1493	0.0596	0.0596	0.0595
	40	0.0831	0.0828	0.031	0.1205	0.0231	0.0579	0.0602
	60	0.0777	0.0785	0.0444	0.1163	0.0274	0.0553	0.0578
	80	0.0891	0.0865	0.0552	0.118	0.0342	0.0537	0.0559
	100	0.0813	0.0815	0.067	0.1247	0.0382	0.0578	0.0579
	200	0.0861	0.0852	0.0927	0.1373	0.0389	0.0559	0.0547
	300	0.0921	0.0906	0.0976	0.1358	0.0411	0.055	0.0537
0.3 0.3	20	0.1085	0.1197	0.1132	0.2148	0.0306	0.0606	0.0591
	40	0.1278	0.1268	0.0743	0.216	0.0214	0.0607	0.0603
	60	0.1341	0.1328	0.1065	0.2202	0.0238	0.0589	0.0587
	80	0.1317	0.1297	0.1281	0.2224	0.0234	0.0523	0.0518
	100	0.1411	0.1384	0.1527	0.252	0.0304	0.0622	0.0603
	200	0.1408	0.134	0.195	0.2729	0.0327	0.057	0.0569
	300	0.1361	0.1295	0.201	0.266	0.0324	0.0536	0.0532
0.3 0.5	20	0.1507	0.1343	0.1566	0.2464	0.0266	0.0566	0.0663
	40	0.1548	0.1527	0.0967	0.2596	0.0171	0.0646	0.0638
	60	0.1606	0.1576	0.1392	0.2647	0.0209	0.0631	0.0609
	80	0.1561	0.1546	0.1695	0.2763	0.0244	0.0656	0.0638
	100	0.1629	0.1593	0.1856	0.3022	0.025	0.065	0.0635
	200	0.164	0.1582	0.2303	0.3248	0.0279	0.0613	0.0608
	300	0.1637	0.1588	0.2526	0.335	0.0284	0.059	0.0586
0.5 0.5	20	0.1715	0.1758	0.0325	0.2468	0.009	0.0754	0.0566
	40	0.1935	0.1896	0.1361	0.3048	0.013	0.0663	0.0601
	60	0.1881	0.1858	0.1859	0.3189	0.0154	0.061	0.0593
	80	0.2024	0.1974	0.2224	0.3437	0.0176	0.0602	0.0602
	100	0.206	0.2016	0.2483	0.3793	0.022	0.0644	0.0637
	200	0.1953	0.1923	0.3071	0.4076	0.0234	0.0562	0.0557
	300	0.1955	0.1888	0.3396	0.4323	0.0279	0.0588	0.0585
0.5 0.8	20	0.2024	0.1805	0.1951	0.2904	0.059	0.059	0.0616
	40	0.2469	0.2502	0.1841	0.3557	0.0069	0.0723	0.0664
	60	0.2445	0.2415	0.2462	0.3797	0.0103	0.068	0.0663
	80	0.2535	0.2508	0.2882	0.3976	0.0099	0.065	0.0627
	100	0.2584	0.2543	0.3155	0.4872	0.0115	0.0665	0.0661
	200	0.2636	0.2606	0.3985	0.5459	0.0166	0.0609	0.0595
	300	0.2516	0.2831	0.199	0.5748	0.0127	0.0627	0.0638

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