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# Coupling detrended fluctuation analysis for multiple warehouse-out behavioral sequences

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## HIGHLIGHTS

- Warehouse-out behaviors exhibit coupling multifractal characteristics.
- The fat-tail distribution contributes more to affecting behavioral dynamics features.
- The long-term memory of rebar will be more influential than that of wire rod.
- Significant coupling multifractal features emerged within time scale interval.

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## ABSTRACT

Interaction patterns among different warehouses could make the warehouse-out behavioral sequences less predictable. We firstly take a coupling detrended fluctuation analysis on the warehouse-out quantity, and find that the multivariate sequences exhibit significant coupling multifractal characteristics regardless of the types of steel products. Secondly, we track the sources of multifractal warehouse-out sequences by shuffling and surrogating original ones, and we find that fat-tail distribution contributes more to multifractal features than the long-term memory, regardless of types of steel products. From perspective of warehouse contribution, some warehouses steadily contribute more to multifractal than other warehouses. Finally, based on multiscale multifractal analysis, we propose Hurst surface structure to investigate coupling multifractal, and show that multiple behavioral sequences exhibit significant coupling multifractal features that emerge and usually be restricted within relatively greater time scale interval.



## 1. Introduction

Mining of human behavioral data uncover a new realm of behavior interpretation and mechanism design. Beginning with human behavior dynamics, the burst feature and power law of behavioral inter-event time distribution [1], as well as the exponential spatial distance distribution of transportation behaviors [2], had received increasing attention. And some of experts characterized emergence of human behaviors by scaling laws [3–5]. Besides, large-scale behavioral data directly supplemented some sociological and social governance issues. For instance, based on online community dataset of Tencent QQ, You et al. [6] studied younger trend of online community, and size of social group and inner interaction with respect to age and gender.

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Yao et al. [7] researched on large-scale warehouse-out behaviors of logistics base, proposed the temporal scale scaling law of commercial individuals and groups, and further discussed the factors that determine the head, middle part and tail of inter-event time distribution. Based on visibility graph algorithm and Hurst exponent, they revealed the fractals features, and primarily demonstrated warehouse-out quantity was both determined by business cycle and systemic persistence. Further, the authors [8] also applied MF-DCCA and MF-DMA algorithms into characterizing cross-correlation multifractal of warehouse-out behaviors among warehouses and products, supplementing insights of cross-correlation of warehouses, products and factors of warehouse-out behaviors persistence. However, still few efforts have been devoted to detecting relationship of multiple sequences and understanding warehouse-out mechanism, especially on interactions between individual and the corresponding rest of group. This work is aiming to comprehensively reveal global behavioral features of warehouse-out system of multiple sequences, and propose a theoretical foundation for behavior-based logistics system optimization.

For origins of multifractal, Zhou [9] systematically studied the components of multifractality in financial returns based on shuffled and surrogated data of DJIA, and found fat-tail distribution plays a major role while temporal structure (linear correlation and nonlinearity) plays the minor one. Further based on partition function approach of multifractal analysis, Zhou [10] showed there is a finite-size effect in the detection of multifractality, and the effective multifractality can be decomposed into the probability distribution component, and the nonlinearity component.

Recently increasing methods are proposed to efficiently detect the multifractal property of multiple time series. DFA proposed by Peng et al. [11] and MF-DFA proposed by Kantelhardt et al. [12] accelerated the application of multifractal theory into time series, and promoted works in financial field on monofractal and multifractal prices time series analysis such as stock market prices [13], future market [14], exchange market [15], oil price [16], asset returns [17], etc.

In 2008, as to multifractal property on cross-correlation, Podobnik and Stanley [18] proposed a detrended cross-correlation analysis, and Zhou [19] extended it into multifractal cross-correlation analysis (MF-DCCA) based on DFA algorithm, and applied it into the analysis of two non-stationary signals. For joint multifractal measure, Meneveau et al. [20] discussed the extension of multifractal formalism from single variable into multivariate measure, which tended to be more useful for characterizing joint log-normal and joint binomial distributions. Wang et al. [21] proposed a new multifractal cross-correlation analysis based on statistical moments (MFSMXA) and applied into volatility series of DJIA and NASDAQ, with better performance compared with conventional multifractal detrending moving average cross correlation analysis (MFXDMA). Based on partition function approach with two moment orders, Xie et al. [22] analytically studied the property of joint multifractal analysis, and applied this new method MF-X-PF $(p, q)$ to multifractal binomial measures. Owieimka et al. [23] proposed a new algorithm called multifractal cross-correlation analysis (MFCCA) to better describe multiscale cross-correlations between two time series than existing MF-DXA. Qian et al. [24] proposed detrended partial cross-correlation analysis (DPXA) to better study intrinsic power-law cross correlations between two nonstationary time series after removing the effects of their common forces.

DFA-based models have also been supplemented by works of correlation coefficients and regression framework. Zebende [25] proposed the DCCA cross-correlation coefficient to quantify the level of cross-correlation based on DFA and DCCA method, which had been proved to be successful in identifying both positive and negative cross-correlations of nonstationary time series. Kwapie et al. [26] introduced a new coefficient other than the existing detrended cross-correlation coefficient, which is not only able to quantify the strength of correlations but also identify the range of detrended fluctuation amplitudes that are correlated in two signals. To correctly detect cross-correlation beyond the influence of autocorrelation, Balocchi et al. [27] proposed the use of $\sigma$ DCCA to quantify the degree of coupling between series. Kristoufek [28] investigated the ability of DCCA coefficient in measuring cross-correlation based on Monte Carlo simulation, and found it dominates the Pearson coefficient for nonstationary series. Further, Kristoufek [29] introduced DMCA coefficient based on moving-average cross-correlation analysis (DMCA), and found DMCA coefficient detects true correlation regardless of nonstationary level. The author [30] had also done great works in proposing a framework to combine detrended fluctuation analysis with standard regression methodology: improve standard least square regression by DFA-based regression with some new estimators.

Alessio et al. [31] first figured out a new multifractal detection method named detrending moving average analysis (DMA), which had been developed into MF-DMA [32]. It is worth mentioning that based on MF-DMA algorithm by Gu and Zhou [32], Jiang and Zhou [33] further proposed a robust method of multifractal detrending moving average cross-correlation analysis (MF-X-DMA). They tested three algorithms of centered, forward and backward MF-X-DMA, and found they outperformed the MF-X-DFA. Based on height–height correlation analysis, Kristoufek [34] carried out the multifractal height cross-correlation analysis (MF-HXA) to detect cross-correlation and multifractal of bivariate signals.

Gieratowski et al. [35] introduced a new method of multiscale multifractal analysis (MMA) based on time scale. They proposed sliding fitting windows to cover all ranges of scale $s$ and obtain a series of overlapping windows, and then calculate the $q$ order fluctuation function $F_q(s)$ of each point within windows. With this method, observing approximately continuous change process of $H_{xy}(q)$ with respect to scale $s$ is available, and the process can be mapped into a surface about $H_{xy}(q, s)$. Gieratowski et al. [36] again applied MMA algorithm into studying the complex fluctuation of human fetal heart rate variability. Wang et al. [37] uncovered the complex structure of traffic sequences, and found MMA algorithm can extract more information than MF-DFA algorithm of fixed time scale. Further they demonstrated that the multifractal property of traffic sequences is rooted in both fatter probability density function and the correlation. Shi et al. [38] extended MMA into DCCA algorithm and proposed the multiscale multifractal detrended cross-correlation analysis (MM-DCCA), further