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Distributed multipliers in MWM for analyzing job arrival processes in massive HPC workload datasets

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HIGHLIGHTS

- We compared three multifractal wavelet models for the job arrival process.
- We find that the point-mass MWM can well match that of the real process.
- We find that the hybrid MWM can also well match that of the real process.
- We find that hybrid MWM has no greater advantage than beta MWM.

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ABSTRACT

There are three distributed multipliers multifractal wavelet model (MWM) on network traffic. The β multifractal wavelet model (β MWM) recently has been introduced as a good choice to yield long range dependence (LRD) and fractal behavior for a job arrival process for parallel workload analysis. In this paper, based on the Multifractal Wavelet Model (MWM), we choose the three kinds of distributions for the multipliers, namely the symmetric β-distribution, a symmetric point-mass distribution, and a hybrid distribution, the influence which distributed multipliers had on the MWM was analyzed with the analysis and comparison between the real job arrival process and the synthesized one. We find that the choice of β-distribution wavelet multipliers $A_{j,k}$ is not necessary. For the job arrival process, we can use different distributed multipliers to control the wavelet energy decay in MWM.

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1. Introduction

High performance computing (HPC) [1] and data-intensive computing [2] now plays an important role in the fields of computational science [3], and is used for a wide range of computationally intensive tasks in various fields. The performance of job schedulers [4–8] in clusters [9–11], grids [5,12–17], clouds [18,19] or data centers [20,21] is greatly affected by the characteristics of the workload it serves [22]. Over the past few decades, many researchers and institutions abroad have completed extensive research on workload analysis and modeling of parallel computers to evaluate scheduler performance [23,24], and to predict job performance [22,25]. Through analyzing supercomputer workloads, we can determine the supercomputer operating characteristics and enable effective resource allocation of these systems. Furthermore, a good understanding of workload characteristics can guide an HPC center to make decisions for purchasing or allocating specific hardware and software for the applications with different resource usage patterns.

Researchers often use real workloads (called traces) in their studies of performance evaluation [26–29]. Although directly using traces reflects the system reality, there are several reasons that show workload models have a number of advantages over traces [30]. Workload modeling creates a general model, which can be used to generate synthetic workloads. However, supercomputer workload is massive and nonlinear, so the general model is not suitable. The best method is to carry out statistical analysis and random signal analysis [30,31]. The arrival time is an important workload attribute, it is necessary to be modeled to apply for studies on performance evaluation. The Multifractal Wavelet Model (MWM) [32], introduced in the context of network traffic, is applied successfully to model the long range dependent and fractal job arrivals by Hui Li in Grids [31]. In the MWM, according to different distributed multipliers, there are β MWM, point-mass MWM and hybrid MWM. Zhang has researched the three distributed multipliers MWM on network traffic [33]; we will analyze them on workload modeling.

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The contributions of this paper are two-folds. First, this paper summarizes the methods of analysis of the characteristics of the job arrival time, and uses them to analyze and compare the modeling effect of different models. Second, through the preceding methods, we analyze and compare original arrive process with the job arrive time synthesized by β MWM, point-mass MWM, and hybrid MWM separately, and see that hybrid MWM and point-mass MWM can also be used for modeling job arrival process for massive supercomputer workload. It is shown that second-order properties such as the autocorrelation function (ACF) and the scaling behavior can be well reconstructed by the three MWM, which has a guiding significance for MWM in the workload modeling.

The rest of this paper is organized as follows. Section 2 introduces background knowledge, including workload characteristics and a research statement, and describes the representing method of the job arrival process. Section 3 presents several important concepts such as long range dependence (LRD) and multifractals, which can be used to analyze and contrast the arrivals synthesized by the three models to determine the advantages and disadvantages in the synthesis of the job arrival process. Section 4 introduces MWM and the three distributions for the multipliers. Section 5 presents the experimental results of the three MWM fittings using real workload data and discusses and analyzes the three models fitting effect. Conclusions and future work are discussed in Section 6.

2. Background and related work

2.1. Parallel workload characterization

Because supercomputer workload is massive and nonlinear, we can put it as a random signal processing. Arrival time, run time, memory and parallelism (the number of processors) are four important workload attributes that must be modeled to apply for studies on performance evaluation. Using log data of workload traces that were recorded on real machines, statistical analysis of workloads was performed to understand the preceding characteristics, such as distributions of job run time and memory usage, of a multicluster supercomputer [31], a grid computing environment [34], or a single HPC system [35].

Workload attributes can be modeled separately; we also model these correlated attributes simultaneously. Job run time, and memory consumption are strongly correlated attributes in many data-intensive workloads. In [31], a mixture of multivariate Gaussians is proposed to model run time and memory attributes simultaneously. Run time and parallelism are more difficult and must be modeled at the same time because it is proven that there exists a cross-correlation between the run time and the parallelism [30,36].

The arrival time attribute can be modeled individually. In [30], a model of arrivals based on two Gamma distributions is proposed. An infinite two-state Markov model was used to describe the characteristics of job inter-arrival in [37] which was extended to a n-state Markov modulated Poisson process to capture autocorrelations in [38]. In [31,39], a MWM is introduced to control the fractal behavior and the temporal correlation of arrival rate processes.

2.2. MWM for workload

As previously stated, the general model cannot meet the modeling requirements, due to the massive size and nonlinear nature of the workload, the best method is to perform statistical analysis and random signal analysis. Wavelets provide a natural framework for analyzing the scaling behavior because of its inherent multiresolution properties. It is a powerful methodology to decompose a signal into the scaling coefficients and wavelet coefficients. First, wavelet coefficients energy has a power-law relationship with the scale and this is used to analyze scaling behavior. Second, the scaling coefficients themselves are the output of modeling if the synthesized process is controlled to reflect the fractal nature of the real data. The MWM [31] is applied for modeling job arrival processes because it has not only wavelet framework for analysis and synthesis of the scaling behavior, but also a guarantee of output positive value, which is consistent with the physical properties of job arrive time. Moreover, through the wavelet energy decay estimated from the original process, MWM can potentially model the scaling behavior with multiple exponents. The construction of MWM is described in Section 4.

The β MWM has been introduced in the context of workload, including job arrive time and I/O workload [31]. According to different distributed multipliers, there are β MWM, point-mass MWM and, hybrid MWM. In this paper, job arrive time will be used in these three models to complete the simulation experiments to discover the advantages and disadvantages in the synthesis of the workload via analyzing and comparing the job arrivals synthesized.

2.3. Job arrival process representation

A job arrival process can be described as a (stochastic) point process, which is a train of individual time events t_n. There are different representations of a point process [31,40]. First, an interarrival time process I_n is a real-valued random sequence with $I_n = t_n - t_{n-1}$. Second, a count process, which depends on the preselected time interval T is formed by dividing the time axis into equally spaced continuous intervals of T to generate a sequence of counts $C_k(T)$, where $C_k(T) = N((k+1)T) - N(kT)$ indicates the number of time events in the kth interval. Third, the rate process $R_k(T)$ is a normalized version of the count process, where $R_k(T) = C_k(T)/T$.

The correlation can be readily associated with the point process in the count/rate process. The inter-arrive time process contains all the information of the point process. But it eliminates the consistency between the time axis and the index number so it only offers rough comparisons with correlation in the point process. Inter-arrive times based measures cannot reliably reveal the fractal natural instincts of the real data, and measures based on count/rate should be trusted. Transforming a rate process into inter-arrivals is completed by the integrate-and-fire (InF) algorithm or a more complex method derived from InF, the so-called controlled-variability integrate-and-fire [38].

In this paper, the rate process will be chosen to describe the empirical data. We need to choose time interval T in advance in the count/rate process. A dyadic scale is used, and time interval T is defined as ($T = 2^j$). We call each j a time scale. Different time scales can be used to represent the same arrival process by different count/rate processes.

3. Scaling behavior analysis

The job arrival process not only has the characteristics of LRD at coarse scales, but also the characteristics of multifractal at fine scales, which is scaling behavior.

3.1. LRD

If $X(t)$ is a discrete-time second-order stationary process, in which mean μ and variance δ^2 do not change over time, ACF can be defined as

$$R(k) = \frac{E[(X_i - \mu)(X_{i+k} - \mu)]}{\delta^2} \tag{1}$$

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