Spatial Correlation and Mobility Aware Traffic Modeling for Wireless Sensor Networks

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***Abstract*—Recently there has been a great deal of research on using mobility in wireless sensor networks to facilitate surveillance and reconnaissance in a wide deployment area. Besides providing an extended sensing coverage, the node mobility along with the spatial correlation of the monitored phenomenon introduces new dynamics to the network traffic. These dynamics could lead to long range dependent (LRD) traffic, which necessitates network protocols fundamentally different from what we have employed in the traditional (Markovian) traffic. Therefore, characterizing the effects of mobility and spatial correlation on the dynamic behavior of the network traffic is particularly important in the effective design of network protocols. In this paper, a novel traffic modeling scheme for capturing these dynamics is proposed that takes into account the statistical patterns of human mobility and spatial correlation. The contributions made in this paper are twofold: first, it is shown that the mobility variability and the spatial correlation can lead to the pseudo-LRD traffic, whose autocorrelation function follows a power law form with the Hurst parameter up to a certain cutoff time lag. Second, it is shown that the degree of traffic burstiness, which is characterized by the Hurst parameter, has an intimate connection with the mobility variability and the degree of spatial correlation. Furthermore, we show that this connection can be utilized to design the mobility-aware traffic smoothing schemes, which point out a new direction for traffic control protocols. Finally, simulation results reveal a close agreement between the traffic pattern predicted by our theoretical model and the simulated transmissions from multiple independent sources, under specific bounds of the observation intervals.**

I. Introduction

In the last few years, a significant number of research efforts have been devoted to the study of developing wide area distributed wireless sensor networks (WSNs) with self-organizing capabilities to cope with sensor node failures, changing environmental conditions, and sensing application diversity [1]. In particular, mobile sensor network (MSN) emerges as a promising candidate to support self-organizing mechanisms, enhancing adaptability, scalability, and reliability [2][12][7].

Although mobility allows sensor nodes to timely react to the changes in the sensing environment and mission planning, it also brings new challenges to the conventional static WSNs, such as randomly distributed topology and time-varying channel conditions. What is more important, spatial correlation, as another unique attribute of MSN, could cooperate with mobility to introduce new dynamics to the network traffic. As an example, a mobile sensor may inject to the network the similar traffic at the proximal locations because the collected information at these location could be spatially correlated. This observation implies that mobility can transfer the correlation from spatial domain to temporal domain. As a consequence, if this newly introduced temporal correlation decays slowly within a large time interval, this could lead to the long range dependent traffic (LRD), which has fundamentally different characteristics from what we have seen in the traditional (Markovian) traffic.

The seminal work of Leland et al. in 1994 [9] established that Ethernet traffic exhibits a property of correlation over many different time scales and suggested that simple LRD models could be applied to effectively capture these correlations. Since then, a great number of research efforts have been devoted to the study of LRD behavior because of the impact of LRD on network performance and resource allocation, which exhibits characteristics significently different from Markovian traffic. For example, LRD traffic can induce much larger delays than predicted by traditional queuing models. Furthermore, buffering, as a resource allocation strategy, becomes ineffective with LRD input traffic in the sense of incurring a disproportional penalty in queuing delay compared with the gain in reduced packet loss probability.

The important consequences of LRD necessitate us to answer the following questions regarding (1) whether the joint effects of mobility and spatial correlation lead to LRD traffic, and (2) if the answer is yes, how they affect the Hurst parameter which is used to characterize LRD traffic. To answer these questions, we construct a flexible statistical model that incorporates the statistical patterns of node mobility and spatial correlation, and study the impact of these attributes on traffic statistics, which leads to several novel findings. These findings provide valuable new insights into questions related to the design of efficient and effective protocols for MSNs. The contributions and findings made in this paper conclude:

1) An analytical traffic model is proposed whose parameters are related to the main attributes of MSNs (e.g., mobility and spatial correlation). This model advances an explicit explanation of the impact of these attributes on the statistical patterns of the network traffic.

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2) We find that the joint effects of mobility and spatial correlation can lead to the pseudo-LRD traffic, whose autocorrelation function approximates that of the LRD traffic with the Hurst parameter up to an certain cutoff time lag.
3) We show that the Hurst parameter is completely determined by the mobility variability and the degree of spatial correlation. Particularly, higher mobility variability and smaller spatial correlation could lead to larger Hurst parameter, which indicates more bursty traffic.
4) The mobility-aware protocols are introduced for traffic smoothing, which can adaptively cope with the traffic patterns in WSNs.

In Section II, we introduce background and motivation. Section III presents the proposed traffic modeling scheme, investigates the effects of mobility and spatial correlation on the traffic statistics, introduces mobility-aware traffic smoothing schemes. Section IV presents experimental results. Finally, Section V provides concluding remarks.

II. Background and Motivation

In this section, we first present the characteristics of MSNs including node mobility and spatial correlation, all of which have significant impact on the traffic nature in MSN. Then we outline the motivation behind this work.

A. Node Mobility

Generally, MSN has two types of mobile nodes: robot and human agent. Compared with human agent, the movement pattern of robots could exhibit much more regularity and predictability because they are either remotely controlled or preprogrammed. Since human agent can have a wide range of mobility variability to cover more scenarios, human-driven sensor node is of interest in this work.

The recent seminal work [13] has investigated the human mobility features based on the real GPS traces. The data reveal that the statistical pattern of human movements can be characterized by a two-state process alternating between pausing and moving. The distance a human object traveled during the moving state is defined as flight. The length of a flight is measured by the longest straight line trip from one location to another that the human object makes without a directional change. The flight length has been revealed to follow heavy-tail distribution [13]. Accordingly, its survival function can be expressed by

$$\overline{F_d}(x) = P(X \geq x) = \left(\frac{b}{x}\right)^{\alpha}, \quad x \geq b \tag{1}$$

where $b \geq 0$ denotes the minimum distance a human agent can travel and α denotes tail index. According to [13], the tail index will be close to 1 for the outdoor environment. In this case, the human mobility will exhibit high variability since the flight length will drastically fluctuate within a wide range of values over three-orders of magnitudes (i.e., 1000 meters).

B. Spatial Correlation

Besides node mobility, spatial correlation is another significant characteristic of MSNs. For typical MSN applications, the mobile sensor nodes are required to observe the interested phenomenon at different locations in the field and send the measured data to the sink(s). The observed phenomenon is usually a spatially dependent continuous process, in which the measured data have a certain spatial correlation. In general, the degree of the spatial correlation in the data increases with the decrease of the separation between two observing locations. To quantify the spatial correlation, the observations $S_1, S_2, ..., S_N$ at N locations are modeled as an N-dimensional random vector $S = [S_1, S_2, ..., S_N]^T$ [5] [14] which has a multivariate normal distribution with $[0, 0, ..., 0]^T$ mean and covariance matrix K with each element defined by

$$k_{ij} = \frac{E[S_i S_j]}{\sigma^2}, \quad i, j = 1, 2, ..., N \tag{2}$$

k_{ij} denotes a correlation function that specifies the correlation model. The correlation function is nonnegative and decreases monotonically with the distance $d_{(i,j)}$ between two locations i and j. Correlation models can be categorized into four groups as Spherical, Power Exponential, Rational Quadratic, and Matern [14]. Each of them characterizes the properties of different physical phenomena.

C. Motivation

As we have seen, MSN not only inherits the characteristics from conventional wireless sensor networks (WSNs), but also possesses the gene from mobile ad-hoc networks (MANETs). The joint effects of these attributes could introduce new dynamics to the network traffic, which are barely observed in conventional static WSNs. These dynamics can be seen in the following aspects.

Mobility along with spatial correlation could lead to temporally correlated traffic. Due to mobility, the data sent in consecutive time slots could be collected at the proximal locations. At these locations, the measured data can be highly correlated because of spatial correlation, Consequentially, the data sent in these consecutive slots have high probability to share similar content. This yields temporal correlation in the network traffic. If this correlation decays slowly as the time lag increases, then the traffic could exhibit LRD behavior. The traffic is called LRD if its autocorrelation function follows a power law form as the lag approaches infinity

$$\rho(\tau) = \frac{\gamma(\tau)}{\sigma^2} \rightarrow c_\rho \tau^{\beta-1}, \text{as } \tau \rightarrow \infty \tag{3}$$

where c_ρ is a positive constant and $0 < \beta < 1$ is the fractal exponent. The quantity $H = (\beta + 1)/2$ is referred to as the Hurst parameter, which expresses the speed of decay of the autocorrelation function.

Previous works [11] [6] [8] have shown that the impact of LRD traffic on network performance and protocol design exhibits characteristics fundamentally different from traditional traffic. To design effective and efficient protocols for MSNs,

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it is essential to investigate the relationship between the LRD behavior and the dynamics induced by mobility and spatial correlation. Accordingly, we propose a novel traffic modeling scheme which can capture the interplays between the statistical patterns of mobility and spatial correlation. In addition, the statistical analysis of this model is performed to reveal the intimate connections between the mobility variability and the uneven patterns of network traffic. These findings provide valuable new insights into questions related to the design of efficient and effective protocols for MSNs.

III. Traffic Modeling for Mobile Sensor Networks

In this section, we propose a structural traffic modeling scheme, which aims to mimic the typical behavior of the mobile node. This scheme is favored because it yields a traffic model whose parameters are related to the traffic generating mechanism and the main attributes of the network (e.g., mobility and spatial correlation). Consequentially, it could provide insight into the impact of network design parameters and control strategies on the pattern of the generated traffic. In the rest of this section, we first abstract the behavior of the mobile sensor node, then the corresponding traffic model is presented. Based on the proposed model, the statistical analysis is given, and the traffic smoothing schemes are proposed accordingly.

A. Mobile Sensor Node Behavior

In a MSN, the behavior of the mobile sensor node can be described by a procedure having two phases: sensing and transmitting. During the sensing phase, the node moves to a location, executes sensing tasks, and performs in-network data compression; during the transmitting phase, the compressed data are sent at certain rate using suitable transmission mechanisms. This node behavior implies that the pattern of their data transmissions can be maturely characterized by a two-state process that alternates between transmission and silence.

Regarding data compression schemes, the entropy coding is employed to remove the data redundancy caused by the spatially correlated observations. This scheme is utilized because it is a general data compressing framework applicable for any specific compression approaches. According to the entropy coding, the sensor node encodes its current sensing data conditioned on the data it sent previously.

B. Single Mobile Node Traffic

According to the abstracted node behavior, we utilize ON/OFF process $X(t)$ to represent the traffic, which alternates between two states: the ON state, during which the source transmits data at a rate r; and the OFF state, during which the source is silent. Let $\tau_a(i)$ and $\tau_b(i)$ denote the duration of the ith ON and the ith OFF state, respectively.

To completely characterize this model, we need to specify the distributions of the ON and OFF periods. As we have reviewed, the distribution of ON period depends on the statistical features of mobility, spatial correlation, and data rate. Meanwhile, the distribution of OFF period is more affected by the specific sensing operations, such as the sensing time and information processing time. To generalize the analysis, we first assume the OFF period follows any survival function, denoted by $\overline{F_{\tau b}}(x)$. Then, our primary task is to derive the expression of the survival function of ON period, which we denote as $\overline{F_{\tau a}}(x)$.

Let V denote the file required to be transmitted during an ON period. The length of the ON period τ_a is simply the time to transmit the file using a certain rate r

$$\tau_a = V/r \tag{4}$$

Without loss of generality, we utilize unit data rate (e.g., $r = 1$). In this case, the ON period length τ_a follows the same distribution as the file size. In the following section, we derive the survival function of file size. To obtain the expression of file size distribution, we first express the file size V in terms of a set of variables related to the network attributes (e.g., spatial correlation and mobility). Then, the probability density function (PDF) of V is derived based on the distributions of these relevant variables.

The file size depends on the number of coded sensing samples which are encapsuled in a file. According to entropy coding theory [3], the minimum amount of coded samples required to describe the gathered information is closely related to the entropy of the monitored phenomena S, which can be expressed by

$$V = 2^{H(S)} \tag{5}$$

Note that equation (5) quantifies the number of the coded samples whose entropy closely approximates the entropy of the monitored phenomenon, while the entropy itself only indicates the average packet size (coding rate) of the samples. Meanwhile, the observed phenomenon at current location i could be correlated with previous location j due to the spatial correlation. Thus the total number of samples V transmitted at current location is a function of conditional entropy, which is expressed by

$$V = 2^{h(S_i|S_j)} = 2^{(h(S_i S_j) - h(S_j))} \tag{6}$$

Here we use differential entropy $h(S_i)$ instead of discrete entropy $H(S_i)$ because the observed phenomenon S is generally a continuous random process.

We proceed to evaluate the file size V in equation (6) by adopting the power exponential correlation model, which is a commonly used model in the WSN studies due to its applicability to a wide range of phenomenon [5] [14] [4]. The correlation function of the adopted model is expressed by

$$k = e^{-(\theta_1 d)^{\theta_2}}, \theta_1 > 0, \theta_2 \in (1, 2] \tag{7}$$

where d is the mutual distance of two locations. The parameters θ_1 and θ_2 control the correlation level within a given distance d. Generally, smaller value of θ_1 or θ_2 indicates higher level of correlation. Combining equations (6) and (7), we obtain the closed expression regarding the size of a file conveyed in an ON period

$$V = (V_{max}^2 (1 - e^{-2(\theta_1 d)^{\theta_2}}))^{\frac{1}{2}} \tag{8}$$

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Where $V_{max} = \sqrt{2\pi e \sigma^2}$ is the maximum file size, which depends on the properties of the physical phenomenon (e.g., variance σ), and d is the traveled distance or flight length in the preceding OFF period. Equation (8) shows that for a given interested phenomenon, the file size distribution depends on the distribution of the flight length defined in (1). Accordingly, we obtain the survival fuction of the file size V

$$\overline{F_v}(x) = (2^{1/\theta_2} b\theta_1)^{\alpha} (\ln(\frac{V_{max}^2}{V_{max}^2 - x^2}))^{-\alpha/\theta_2} \quad (9)$$

where b is the minimum traveled distance or flight length. Assuming the minimum file size of 1 yields the simple form of the survival function of the ON period length

$$\overline{F_t}(x) = (\ln \frac{t_{max}^2}{t_{max}^2 - 1})^{-\alpha/\theta_2} (\ln \frac{t_{max}^2}{t_{max}^2 - x^2})^{\alpha/\theta_2} \quad (10)$$

where $t_{max} = V_{max}$. Equation (10) shows that the distribution of the ON period length is determined by two factors: the degree of spatial correlation (e.g., θ_2) and mobility variability (e.g., α). Larger θ_2 (or α) indicates smaller degree of spatial correlation (or smaller mobility variability). To facilitate further analysis, we define characteristic index as

$$\beta = \frac{\alpha}{\theta_2} \quad (11)$$

This index β reflects the joint effect of mobility and spatial correlation that has direct impact on the traffic patterns, which we discuss in details in the following section.

C. Statistical Analysis

In this section, we derive the autocorrelation function of the single node traffic. Particularly, we focus on investigating the inherent relationship between the autocorrelation function and network attributes, such as mobility and spatial correlation. The revealed results could provide valuable new insights into questions related to the design of efficient and effective protocols for MSNs. These protocols are briefly introduced in the next section.

Before evaluating the autocorrelation function, we first investigate the properties of the ON period length, which have a profound impact on the characteristics of the autocorrelation function.

Proposition 1: If the characteristic index $\beta < 1$, then the length of the ON period follows a power law probability density with tail index $\gamma_a \approx 2\beta < 2$ within the characteristic region $t \in [t_{min} \;\; t_{max}R]$, where

$$R = \sqrt{9/4 - 2\beta} - 1/2 \quad (12)$$

Proof:

According to equation (10), we can express the tail index as

$$\gamma(x) = \frac{d \log \bar{F}(x)}{d \log(x)} = \frac{2\beta x^2}{t_{\max}^2 - x^2} / \ln(\frac{t_{\max}^2}{t_{\max}^2 - x^2}) \quad (13)$$

Equation (13) indicates that the tail index is a function of time x. It is easy to show that $\gamma(x)$ is an increasing function with respect to x. Therefore, we can obtain the minimum tail index γ_{min} within the region $x \in [t_{min} \;\; t_{max}]$ by evaluating $\gamma(x)$ at t_{min}. That is, $\gamma_{min} = \gamma(t_{min}) \approx 2\beta$. This further implies that there exists a region of $x \in [t_{min} \;\; t^*]$ with the tail index $\gamma(x) \leq 2$. To determine the upper bound t^*, we define $R = (x/t_{max})^2$ and simplify $\gamma(x)$ to be

$$\gamma(x) = \frac{2\beta R}{(R-1)\ln(1-R)} \approx \frac{4\beta}{(1-R)(2+R)} \quad (14)$$

Let equation (14) be equal to 2. We obtain the upper bound $t^* = t_{max}R$ with

$$R = \sqrt{9/4 - 2\beta} - 1/2. \quad (15)$$

Because $\gamma(x)$ varys slowly within the region $[t_{min} \;\; t^*]$, we proceed to approximate $\gamma(x)$ by a constant value γ_a. Making use of linear approximation and Maclaurin expansion yields the final result of γ_a

$$\gamma_a = \frac{\log_{10} \overline{F_t}(t_{\max}) - \log_{10} \overline{F_t}(t_{\min})}{\log_{10}(t_{\max}) - \log_{10}(t_{\min})} \approx 2\beta \quad (16)$$

■

Proposition 1 shows that the suvival function of the ON period length decays slowly within the region $t \in [t_{min} \;\; t_{max}R]$. The decay speed is completely controlled by β or the joint effects of spatial correlation degree (α) and mobility variability (θ_2).

We proceed to derive the autocorrelation function of the process of $X(t)$. To express the result in a closed form, we need to specify the survival function of the OFF period. To generalize the analysis, we assume that the OFF period follows truncated Pareto distribution. With this distribution, OFF period can exhibit a wide range of variability by adjusting the corresponding parameters. The PDF of the OFF period τ_b is expressed by

$$f_{\tau_b}(x) = \frac{\gamma_b x^{-(\gamma_b+1)}}{l_{\min}^{-\gamma_b} - l_{\max}^{-\gamma_b}} \quad (17)$$

where $l_{\min}(l_{\max})$ denotes the minimum (maximum) OFF time. γ_b denotes the tail index which controls the variability of OFF interval. As γ_b increases, the density of the OFF length becomes more concentrated near the low boundary, $l_{\min}$, with proportionally fewer lengths near $l_{\max}$. To simplify the analysis, we consider the case in which the OFF period is dominated by the time for sensing and information processing, thus implying that the OFF and ON period lengths are independent.

Proposition 2: If $\beta < 1$, the autocorrelation function of the process $X(t)$, denoted by $R_m(\tau)$, follows the power law form

$$R(\tau) = D_1 t^{1-\gamma_a} + D_2 t^{1-\gamma_b}$$

in the region $t_{\min} \ll |\tau| \ll t_{\max}$ with some constants D_1 and D_2.

Proof:

The power spectrum density of an ON/OFF process with arbitrary distributions of ON and OFF lengths [10] takes the form

$$S(\omega) = E[X(t)]\delta(\frac{\omega}{2\pi}) + \frac{2(\omega)^{-2}}{E[\tau_a]+E[\tau_b]}\mathrm{Re}\left\{\frac{[1-\varphi_{\tau_a}(\omega)][1-\varphi_{\tau_b}(\omega)]}{1-\varphi_{\tau_a}(\omega)\varphi_{\tau_b}(\omega)}\right\} \quad (18)$$

where φ_{τ_b} and φ_{τ_b} are the characteristic functions associated with the distributions for ON period length τ_a and OFF period length τ_b, respectively. According to proposition 1, the PDF of τ_a follows the power law form with $x \in [t_{min} \ \ t^*]$ and tail index $\gamma_a < 2$. Accordingly, the PDF of τ_a can be approximated by the truncated Pareto distribution, which takes the form

$$f_{\tau_a}(x) = \frac{\gamma_a x^{-(\gamma_a+1)}}{t_{\min}^{-\gamma_a} - t_{\max}^{-\gamma_a}} \quad (19)$$

Equation (19) can perfectly preserve the power law nature of τ_a without affecting its characteristic function. Thus, the characteristic function of τ_a has the same form as the truncated Pareto, which is expressed by

$$\varphi_{\tau_a}(\omega) = \frac{\alpha(j\omega)^{\gamma_a}}{t_{min}^{-\gamma_a} - t_{max}^{-\gamma_a}}\int_{j\omega t_{min}}^{j\omega t_{max}} e^{-x}x^{-(\gamma_a+1)}dx \quad (20)$$

Since $k_2^{-1} \ll f \ll k_1^{-1}$ and $\gamma_a < 2$, we have [10]

$$1-\varphi_{\tau_a}(\omega) = \frac{t_{min}\gamma_a}{\gamma_a - 1}j\omega - (\gamma_a-1)^{-1}\Gamma(2-\gamma_a)t_{min}^{\gamma_a}(j\omega)^{\gamma_a} \quad (21)$$

For OFF period, the similar approach leads to

$$1-\varphi_{\tau_b}(\omega) = \frac{l_{min}\gamma_b}{\gamma_b - 1}j\omega - (\gamma_b-1)^{-1}\Gamma(2-\gamma_b)l_{min}^{\gamma_b}(j\omega)^{\gamma_b} \quad (22)$$

Inserting equations (21) and (22) into (18), and ignoring the high order terms, we can obtain the mid-frequency approximation of the power spectrum density within the region $1/(Rt_{max}) \ll f \ll 1/(t_{min})$

$$S(\omega) = C_1\omega^{\gamma_a-2} + C_2\omega^{\gamma_b-2} \quad (23)$$

where C_1 and C_2 are some constants.

Based on the relationship between the PSD of a real-valued process and its autocorrelation function, we obtain the autocorrelation function $R(t)$ of the process $X(t)$

$$R(\tau) = D_1 t^{1-\gamma_a} + D_2 t^{1-\gamma_b} \quad (24)$$

where D_1 and D_2 are some constants.

According to equation (24) and Proposition 1, we obtain the Hurst parameter of process $X(t)$

$$H = \frac{3-\min(\gamma_a,\gamma_b)}{2} \approx \frac{3-\min(2\beta,\gamma_b)}{2} \quad (25)$$

■

Proposition 2 suggests that the joint effects of mobility and spatial correlation can lead to the power law autocorrelation function with the Hurst parameter up to the cutoff time lag Rt_{max}. In addition, Proposition 2 shows that index β controls the value of the Hurst parameter, which can be used to indicate the traffic burstiness. This means that the single node traffic can exhibit different degree of hurstiness under different monitored environment (e.g., spatial correlation) and different node behavior (e.g., mobility variability).

D. Mobility-Aware Traffic Smoothing Protocols

According to Proposition 2, we have two results. First, higher mobility variability (smaller α) along with smaller spatial correlation (larger θ_2) could lead to more bursty traffic (higher H). Second, the joint effect of the mobility and correlation could lead to non-bursty traffic if a certain condition holds (e.g., $\beta > 1$).

These novel findings point out us in new directions for traffic smoothing schemes in MSN. For example, the movement coordination protocols can be proposed to smoothen the network traffic. This can be realized by two protocols for different conditions. First, if the correlation model of the monitored phenomenon is unknown, then the best effort to reduce the traffic burstiness is to let each mobile node move evenly in the sensing area so that the resulting Hurst parameter is minimized by maximizing α. Furthermore, if the correlation structure (e.g., θ_2) of the monitored phenomenon can be estimated in advance, the node may be allowed to move in a more random manner as long as the mobility variability does not exceed a certain threshold, in which case, α should be always larger than θ_2 so that $\alpha/\theta_2 > 1$.

IV. SIMULATION RESULTS

In this section, we test the validity of the proposed model through simulations, and investigate the effects of the mobility and spatial correlation on the traffic patterns through the simulated results.

A. Simulation Parameters

Unless otherwise specified, the simulation parameters are set as follows. The tail index of flight length α is set to be 1.2, which is a typical setting for human mobility pattern in outdoor environment. For the spatial correlation model, the correlation coefficient θ_2 is set to be 2, which indicates the correlation $\beta < 1$. The minimum duration of ON period and OFF period is 1 second. We also assume that the tail index of OFF period length is larger than 2. This assumption leads to a single node traffic whose pattern only depends on the statistical features of ON period, which further makes traceable the impact of mobility and spatial correlation on the network traffic.

B. Autocorrelation Function

To estimate autocorrelation function, we measure the corresponding power spectrum density (PSD) as it is more convenient and yields the same result. Figure 1 shows the averaged PSD based on the results from 50 trace measurements and Figure 1 clearly shows the power law decaying PSD, which has a straight line with slope 0.8 in the mid-frequency range from 1 rad to the order of magnitude of 1000 rads. This observation indicates that the corresponding autocorrelation also exhibits

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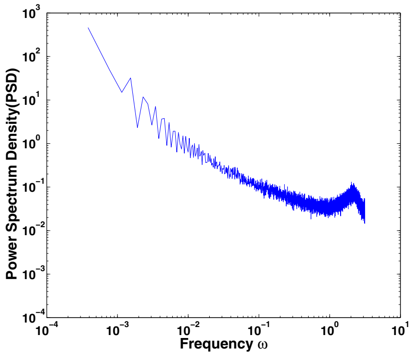

Fig. 1. Averaged PSD

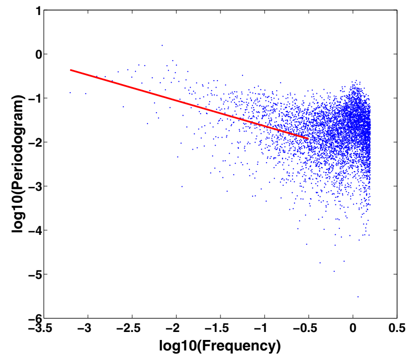

Fig. 2. Periodogram

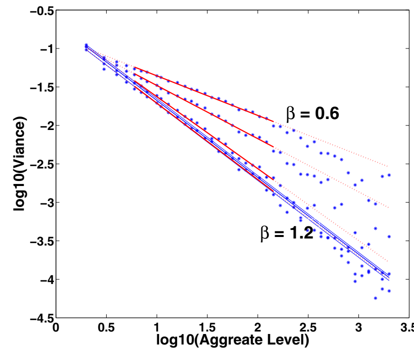

Fig. 3. The effect of Characteristic Index

power law behavior. This is expected because the correlation parameter β is less than 1 according to the simulation settings, and under this condition proposition 2 points out that the PSD of the the single node traffic obeys a power law in mid-frequency, which indicates pseudo-LRD traffic. To determine the Hurst parameter, we employ Periodogram-based analysis. According to this approach, an estimate of $1-2H$ is given by computing the slope of a regression line of the periodogram plotted in log-log grid. Figure 2 depicts the periodogram of a single trace used in Figure 1. The periodogram plot shows a slope of 0.7376, yielding an estimate of H as 0.8683. The estimated H closely approximates the theoretical $H = 0.9$ according to proposition 2.

C. Effects of Characteristic Index on Autocorrelation

We now investigate the impact of characteristic index β on the autocorrelation function. Figure 3 depicts the variance-time plot of the traffic trace under different correlation parameter β ranging from 0.5 to 1.2. It is seen that the variance-time plot is linear and shows a slope that is different from -1. The slope yields an estimate for $2H-2$. It can be seen in Figure 3 that larger β yields the slope with smaller deviation from -1, which indicates smaller H and less bursty traffic. It can be also observed that when β becomes larger than 1, the variance-time curve overlaps with the straight line with slope of -1, which suggests that the traffic is non-bursty. The results are as expected because proposition 2 points out that high mobility variability with small spatial correlationyields smaller β. This leads to hyperbolic autocorrelation function with larger Hurst parameter, thus indicating more bursty traffic.

V. Conclusions

This paper proposed a novel traffic model for MSNs, which captures the statistical patterns of the mobility and spatial correlation. It is shown that the mobility and spatial correlation can lead to the pseudo-LRD traffic, which has the Hurst parameter completely determined by the mobility variability and the spatial correlation degree. Particularly, high mobility variability and small spatial correlation could yields higher Hurst value, which indicates more bursty traffic. These findings have been exploited to design effective resource allocation schemes which adaptively cope with the traffic patterns in WSNs. The simulation results have been shown in close agreement between the theoretical propositions and the observed statistical properties.

VI. Acknowledgement

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