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Effects of Different Mobility Models on Traffic Patterns in Wireless Sensor Networks

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***Abstract*—Recently, there has been a great deal of research on investigating the effects of mobility on network attributes such as capacity, connectivity, and coverage. In this paper, the node mobility is studied from a new perspective with an objective to reveal the inherent impact of different mobility models on the the traffic patterns in wireless sensor networks. Specifically, the transmission pattern of a mobile sensor node is first characterized by an alternating renewal process that changes states between the active and the inactive. Then, the active state distribution is investigated under four commonly used mobility models: random walk, random waypoint, discrete Brownian motion, and extended Levy walk. For each mobility model, the spectrum of the traffic oriented from a single node is analyzed based on renewal theory. According to this analysis, novel results regarding the impact of each mobility model on the traffic nature are found: random walk, random waypoint, and discrete Brownian motion can only induce short range dependent traffic, whose autocorrelation function decays exponentially fast. In contrast, the traffic under extended Levy walk exhibits pseudo long range dependence, in which the autocorrelation function decays slower than exponential and follows a power law form at large time lags. Finally, the revealed findings are verified by the statistical analysis on the collected traffic traces from the simulated transmissions.**

I. Introduction

The node mobility has been demonstrated to have a significant impact on the performance of mobile ad-hoc networks (MANETs) and warless sensor networks (WSNs). Specifically, mobility has been found to increase capacity [5], help security [3], improve k-clustered connectivity [8], and enhance sensing reliability [1] in MANETs and WSNs. However, mobility can also result in performance degradation by causing dynamically changing links and unpredictable random topology.

Besides above mentioned impact, our previous work [7] shows that mobility plays a critical role in determining the temporal property of network traffic in WSNs, which directly affects the design of effective network control and resource provisioning schemes. Specifically, it is proven that the traffic burstiness contributed by a single node is closely related to the mobility variance of that node and the spatial correlation of the monitored phenomenon. Particularly, the bursty traffic is more prone to appear in the scenario with high mobility variance and low spatial correlation. Conversely, the occurrence of smooth traffic is more evident as mobility variance decreases and spatial correlation increases. These observations indicate that different mobility attributes can result in different temporal structures of network traffic. Different from our previous work in which only Levy walk mobility model is considered, in this paper. we aim to studying the effects of four mobility models on traffic patterns in WSNs. That is, for each mobility mode, we will investigate whether long range dependence or short range dependence is dominant in network traffic. These findings can provide valuable implications for traffic engineering and network performance, based on the analytic queueing results with short range dependent (SRD) and long range dependent (LRD) input streams.

The presence of long-range dependence in a time-dependent process indicates that the statistically significant correlations exist across large time lags. This makes the LRD processes exhibit characteristics fundamentally different from those possessed by SRD processes, e.g., Markovian processes. In other words, the SRD processes are characterized by the autocorrelation function that decays exponentially. In processes with long range dependence, the decay of the autocorrelation function is much slower than exponential and typically follows a hyperbolic form. Due to this characteristic, the impact of LRD traffic on the network performance is significantly different from that of SRD traffic. For example, LRD traffic can induce much larger delays than predicted by traditional queueing models that take SRD stream as inputs. Furthermore, when LRD traffic is fed into the network, the buffer ineffectiveness phenomenon occurs so that increasing buffer sizes beyond a certain value results in only a slight decrease in loss rates.

To study the dependence structure of network traffic under different mobility models, we first characterize the behavior of the mobile sensor by a renewal process that alternates between active and inactive states. Then, the active state distribution is derived under four representative mobility models including random walk, random waypoint, discrete Brownian motion, and extended Levy walk. For each mobility model, the sensor node traffic is analyzed in the spectrum domain by estimating its power spectrum density. According to this analysis, new results regarding the traffic patterns under each mobility model are found. Specifically, the traffic under random walk, random waypoint, and discrete Brownian motion exhibits the exponentially decaying autocorrelation function, which implies the

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presence of short range dependence. In contrast, pseudo long range dependence is found in the traffic under extended Levy walk since the autocorrelation function decays slower than exponential and follows a power law form up to a large time lag.

In Section II, we introduce background on mobility models and long range dependence. Section III characterizes the behavior of the mobile sensor. Section IV presents the effects of the four mobility models on the dependency property of network traffic. Section V gives experimental results. Finally, Section VI provides concluding remarks.

II. Mobility Models

A. Mobility Models

In this research, we investigate four common mobility models used by researchers, which include random walk, random waypoint, discrete Brownian motion, and extended Levy walk.

1) Random Walk: In this mobility model, a mobile node (MN) moves from its current location to a new location by randomly choosing a direction and speed from pre-defined ranges, $[speedmin, speedmax]$ and $[0, 2\pi]$ respectively. Each movement in this model occurs in a constant time interval T. At the end of each movement, a new direction and speed are calculated. Assume the speed is uniformly selected from the pre-defined range. The CDF of the traveled distance during each time interval follows

$$F^{rw}(d) = \frac{d - d_{min}}{d_{max} - d_{min}}, \quad (1)$$

where $d_{max} = speedmax \times T$ and $d_{min} = speedmin \times T$.

2) Random Waypoint: In this mobility model, a MN moves from its current location to a new location, which is randomly selected in an area. The MN then travels toward the newly chosen destination at the speed selected from a predefined range. Let the new location uniformly distributed in the circular region centered at the current location with radius $r \leq R_{max}$. The CDF of the distance between the current and the new locations takes the form

$$F^{rwp}(d) = \frac{d^2}{R^2_{max}}. \quad (2)$$

3) Discrete Brownian motion: In this mobility model, time are slotted with constant slot interval T. At the beginning of each slot i, a MN selects the destination (X_{i+1}, Y_{i+1}) based on current location, (X_i, Y_i), i.e.,

$$\begin{aligned} X_{i+1} &= X_i + \eta W_1 \\ \mathrm{Y_{i+1}} &= \mathrm{Y_{i+1}} + \eta W_2, \end{aligned} \quad (3)$$

where W_1 and W_2 follows normal distribution. η is the variance of Brownian motion. Accordingly, the traveled distance during a slot follows the distribution

$$F^{bm}(d) = 1 - e^{-\frac{d^2}{2\eta^2}} \quad (4)$$

4) Extended Levy Walk: Levy walk is a variant of random walk in which the traveled distance of each movement is distributed according to a heavy-tailed distribution, which follows a power law form $F(d) = 1 - (\frac{a}{d})^{\alpha}$. In this model, the upper bound of the traveled distance can be only set as infinity. To address this limitation, the extended Levy model is investigated so that probability-density cutoffs are imposed at both small and large distances. Specifically, the CDF of the traveled distance of the extended Levy walk is expressed by

$$F^{lw}(d) = 1 - \frac{\gamma^{\alpha}(d^{-\alpha} - v^{-\alpha})}{1 - (\gamma/v)^{\alpha}}, \quad (5)$$

where γ and v are the minimum and maximum distances, respectively. From (5), it is evident that Levy walk is a special case of its extended version by setting v as infinity.

The mobility models introduced above can be applied to different scenarios. The random walk and random waypoint models are generally used to mimic the erratic movement of MNs since many entities in nature move in extremely unpredictable ways [2]. The discrete Brownian motion can offer different levels of randomness by one tuning parameter η. By altering the parameters α, γ, and v, the extended Levy walk can effectively capture the movement features of human agents under different surroundings such as campus and downtown area [6].

III. Characterization of Mobile Sensor Behavior

A. Two-phase Alternating Transmission Pattern

In a WSN, the transmission pattern of an mobile sensor can be characterized by a two-phase process alternating between inactive phase and active phase. During the inactive phase, a sensor node travels to a new location, retrieves the sensing information from the field, and performs local compression on the gathered data. During the active phase, the compressed data are forwarded to other nodes or local processing centers or sinks. To formulate this transmission pattern, we adopt the alternating renewal process $S(t)$, which alternates between 0(OFF) and 1(ON) states. The time $\{X_n : n \in Z\}$, which is spent in state 1, is a random variable with probability density function (pdf) $f_1(t)$, and and the time $\{Y_n : n \in Z\}$, which is spent in state 0, is a random variable with pdf $f_0(t)$. Let the associated means times be $\mu_1 = E[X_n]$ and $\mu_0 = E[Y_n]$. The expected value of $S(t)$ is $E[S(t)] = \mu_1/(\mu_0 + \mu_1)$. The power spectrum density (psd) of $S(t)$ equals

$$\begin{aligned} S(\omega) &= E[S(t)]\delta(\frac{\omega}{2\pi}) \\ &\quad + \frac{2(\omega)^{-2}}{\mu_0 + \mu_1}\mathrm{Re}\left\{\frac{[1-\varphi_0(\omega)][1-\varphi_1(\omega)]}{1-\varphi_0(\omega)\varphi_1(\omega)}\right\} \end{aligned} \quad (6)$$

where $\varphi_0(\omega)$ and $\varphi_1(\omega)$ are the characteristic functions of $f_0(t)$ and $f_1(t)$.

In the rest of this section, we will evaluate the pdfs of OFF and ON states since they completely characterize the structure of $S(t)$. Specifically, the OFF state is determined by the configurations of sensing operations, e.g., the sensing duration and data processing complexity. Thus, the OFF state can follow an arbitrary distribution. Particularly, the exponential distribution with parameter λ is assumed so that the OFF state will contribute no burstiness to network traffic. On the other hand, the ON state distribution, $f_1(t)$, depends on the amount of data transmitted at each sensing location. This quantity, which is shown in the next subsection, is closely related to two factors: the performance of compression operations and the distance between two sensing locations. Moreover, the latter factor is determined by the specific mobility model.

B. Explicit Entropy Coding

Explicit entropy coding is a low-complexity in-network data compression technique that is widely applied in wireless sensor networks to effectively remove correlation-induced data redundancy. This scheme allows sensor node encodes/decodes its currently sensed data only conditioned on the its previously retrieved data (explicit side information) with no need to know the correlation structure a priori.

To illustrate the operations of explicit entropy coding, we consider a typical scenario, in which a sensor node treats n consecutive sensing samples as a $typcial\ event$ and only reports the events that are not detected before. According to entropy coding theory [4], the total number M of such typical events is $M = 2^{nH(S)}$. Moreover, due to the spatial correlation, some events detected at current location i may be already detected and reported at previous location $i-1$. Consequently, by performing the explicit entropy coding, only $2^{nh(S_i|S_{i-1})}$ events are required to be reported at location i. Here differential entropy $h(S_i)$ is applied to characterize the observed phenomenon S, which is generally a continuous random process. Given the random Gaussian field as the interested monitoring field and power exponential correlation function, we have the number of notifications at location i

$$M_i = 2^{nh(S_i|S_{i-1})} = (C(1-e^{-2(\theta_1 d)^{\theta_2}}))^{\frac{n}{2}}, \qquad (7)$$

where the parameters θ_1 and θ_2 control the correlation degree within a given distance d. $C = (2\pi e\sigma^2)^{n/2}$ and d is the traveled distance between two sensing locations. Equation (7) proves that the number of event notifications is determined by the specified mobility models, each of which has a different distribution of the traveled distance d.

C. Transmission Duration Distribution

To simplify the analysis, we assume the constant transmission rate is employed so that the transmission duration follows the same form as the number of notifications described by (7). The cumulative density function (cdf) of the transmission duration (ON state) $F_1(t)$ is derived under the four mobility models, based on the traveled distance distributions presented in section II.

1) Random Waypoint:

$$F_1^{rwp}(t) = (\frac{1}{\theta_1 R_{\max}})^2 (\frac{1}{2}\ln\frac{C^{\frac{2}{n}}}{C^{\frac{2}{n}} - t^{\frac{2}{n}}})^{\frac{2}{\theta_2}}, \qquad (8)$$

where R_max is the maximum traveled radius.

2) Random Walk:

$$F_1^{rw}(t) = \frac{1}{(d_{\max}-d_{\min})\theta_1}(\frac{1}{2}\ln\frac{C^{\frac{2}{n}}}{C^{\frac{2}{n}} - t^{\frac{2}{n}}})^{\frac{1}{\theta_2}} - \frac{d_{\min}}{d_{\max}-d_{\min}}, \qquad (9)$$

where d_{min} and d_{max} are the maximum and minimum traveled distance, respectively.

3) Discrete Brownian Motion:

$$F_1^{bm}(t) = 1 - \exp(\frac{-(1/\theta_1)^2(1/2)^{2/\theta_2}}{2\eta^2}(\ln\frac{C^{\frac{2}{n}}}{C^{\frac{2}{n}} - t^{\frac{2}{n}}})^{2/\theta_2}), \qquad (10)$$

where η is the variance of Brownian motion.

4) Extended Levy Walk:

$$F_1^{lw}(t) = 1 - \frac{(\gamma\theta_1 2^{1/\theta_2})^\alpha}{1-(\gamma/v)^\alpha}(\ln\frac{C^{\frac{2}{n}}}{C^{\frac{2}{n}} - t^{\frac{2}{n}}})^{-\alpha/\theta_2} + \frac{(\gamma/v)^\alpha}{1-(\gamma/v)^\alpha}, \qquad (11)$$

where γ and v are the minimum and maximum traveled distance, respectively. α is the tailed index.

The above cdfs indicate that the transmission duration could exhibit different statistical features under different mobility models. Specifically, the mobility related parameters, such as R_{max}, d_{max}, d_{min}, γ, v, and α, directly affect the variability of the transmission duration. For example, smaller α in (11) implies higher probability that long transmission durations occur. This indicates higher probability that a certain level of burstiness exists in the network traffic.

IV. Effects of Different Mobility Models on Traffic Patterns

As introduced in section II, the structure of autocorrelation function can distinguish the SRD traffic from the LRD one. Thus, the traffic pattern of a sensor node associated with a certain mobility model can be predicted by investigating the autocorrelation function of the alternating renewal process $S(t)$, given the corresponding transmission duration distribution. This predicted result will further provide valuable guidelines for the resource provisioning schemes for MSNs under different mobility scenarios.

Proposition 1: The traffic $S(t)$ under random waypoint mobility model is SRD traffic.

Proof: Let $\varphi_1^{rwp}(\omega)$ be the characteristic function of $F_1^{rwp}(t)$ in (8). To derive the closed form of $\varphi_1^{rwp}(\omega)$, we first approximate $F_1^{rwp}(t)$ by

$$F_1^{rwp}(t) = \begin{cases} a_1 t + b_1, & if\ \theta_2 = 1 \\ a_2 t + b_2, & if\ \theta_2 = 2 \end{cases} \qquad (12)$$

where $t \in [t_{min}\ t_{max}]$ with $t_{min} = 0$ and $t_{max} = C(1-e^{-2(\theta_1 R_{\max})^{\theta_2}})^{n/2}$. $a_1 (a_2)$ is a constant. Let $a = a_1$ or a_2 and $b = b_1$ or b_2. Then, we have $b = \delta(t-t_{max})(1-at_{max})$. By (12), it holds that

$$\varphi_1^{rwp}(\omega) = -\frac{a}{\omega}j + (1-at_{max})e^{-j\omega t_{max}}, \qquad (13)$$

Next, we approximate the psd in the middle frequency range, the low-frequency limit, and the high-frequency limit, respectively.

1) The middle frequency approximation. Since $1/t_{max} \ll f \ll 1/(t_{min})$, we have $\omega t_{max} \to \infty$ and thus

$$\varphi_1^{rwp}(\omega) \to -\frac{a}{\omega} j. \tag{14}$$

Since the OFF state follows exponential distribution, we obtain

$$\varphi_0(\omega) = \frac{\lambda}{\lambda + j\omega}. \tag{15}$$

Inserting equations (14) and (15) into (6),, we can obtain the mid-frequency approximation of the power spectrum density

$$S(f) = \frac{2(\lambda^2 + a\lambda)(\mu_1 + \lambda)^{-1}}{(\lambda^2 + 2a\lambda)(2\pi f)^2 + a^2\lambda^2}. \tag{16}$$

According to the middle-frequency spectrum in (16), we can obtain the autocorrelation function in the range $t_{max} \geq \tau \geq t_{min}$

$$\rho(\tau) \to a_1 e^{-b_1 \tau}, \text{as } \tau \to \infty \tag{17}$$

where a_1 and b_1 are some constants. This exponentially decaying autocorrelation function predicts the presence of long range dependence under random waypoint model. ■

Proposition 2: The traffic $S(t)$ oriented from the sensor node following random walk mobility model is SRD traffic.

Proof: According to (8) and (9), the random walk and random waypoint mobility models share the similar form of transmission duration distribution. Thus, it is easy to show that the random walk leads to the spectrum in the same form as the random waypoint except that each mobility scenario arises the spectrum with different parameters, such as a, μ_1, and $Var[X_n]$ in (16). These parameters, however, only affect the magnitude of the autocorrelation function without changing its exponentially decaying structure. ■

Proposition 3: The traffic $S(t)$ oriented from the sensor node following discrete Brownian motion is SRD traffic.

Proof: To derive the closed form of the spectrum, we approximate $F_1^{bm}(t)$ in (10) by the Chebyshev approximation, which is very nearly the optimal polynomial approximation that has the smallest maximum deviation from the true function $F_1^{bm}(t)$. Moreover, the approximated cdf has to be an increasing function, which reaches 1 as t approaches its maximum value. Thus, we obtain

$$F_1^{bm}(t) \approx \begin{cases} pt & 0 < t < k \\ \frac{8c_3}{C^2}t^2 + \frac{2c_2 - 8c_3}{C}t + \frac{1}{2}c_1 - c_2 + c_3 & k \leq t < C \\ \delta(t - C)(1 - \frac{1}{2}c_1 - c_2 - c_3) & t \geq C \end{cases} \tag{18}$$

where $\{c_{i=1}^3\}$ are some constants called Chebyshev coefficients. $k = \frac{C}{2} - \frac{c_2 C}{8c_3}$ and $p = F_1^{bm}(\frac{1}{2C} - \frac{c_2}{8c_3 C})/(\frac{1}{2C} - \frac{c_2}{8c_3 C})$.

Let $\varphi_1^{bm}(\omega)$ be the characteristic function of $F_1^{bm}(t)$. Since $1/t_{max} \ll f \ll 1/(t_{min})$, we have $\omega t_{max} \to \infty$ and thus

$$\varphi_1^{bm}(\omega) \to \frac{16c_3}{C^2}(\frac{k}{j\omega} - \frac{1}{\omega^2}), \tag{19}$$

To simplify the notations, we use quantities A and B to represent fixed constants. Inserting equations (19) and (15) into (6) yields the spectrum in middle frequency range

$$S(f) \approx \frac{2(u_1 + \lambda)^{-1}}{(2\pi f)^2 + 2A\lambda + \lambda^2}, \tag{20}$$

where $A = \frac{16c_3 k}{C^2}$.

By (20), we can obtain the autocorrelation function in the range $t_{max} \geq \tau \geq t_{min}$

$$\rho(\tau) = a_2 e^{-b_2 \tau}, \tag{21}$$

where a_2 and b_2 are some constants. Equation (21) implies the exponentially decaying autocorrelation function. Thus, SRD traffic is expected under discrete Brownian motion. ■

Proposition 4: The extended Levy motion can lead to pseudo LRD traffic, which has power law decaying autocorrelation function $\rho(\tau)$ in the range $t_{min} \geq \tau \geq t_{max}$, i.e., $\rho(\tau) = Dt^{1-\beta}$, where D is some constant and $0 < \beta = 2\alpha/n\theta_2 < 2$.

Proof: The extended Levy walk provides the effective way to describe the movement pattern of human agents [6]. According to the experiments in [6], the upper bound γ of the traveled distance is much larger than the lower bound v, i.e., $\gamma \ll v$. Therefore, we can rewrite the equation (11) by

$$F_1^{lw}(t) = 1 - (\gamma\theta_1 2^{1/\theta_2})^{\alpha} (\ln \frac{C^{\frac{2}{n}}}{C^{\frac{2}{n}} - t^{\frac{2}{n}}})^{-\alpha/\theta_2}. \tag{22}$$

The above cdf can be further approximated by truncated Pareto distribution by using the similar techniques in [7]. By analyzing the power spectrum density in (6), we can obtain the spectrum in mid-frequency range

$$S(f) = \frac{\Gamma(2 - \beta)\gamma^{\beta} \cos(\frac{\pi\beta}{2})}{2(\mu_1 + \lambda)(\beta - 1)} (2\pi f)^{\beta - 2}. \tag{23}$$

and the autocorrelation function in the range $t_{max} \geq \tau \geq t_{min}$

$$\rho(\tau) = Dt^{1-\beta} \tag{24}$$

where D is constant. ■

The aforementioned Propositions state that except extended Levy walk that results in pseudo LRD traffic, the other three mobility models including random walk, random waypoint, and discrete Brownian motion only induce short range dependent traffic.

V. Simulation Results

In this section, we verify our findings by the statistical analysis on the collected traffic traces from the simulated transmissions. Specifically, we let sensor nodes follow the predefined movement patterns, collect data at each destination (sensing location), and send out the data after performing the explicit entropy coding. Then, the traffic traces corresponding to each mobility model are collected and analyzed by the statistical tools including time-variance and periodogram (spectrum) plots. Finally, the analysis results are compared with the theoretical predictions to verify the presence of long range dependence and short range dependence in the network traffic.

Figure 1 shows the spectrum under random walk (Figure 1a), random waypoint (Figure 1b), and discrete Brownian motion 1c). It is seen that all the spectrums in Figure 1 share similar structure, in which different behavior is exhibited at different frequency range in the log-log plot. In high frequency limit, the slop of the spectrum approximates -2. As the frequency approaches zero, the spectrum approximates constant in middle and low frequency range. The observed spectrum under each mobility scenario follows the same form as Markovian traffic shown in Figure 1. This implies that random walk, random waypoint, and discrete Brownian motion result in short range dependence in network traffic. This conclusion is consistent with the theoretical predications presented in Proposition 1, 2, and 3.

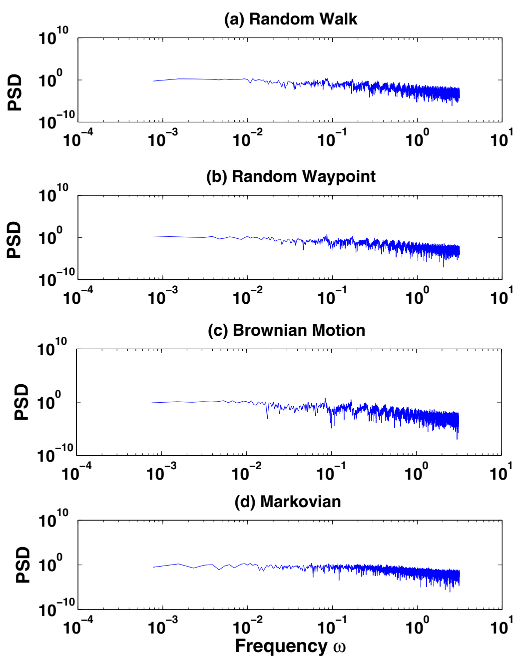

Fig. 1. Spectrum under(a) random walk, (b) random waypoint, (c) discrete Brownian motion, and (d) Markovian stream input

Figure 2 depicts the variance-time plots under extended Levy walk, varying the mobility parameter α between 1 and 2. It is seen that all the variance-time plots are linear. Since the slope of the straight line in variance-time plot yields an estimate for $2H - 2$ and all lines in Figure 2 have slopes larger -1, this indicates $H > 0.5$. As introduced in section II, $H > 0.5$ implies the presence of LRD traffic. This observation is as expected since Proposition 4 predicts that extended Levy walk can result in pseudo long range dependence. It can be also seen from Figure 2 that the value of H increases as α, the tail index of the extended Levy walk, increases. This is consistent with the linear relationship between Hurst parameter H and α as indicated in Proposition 4.

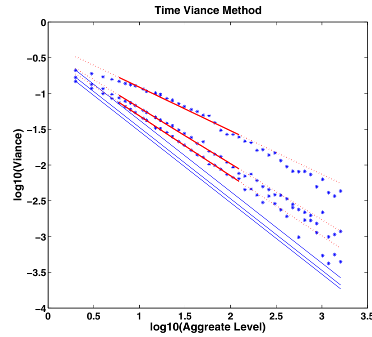

Fig. 2. Variance-time plot of extended Levy walk. Upper, middle, and lower straight line corresponds $\alpha = 1$, $\alpha = 1.5$, and $\alpha = 1.9$, respectively

VI. Conclusions

This paper studies the effects of four representative mobility models on traffic patterns in wireless sensor networks. To find the underlying relationship between the temporal property of network traffic and the spatial property of mobility models, the behavior of the mobile sensor is first characterized by an alternating renewal process, which switches between ON and OFF states. Then, the ON state distribution is proven to be close related to the traveled distance distribution of each mobility model. Next, the spectrum of the traffic oriented from a single sensor is estimated under each mobility scenario. The analysis results show that extended Levy walk can lead to pseudo long range dependence in network traffic, while other three models, random walk, random waypoint, and discrete Brownian motion, only induce short range dependent traffic, These findings are validated by comparing the theoretical predictions with the statistical attributes of the traffic traces collected from the simulated transmissions.

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