Empirical Study on Human Mobility for Mobile Wireless Networks

Ming Zhao   Levi Mason   Wenye Wang

Department of Electrical and Computer Engineering

North Carolina State University, Raleigh, NC 27695

Abstract—The knowledge of human mobility is essential to routing design and service planning regarding both civilian and military applications in mobile wireless networks. In this paper, we study the inherent properties of human mobility upon our collected GPS moving traces. We found that power laws characterize the human mobility in both spatial and temporal domains. In particular, because of the diurnal cycle patterns of human daily activities in associated social territories with limited size, there always exists a characteristic distance in the power law distributions of trip displacement and distance between site locations and a characteristic time in the power law distributions of pause and site return time, respectively. Thus, the CCDF of human movement metrics in spatial and temporal domains always has a transition from power-law head to exponential tail delimited by the associated characteristic distance and characteristic time, respectively. Furthermore, we found that either human random moving direction process without pause or the power law distribution of trip displacement lead to a superdiffusive human mobility pattern, while the power law distribution of pause time causes a subdiffusive human movement pattern.

I. INTRODUCTION

As wireless devices are generally carried by humans, almost all the desired civilian and military applications in mobile ad hoc networks (MANETs) are tightly coupled with humans' moving behaviors, which are governed by their daily activities [1]–[5]. The human daily activities are regulated by their associated societal duties and working patterns in networks, which are very dynamic and difficult to predict upon diversified locations and times. By far, it is still not clear how to specify the complicated human mobility by mobility modeling, which, however, is essential to design and plan the demanding MANET applications for humans.

Human mobility patterns are manifested by the corresponding human moving capabilities. Because of the complexity of human activities in networks, finding the essential mobility metrics which can characterize the human mobility patterns and quantify the human moving capability as well is a very challenging issue. Furthermore, existing synthetic mobility models are not suitable to mimic the human moving behaviors in the societal context. Instead, the inherent properties of human mobility can only be effectively generalized from real human mobility traces [1], [3], [5], [6].

Recent empirical studies of human mobility traces in [7], [8] respectively showed that human mobility patterns and moving capability can be effectively manifested by his/her

diffusive capability (order) r, which characterizes the relationship between the mean square displacement ($MSD(t)$) and the diffusive process time t, that is, $MSD(t) \propto t^r$. In general, the human diffusive behaviors are heavily influenced according to spatial effects such as trip length [6]–[8] or temporal effects such as pause time [6], and return time [5] in mobile wireless networks. Consequently, the study of human diffusive behaviors from the collective spatial and temporal effects is desirable. However, a complete dataset recording human daily activities by moving traces is not available in the research community. Therefore, in this paper, we are motivated to study the inherent properties of human mobility in both spatial and temporal domains and their direct impacts on human diffusive movement patterns by collecting a new set of GPS logged daily moving traces for three months.

Specifically, upon the collected traces, we generalize the human mobility properties in spatial domains regarding travel distance between site locations and trip displacement; and in temporal domains according to site return time and pause time. The results of all these metrics reveal a heavy dependence on human time-varying societal duties in different territories. First, we find that power law is an inherent factor characterizing the human mobility in both spatial and temporal domains. In consequence, we show that power law distribution of trip displacement leads to a superdiffusive ($r > 1$) human movement pattern, while the power law distribution of pause time results in a subdiffusive ($r < 1$) human movement pattern. Interestingly, we also find that the complementary cumulative distribution function (CCDF) of human movement metrics in spatial and temporal domains always has a transition from power-law head to exponential tail delimited by the associated characteristic distance and characteristic time, respectively. Overall our results provide a deep understanding of human moving behaviors. In addition, the knowledge of power law property and the order of characteristic distance in human (solider) trip displacement can benefit the military application with supported threat detecting sensors in a deployed combat environment. And the human diffusive mobility patterns can be applicable to investigate methods of mitigating the effects of dynamic motion on soldier performance in the battle fields.

The rest of paper is organized as follows. Section II introduces the preliminaries of node and human diffusive movement process. In Section III, we analyze the collected GPS traces dataset. In Section IV, we study the spatial effect on on human diffusive behaviors, followed by the temporal effects in Section V. Finally, Section VI concludes this paper.

1

II. PRELIMINARIES AND DEFINITIONS

Recent study showed that the human diffusive behaviors play an essential role in routing design and performance evaluation in mobile wireless networks [6]. However, very few studies have been done on assessment of human diffusive movement patterns according to his/her diffusive capability. On the other hand, the node (particle) and animal diffusive behaviors in physics and biology have been well studied in recent decades [9]–[11]. In this section, we introduce preliminaries and definitions associated with a node diffusive movement process, which will help understand the corresponding human diffusive movement patterns studied in this work.

A. Properties of Power Law Distributions

In this paper, we specify that a power law probability density distribution (pdf) $f(t)$ has the form $f(t) \sim t^{-(1+b)}$, where b denotes the *power law coefficient*. Accordingly, the Complementary Cumulative Distribution Function (CCDF) of $f(t)$ exhibits the *linear* relationship between $\log f(t)$ and $\log t$ with the slope $-b$ in the log-log coordinate. This linear decay of a random variable in its CCDF distribution is often called the *signature* of a power law distribution.

B. Metrics of A Node Movement Process

Definition 2.1: Let $M(t)$ denote a node position (waypoint) at time t. Then, $S(t)$ is the *displacement* of the node movement process by time t, i.e., the Euclidean distance between the waypoints at time 0 and t, that is, $S(t) = |M(t) - M(0)|$. The mean square displacement $MSD(t)$ is defined as $MSD(t) = E\{S(t)^2\} = E\{|M(t) - M(0)|^2\}$.

Definition 2.2: The *diameter* $D(T)$ of a moving trace is defined as the maximum distance between two waypoints among all waypoint pairs collected during time T, that is,

$$D(T) = \sup_{0 \le s,t \le T} \{|M(t) - M(s)|\}. \tag{1}$$

The diameter $D(T)$ directly manifests the node diffusive capability, and $S(T) \le D(T)$ for any mobility trace during time T. It is evident that the larger diameter of the moving trace, the further a node moves away from its initial location.

C. Node Diffusive Movement Patterns

A node diffusive movement pattern is specified by its diffusive order r (capacity), [10], defined as follows.

Definition 2.3: The stochastic process of the moving trace $\{M(t)\}$ is diffusive at the order $r \in (0, 2]$, if $MSD(t) \propto t^r$.

From Definition 2.3, it is evident that the straight line movement without pause has the maximum diffusive order r, that is, given a specific speed value v, $MSD(t) = v^2 \cdot t^2 \propto t^2$. Accordingly, the maximum human diffusive order of a movement process is $r_{\max} = 2$.

Definition 2.4: Given the value of diffusive order r, the node (human) diffusive movement pattern could be either a *Normal diffusive* ($r = 1$) or *Anomalous diffusive* ($r \neq 1$). Furthermore, mobile nodes (humans) can have two anomalous diffusive movement patterns: *Superdiffusive* ($r > 1$) and *Subdiffusive* ($0 < r < 1$) [10] [10].

Definition 2.5: Superdiffusive is an anomalous diffusive movement pattern in which $MSD(t) \propto t^r$, where $r > 1$. It is characterized by *faster-than-linear* growth of the $MSD(t)$.

Definition 2.6: Subdiffusive is an anomalous diffusive movement pattern in which $MSD(t) \propto t^r$, where $r < 1$. It is characterized by *slower-than-linear* growth of the $MSD(t)$.

D. Normal Diffusive Movement Process

Now we see that diffusive movement patterns are categorized by the diffusive order r of $MSD(t)$ proportion to the time t. From Definition 2.1, the value of $MSD(t)$ of a diffusive process depends on the distribution of node displacement $S(t)$. For simplicity, the node displacement $S(t)$ can be studied by a one-dimensional continuous time random walk (CTRW) model [10]. Specifically, in the CTRW model, X_i denotes the independent identically distributed (i.i.d) displacement of a walker at the ith step, and $N(t)$ denote the total number of steps occurred in the time interval $[0, t]$. Also, let Δt be the time increment between two successive steps, that is $\Delta t = t/N$. Then $S_N(t)$, the position of the walker by time t, is represented by $S(t) = S_{N(t)} = \sum_{n=1}^{N(t)} X_n$. That is, the node displacement $S(t)$ is a function of step length X_i and the time increment Δt, i.e., the pause time, between two successive steps. Hence, the distribution of $S(t)$ heavily depends on the properties of X_i and Δt. In particular, the different types (light-tailed or heavy-tailed) of distribution of X_i and Δt can lead to different types of diffusive mobility patterns [10]. For instance, let both random variables of step length X_i and pause time Δt follow a light-tailed distribution, so that X_i and Δt have finite mean and variance. And $P(x, t)$ denotes the probability that a walker's position is x at time t. Accordingly, let $f(x, t)$ denote the pdf of $P(x, t)$ in CTRW model, then we have [10]

$$\begin{aligned} f(x,t)dx &= \lim_{t \to \infty} Prob\{x < \frac{S_{N(t)}}{t^{1/2}} < x + dx\} \\ &= \frac{1}{\sqrt{4\pi kt}} e^{-x^2/4kt} dx, \end{aligned} \tag{2}$$

where k is called *diffusion constant*. From (2), $MSD(t)$ can be derived as

$$MSD(t) = E\{x^2(t)\} = 2kt \propto t^1, \text{ and } k = \frac{E\{\Delta x^2\}}{E\{\Delta t\}}. \tag{3}$$

Equation (3) indicates that $MSD(t)$ grows linearly with time t, that is, the normal diffusive order $r = 1$. Given Definition 2.4, it is evident that the node has a *Normal diffusive movement process*. In fact, the result of (2) is obtained by applying central limit theorem (CLT), when both step length Δx and pause time Δt have finite mean and variance, i.e., follow a lighted-tailed distribution. However, the CLT theorem cannot be applied when either step length Δx or pause time Δt has infinite moments (first or second) [9].

Note that the above analysis is based on CTRW model, however, it is still unknown whether the real human mobility is complied with the above aforementioned conditions of step length (trip displacement) and pause time. Otherwise, rather than a normal diffusive movement pattern, humans may be

2

characterized by anomalous diffusive (superdiffusive or subdiffusive) movement patterns. Therefore, to tackle this issue, we study our collected human traces through GPS receivers for investigating inherent properties of human mobility metrics.

III. EXPERIMENTAL HUMAN TRACE STUDY

People have observed that human mobility is driven by his/her social behaviors [2], [4], which can be generalized from the complete information of human successive daily travel activities. Though, there are many available experimental human mobility datasets, almost all of them provide only partial information of daily travel activities. For instance, existing traces either focus on temporal metrics such as the direct association time between mobile devices carried by humans [3], [5], or spatial metrics such as the geographical information of human movements [6]. However, the complete trace log information of human daily travel activities in both spatial and temporal domains is necessary for investigating spatial-temporal limitations of human social behaviors, which indeed govern human diffusive movement patterns.

In this empirical study, we collected student daily travel traces over NCSU campus for three months. In detail, we let a group of volunteer students carry GPS loggers during each travel, either by walk or vehicles. Each volunteer records his/her travel trace more than one week. Specifically, each GPS logger takes measurements every 10 seconds, and records the time-stamped dataset, including current time, latitude, longitude, and speed. By this means, the trace dataset contains both human spatial and temporal information necessary for this study. In addition, previous empirical trace studies mainly either focused on car traces [12] or walking traces [3], [6]. In contrast, our collected GPS traces are more diversified including traces made by foot, bus, and car. Therefore, our trace files not only provide more spatial and corresponding temporal information, but also cover a broad range mobility patterns with trip distance up to 20 kilometers. By this means, we aim to find the common and inherent properties of human mobility from diversified human traces. Because all the volunteer subjects are graduate students, though our collected traces particularly manifest human mobility in the proximity of campus during weekdays, they are more diversified during the weekends and holidays.

A. Trace Extraction

In this paper, we define a *trip* as the travel between the source and destination. For the purpose of determining trip destinations from each subjects raw dataset, we utilize the similar trace extracting strategies introduced in [12]. Briefly, we consider that trips are truly separated if there is either a gap or pause time more than 3 minutes between two consecutive timestamps of the trace dataset. Since the direction during a trip can change frequently, we define the line segment associated with each direction as a *leg*. Thus, a trip is composed of multiple legs. Specifically, we use the direction model introduced in [6] to differentiate legs in a trip, where the relative angle between two successive legs is larger than a direction threshold θ_{th}. An example of a trip

extracted by the direction model is shown in Fig. 1. In the figure, the dotted line represents the GPS trace, marked by the logger waypoints every 10 seconds. After running the direction model, the trip is abstracted and decomposed into three legs. Specifically, θ_i and l_i denotes the direction and the length of the ith leg, respectively. And the trip direction θ is measured by the starting position and ending position of the trip. Correspondingly, L denotes the trip displacement.
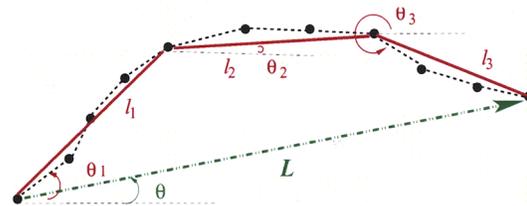

Fig. 1. Example of an extracted trip.

B. Trace Statistics

The statistics of the collected traces are shown in Fig. 2, Table I, and Table II, respectively. From Fig. 2, we find that on average the students have only few trips and visiting sites per day. For instance, most students take less than 4 trips and visit less than 5 different locations each day. This implies that students (mobile users) limit their activities to a few key sites in their daily routine. Most of them are occasionally mobile during a day and spend a considerable amount time at certain places, such as home and lab office, which can also be revisited multiple times during one day. Table I illustrates the statistics of collected traces with respect to individual students. Interestingly, we notice that the trips resulting from different people share the common properties. Specifically, we find that the average trip displacement is at the order of 1000 meters. The average travel time per trip is typically less than 30 minutes, while the average pause time is 10 times longer than the average travel time of each user. Due to the limited number of trips and short travel times, on average a long pause time occurs between two consecutive trips.
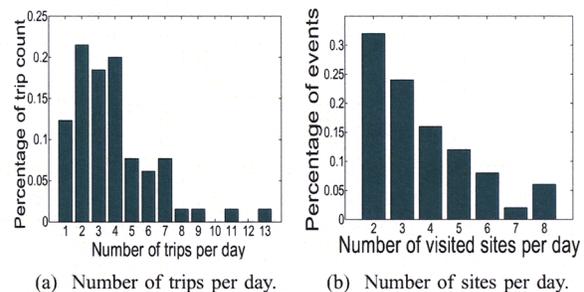

(a) Number of trips per day.   (b) Number of sites per day.

Fig. 2. Experimental GPS traces statistics.

TABLE I
STATISTICS OF INDIVIDUAL TRIPS OF COLLECTED GPS TRACES.

Student ID:	1	2	3	4	5
Avg trip displacement (m):	2333	2131	1456	1594	7920
Avg travel time (min)	24.2	20.1	8	8.8	33.87
Avg pause time (min)	291.5	285	423	194	368.5
Avg sites visited daily	5	5	3	4	4
Different sites visited weekly	15	14	8	11	12

3

Trip displacement L range (m)	$[30, 500)$	$[500, 1000)$	$[1000, 2000)$	$[2000, 5000)$	$[5000, 10000)$	$[10000, 20000)$
Number of trips	68	24	47	10	16	21
Prob($L = D$)	0.897	0.667	0.553	0.3	0.063	0.191
Avg # of direction changes	1	3	6	10	11	16

Furthermore, we aggregate all collected traces and investigate the overall human trip statistics, which are shown in Table II. Though the trip displacements can reach up to 20 kilometers, we see that the majority of trip displacements are within 2000 meters, which is the same order as the side length of our campus. Especially, within the range of 500 meters, we find that most (about 90%) trip diameters (D) are the same as the trip displacements (L). This implies that mobile users have an intended destination for a trip and prefer to move approximately along a straight line if possible. However, this observation cannot be directly supported when the trip displacements are beyond 2000 meters, due to the frequent direction changes. As we expected, the number of direction variation increases with the length of trip displacement. Therefore, the impact of geographical constraints on human mobility traces is more significant for the long trip displacements.

Given the knowledge of the extracted traces, we investigate the human diffusive movement patterns. Interestingly, recent study in [7] showed that the human mobility may not satisfy the conditions of trip displacement and pause time for applying CLT theorem to determine human diffusive movement pattern, as we discussed in Section II-D. Thus, it is not clear whether the human mobility follows the *normal diffusive* pattern ($r = 1$) exclusively. If it is not, it is unknown yet why and how human mobility complies with *anomalous diffusive* patterns ($r \neq 1$). Note that trip displacement is a spatial factor, while pause time is a temporal factor. Hence, to tackle this issue, we study the human diffusive mobility pattern from spatial and temporal domains, respectively.

IV. SPATIAL EFFECT ON HUMAN DIFFUSIVE BEHAVIORS

In this section, we investigate the spatial effect of mobility metrics including direction, inter-site distance and trip displacement on human diffusive behaviors.

A. Direction Effect

Here, we focus on the directional effect on human diffusive mobility pattern through a random direction process without considering pause time, i.e., excluding temporal effects. In detail, let a node move at a constant speed v during time interval T. It randomly changes direction during the trip, and moves at direction θ_u with time interval t_u. Assume that θ_u is i.i.d and uniformly distributed over a limited domain $[a, b]$, $0 \leq a \leq b \leq 2\pi$, and $\sum_{u=1}^{m} t_u = T$. This is the typical mobility pattern defined in *Random Direction* (RD) model, a variant of CTRW model. The corresponding movement process is illustrated in Fig. 3, upon which we have our main result as follows.

Theorem 1: An arbitrary random direction movement process $M(t)$ without pause time has a superdiffusive mobility

pattern, i.e., $r \in (1, 2]$. The minimum order $r_{\min}$ occurs when the direction R.V. θ is uniformly over $[0, 2\pi]$.
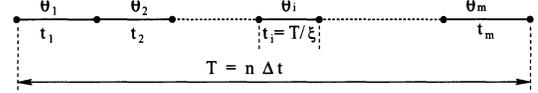

Fig. 3. Random direction movement process during time T.

Proof: Let $M(0) = 0$ be the initial position, then for a large time T, the node position $M(T)$ is represented as the sum of m position vectors, that is, $M(T) = \sum_{u=1}^{m} v \cdot t_u \cdot e^{(i\theta_u)}$. From Definition 2.1, the $MSD(T)$ is given by

$$
\begin{aligned}
MSD(T) &= E\{|M(T)|^2\} = v^2 \cdot T^r \sim T^r \\
&= E\{|M(T)M(T)^*|\} = E\{\sum_{u=1}^{m} \sum_{k=1}^{m} v^2 \cdot t_u \cdot t_k \cdot e^{i(\theta_u - \theta_k)}\} \\
&= \sum_{u=1}^{m} v^2 t_u^2 + \sum_{u=1}^{m} \sum_{k=1, u \neq k}^{m} v^2 t_u \cdot t_k \cdot E\{e^{i\theta_u}\} \cdot E\{e^{-i\theta_k}\}.
\end{aligned}
$$
(4)

Let $G_\theta = E\{e^{i\theta_u}\} \cdot E\{e^{i\theta_k}\}$, it is evident to see that G_θ is over $[0, 1]$. Especially, when the range of random direction $[a, b]$ to be $[0, 2\pi]$, i.e., θ_u is over $[0, 2\pi]$, then $G_\theta = 0$. In this case, from (4), we can see the second item on RHS becomes zero, which leads to the minimum order, r_{min} because this item is a positive value for $G_\theta \neq 0$. Therefore, the minimum order r_{min} occurs when direction θ is uniformly over $[0, 2\pi]$ in the random process. Upon (4), the diffusive order of an arbitrary random process, whose range of the random direction is over $[a, b]$, has the following property

$$
\begin{aligned}
T^{r/2} &= \left(\sum_{u=1}^{m} t_u^2 + \sum_{u=1}^{m} \sum_{k=1, u \neq k}^{m} t_u \cdot t_k \cdot G(\theta) \right)^{1/2} \\
&\geq (\sum_{u=1}^{m} t_u^2)^{1/2} = (\frac{m \cdot \sum_{u=1}^{m} t_u^2}{m})^{1/2} \\
&= m^{1/2} (\frac{\sum_{u=1}^{m} t_u^2}{m})^{1/2} \geq m^{1/2} (\prod_{u=1}^{m} t_u)^{1/m}.
\end{aligned}
$$
(5)

Let $\frac{T}{\xi} = \{\min t_u \mid \sum_{u=1}^{m} t_u = T, 1 \leq u \leq m\}$, then

$$
T^{r/2} \geq m^{1/2} (\prod_{u=1}^{m} t_u)^{1/m} \geq m^{1/2} (\prod_{u=1}^{m} \frac{T}{\xi})^{1/m} = m^{1/2} \cdot \frac{T}{\xi}
$$

$$
\implies \frac{\xi}{m^{1/2}} \geq T^{1-r/2}.
$$
(6)

Recall that in Fig. 3, m represents the total number of direction changes by time T, i.e., $m \leq \xi \leq T$. Hence, with

4

(6), for a large T, the lower bound of r is given by

$$r \geq 2 - 2\log_T(\xi m^{-1/2})$$
$$\geq 2 - 2\log_T(m^{1/2}) = 2 - \log_T m. \qquad (7)$$

Upon (7), the value of r of a random process decreases monotonously as increasing m which represents the number of direction changes during time interval T. In one extreme case, when $m_{\min} = 1$, i.e., the node moves along a straight line during $[0, T]$, there exists the maximum diffusive order $r_{max} = 2$. On the contrary, when $m_{\max} = T$, we have $r_{min} = 1$. Therefore, the diffusive order r of random direction movements without pause time is between $[1, 2]$. ∎

Note that, given the collected trace statistics in Section III-B, we observed that humans have a strong "memory" of direction during the travel, as the destination is generally determined right before the beginning of the trip. Hence, compared to the typical node movement in a random direction process, humans change moving direction less frequently during the trip, which in turn, leads to a *superdiffuisve* movement pattern.

By far, we have studied the exclusively directional effect, which shows that the random direction change in node (human) moving trajectories without pause time leads to a superdiffusive mobility pattern. Next, we proceed to investigate the property of inter-site distance and its resulting trip displacement effect on human diffusive mobility.

B. Inter-Site Distance Effect

From Fig. 2 and Table I, we observed that humans will travel between a limited number of sites per day. In addition, human daily activities are generally constrained within few limited societal territories. In fact, the intrinsic human mobility is dominated by its sociological activities [2], [13]. Therefore, the societal duties and working patterns significantly regulate the daily human activities. Accordingly, in this study, Fig. 4 and Fig. 5 respectively illustrate the aggregated site locations of all volunteers and the corresponding CCDF of aggregated inter-site distance from our collected GPS traces. It is clear to see in Fig. 4 that the majority site locations students daily visited are within the 2km-wide campus area, where the originate coordinate $(0, 0)$ represents the location of parking deck in front of our department. Specifically, we find that 75% of inter-site distances are less than 2000 m, which is consistent with the statistic results of trip displacements shown in Table II. Though most inter-site distances are short, from Fig. 4, we still can see many long distances between site locations outside campus area. Note that the properties of inter-site distances directly manifest the human daily activities, which in turn, characterize the human diffusive behaviors. Hence, we are interested in finding the distribution of human inter-site distance.

Specifically, Fig. 5 illustrates the aggregated CCDF of inter-site distances among all student volunteers in log-log scale. Interestingly, from Fig. 5, we can see that the CCDF values decay linearly over the domain $[30, 2000]m$, thus suggesting a power law decay as described in Section II-A. When the value of inter-site distance is larger than 2000 meter, the
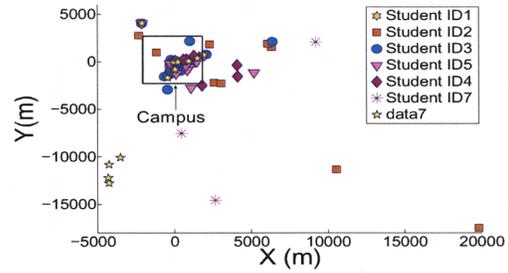
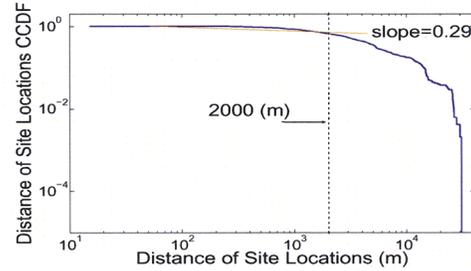

Fig. 4. Aggregated site locations upon GPS trace.

Fig. 5. The CCDF of aggregated distance of site locations.

CCDF values decay abruptly faster, i.e., decay exponentially. In fact, our observations in Fig. 5 are consistent with what have been recently found in [5], where the authors showed that there is a "power law – exponential" *dichotomy* in the CCDF of inter-meeting time between two mobile nodes (humans). Specifically, there always exists a *characteristic time*, before which the CCDF has a power law decay, and after which it drops exponentially. Similar to their denotation of *characteristic time* in the CCDF of inter-meeting time, we define the distance of 2000 meter as the *characteristic distance* of the CCDF of inter-site distance shown in Fig. 5. Note that the value of characteristic distance varies with the size of societal territories where human daily travels. In this empirical study, all the student volunteers' daily movements are associated with campus activities and live close to the campus. Hence, there exists an "invisible" virtual boundary of campus-associated territory, which covers the majority of trips between site locations in the campus. This is why the value of characteristic distance of CCDF of inter-site distance is at the same order of the side length of our campus.

C. Trip Displacement Effect

Intuitively, the property of trip displacement is dominated by the distances among different locations where humans daily visit. In previous section, we found that the human inter-site distance follows a power law distribution before the characteristic distance. Here, we investigate the property of trip displacement and its direct effect on human diffusive mobility patterns. In particular, Fig. 6 shows the CCDF of aggregated trip displacement of all volunteers in log-log scale. As we expected, it is clear to see that the CCDF of trip displacement follows a power law distribution over the range $[30, 1000]m$. This further indicates that a characteristic distance, which is

5

1000m in this case, exists in the CCDF of trip displacement. This result agrees with observations of the previous studies on trip length of human walk by foot [6]. In contrast to their traces, our data traces are collected over daily activities by foot, buses, and cars, and have a larger scale measurement of trip length. Hence, we assert that the power law distribution of trip displacement is a universal property of human mobility. Hence, upon the power law property described in Section II-A, within the range of characteristic distance denoted by D_c, the pdf of trip displacement L is given by,

$$f_L(l) \sim \frac{1}{l^{1+\beta}} \quad \beta > 0 \;, l < D_c, \qquad (8)$$

where β is the power law coefficient, and is close to 0.31 as shown in Fig. 6. According to the theory of particle diffusive process in physics [10], when $0 < \beta < 2$ in (8) and D_c is considerable large, either the first or the second moment of the trip displacement L can be infinite, which contradicts the condition of the trip length with finite moments for applying CLT theorem in Section II-D. Thus, rather than having a *normal* diffusive pattern, the power law distribution of trip displacement, which contains the non-negligible elements of very large trip displacements, leads to a *superdiffusive* ($r > 1$) movement pattern. Especially, the diffusive order r is the function of the coefficient β of the trip displacement.
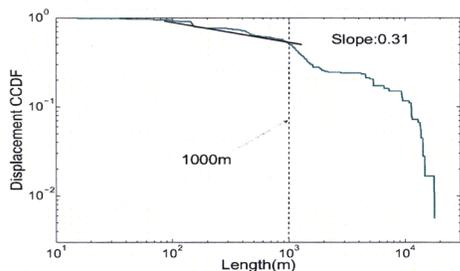

Fig. 6. Aggregated trip displacement CCDF.

Remark 1: Power law characterizes the distance between site locations associated with human daily activities, which results in the power law distribution of human trip displacement. Because the inter-site distances are constrained by societal territories with limited size, there always exists the characteristic distance of "power law − exponential" *dichotomy* in the CCDF of inter-site distance and trip displacement. Especially, the characteristic distance of inter-site distance is at the same order as that of trip displacement. In summary, the power law property of inter-site distance dominates that of human trip displacement, which in turn, characterizes the resulting human superdiffusive ($r > 1$) capability.

V. TEMPORAL EFFECT ON HUMAN DIFFUSIVE BEHAVIORS

In previous section, we demonstrate that power laws of inter-site distance and resulting trip displacement lead to superdiffusive human behaviors. Here, we investigate the temporal effect on human diffusive mobility patterns according to site return time and pause time in sequence.

A. Site Return Time Effect

According our collect GPS traces, people visit different site locations in different frequencies and the return time varies dramatically regarding the site locations. Intuitively, humans would execute different types of tasks in different locations. For instance, students take a class in campus while buying foods in a grocery store. That is, upon different task temporal regularities, human site return times vary with different site locations. Moreover, recent studies [1], [13] showed that governed by location-varying social duties, humans are expected to return certain locations, such as home and office, upon their diurnal cycle patterns. Therefore, the *human return time* to a specific site is an interesting issue that can be used to predict the locations of mobile users.

In this empirical study, as students are likely to play a similar role in campus, we interestingly find that there are several common sites that students have visited. For instance, we demonstrate two examples of common sites in campus area in Fig. 7(a) by reducing the observing size of aggregated site locations of Fig. 4. From Fig. 7(a), we see that several students visit a same class room for taking classes at the same location. More interestingly, we find that our research lab office is a common site where all volunteers have visited. And typically, each student visits the lab office at least once per day. The existence of common site of mobile users implies that there surely exists a possibility that mobile nodes can meet each other. Accordingly, the *return time to a common site* dominates the value of this probability, which in turn, characterizes the inter-meeting time between two mobile users [3], [5].
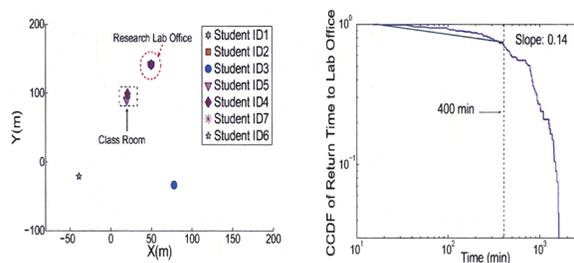
(a) Illustration of common visited sites. (b) The CCDF of return time to a common site (lab office).

Fig. 7. Property of return time to a common site.

In this paper, we study the CCDF of aggregated return time to the common site, i.e., the lab office, in Fig. 7(b) at the log-log scale. Similar to the CCDF of trip displacement, we observe that power law also dominates the return time of human mobility. Similar to our observation of a characteristic distance on the CCDF of trip displacement and inter-site distance, we again observe a "power law − exponential" *characteristic time* which exists in the CCDF of site return time. Specifically, the *characteristic time* is in the order of 400 minutes. In addition, recent studies of human mobility on campus from both WLAN traces [1] and user PDA traces [14] have shown that human activities follow diurnal cycle patterns. This implies that students would like to periodically visit certain places such as lab office in campus. And the period is generally less than a day. In this case study, the time interval between two consecutive visits to lab office is typically at the order of 400 minutes.

6

The site return time is an important temporal metric, which also heavily affects the property of pause time. For instance, the average human pause time should be less than the average site return time. Otherwise, humans may pause at a certain site location too long to return other locations regarding the site return time. In addition, we note that the trip displacement $S(t)$ approaches to 0 when mobile users return to their original positions, i.e., $M(t) - M(0) \sim 0$, regardless of the distances they moved away. Hence, given a specific site which a mobile user would visit multiple times, the diffusive pattern should be evaluated within the time scale of the corresponding return time. In contrary to site return time, pause time is the essential temporal metric directly characterizing the human diffusive behaviors, which is discussed next.

B. Pause Time Effect

By combining results shown in Fig. 2 and Table I, it is observed that all students (humans) have very limited trips per day and the majority of travel times are short, i.e., no longer than 30 minutes. This implies that long pause time frequently occurs between two consecutive trips, which is common in human mobility. Accordingly, Fig. 8 illustrates the respective pause time CCDF of one single student and the aggregated CCDF of all volunteers in log-log scale. It is clear that these two CCDF values decay in a very similar way, which indicates that the same type of humans in one network domain, e.g., students in a campus, share the same properties on the pause time between two successive trips. In particular, we observe that the CCDF values follow a straight line over a range $[10, 360]$ minutes. Hence, the pause time in human mobility also follows a power law distribution. Similar to site return time, the *characteristic time*, denoted by T_c, also exists in the CCDF of pause time, which is at the order of 360 minutes in our collected trace dataset. Let T_p denote the pause time, then the pdf of pause time is represented as

$$f_{T_p}(t) \sim \frac{1}{t^{1+\alpha}} \quad \alpha > 0, \quad t < T_c, \tag{9}$$

where α is the power law coefficient, and is close to 0.42 as shown in Fig. 8. According to particle diffusive theory in physics [10], when $0 < \alpha < 2$ and T_c is considerable large, the power law distribution of pause time leads to a *subdiffusive* $(0 < r < 1)$ movement pattern. Especially, the diffusive order r is the function of the coefficient α of the pause time.
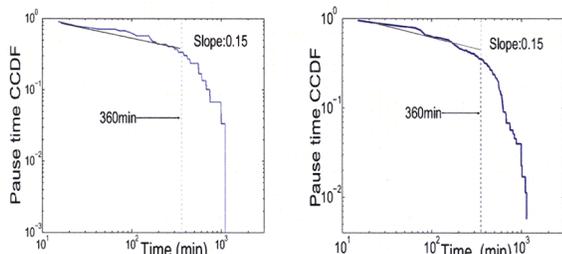
(a) Pause time CCDF of single student. (b) Aggregated pause time CCDF.

Fig. 8. The CCDF of pause time in collected GPS traces.

Remark 2: The power law distribution of site return time and pause time is a universal property of human mobility. Because humans visit site locations periodically, especially following the diurnal cycle patterns, there always exists a "power law – exponential" characteristic time in the CCDF of site return time and pause time, respectively. Both characteristic times are at the order of hours. Especially, the power law distribution of pause time leads to a human *subdiffusive* $(0 < r < 1)$ movement pattern.

VI. CONCLUSION

In this work, we investigate the human diffusive behaviors from an empirical study upon our collected GPS moving traces. We find that a human's diffusive mobility is driven by his/her societal roles in different social territories. We found that the power law inherently characterizes the human mobility in both spatial and temporal domains. In particular, the anomalous human diffusive behaviors $(r \neq 1)$, which include the superdiffusive behavior $(r > 1)$ due to power law of trip displacement and the subdiffusive behavior $(r < 1)$ resulting from power law of pause time, are often observed over diverse mobility traces collected from pedestrian, buses, and cars. The "power law – exponential" characteristic distance shown in spatial metrics of human mobility is constrained by the limited size of social territories. Accordingly, the existence of characteristic time in temporal metrics of human mobility is dominated by the temporal regularities of societal duties, such as diurnal cycle working patterns, which is in general at the order of hours. And the site return time dominates the time scale for evaluating the human diffusive behaviors.

REFERENCES

[1] D. Kotz and K. Essien, "Analysis of a Campus-Wide Wireless Network," in *Proceedings of ACM MOBICOM*, 2002, pp. 107–118.
[2] A.-L. Barabasi, "The Origin of Bursts and Heavy Tails in Human Dynamics," *Nature*, vol. 435, pp. 207–211, May 2005.
[3] A. Chaintreau, P. Hui, J. Crowcroft, C. Diot, R. Gass, and J. Scott, "Impact of Human Mobility on the Design of Opportunistic Forwarding Algorithms," in *Proceedings of IEEE INFOCOM*, 2006.
[4] J. Ghosh, S. Philip, and C. Qiao, "Sociological Orbit Aware Location Approximation and Routing (SOLAR) in MANET," *Ad Hoc Networks*, vol. 5, no. 2, pp. 189–209, March 2007.
[5] T. Karagiannis, J.-Y. LeBoudec, and M. Vojnovic, "Power Law and Exponential Decay of Inter Contact Times Between Mobile Devices," in *Proceedings of ACM MOBICOM*, 2007, pp. 183–194.
[6] I. Rhee, M. Shin, S. Hong, K. Lee, and S. Chong, "On the Levy-Walk Nature of Human Mobility," in *Proceedings of IEEE INFOCOM*, 2008.
[7] D.Brockmann, L.Hufnagel, and T.Geisel, "The Scaling Laws of Human Travel," *Nature*, vol. 439, pp. 462–465, January 2006.
[8] C. Lee, S. Kim, and D. Eun, "Super-Diffusive Behavior of Mobile Nodes from Mobility Traces," NC State University," Technical Report, 2007.
[9] M. F. Shlesinger, J. Klafter, and Y. M. Wong, "Random Walks with Infinite Spatial and Temporal Moments," *IEEE Journal of Statistical Physics*, vol. 27, no. 3, pp. 499–512, March 1982.
[10] R. Metzler and J. Klafter, "The Random Walk's Guide to Anomalous Diffusion: A Fractional Dynamics Approach," *Physics Reports*, vol. 339, pp. 1–77, 2000.
[11] J. Klafter and L. M. Sokolov, "Anomalous Diffusion Spreads its Wings," *Physica A*, vol. 117, no. 1, pp. 179–188, August 2005.
[12] J. Krumm and E. Horvitz, "The Microsoft Multiperson Location Survey," Technical Report MSR-TR-2005-103, 2005.
[13] Q. Zheng, X. Hong, and J. Liu, "An Agenda based Mobility Model," in *Proceedings of 39th Annual Simulation Symposium*, April 2006.
[14] M. McNett and G. M. Voelker, "Access and Mobility of Wireless PDA Users," in *Review of 2005 Mobile Computing Communications*, April 2005, pp. 40–55.