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Anh-Dung Nguyen, Patrick Sénac, Michel Diaz. Modeling opportunistic networks - from mobility to structural and behavioral analysis. *Ad Hoc Networks*, 2013, Volume 24, Part B, pp.161-174. <10.1016/j.adhoc.2014.07.017>. <hal-04354284>

**HAL Id: hal-04354284**

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Submitted on 19 Dec 2023

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# Modeling opportunistic networks - from mobility to structural and behavioral analysis

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## ABSTRACT

In this work, we propose a modeling framework which captures the most fundamental behavioral and structural properties of opportunistic networks from mobility to structural level. This framework provides to researchers an in-depth and clear understanding of opportunistic networks and to practitioners a simulation environment to evaluate their opportunistic network protocols. First, we introduce Spatio-TEmporal Parametric Stepping or STEPS – a simple parametric mobility model which can cover a large spectrum of human mobility patterns. STEPS abstracts the fundamental spatio-temporal behavior of human mobility by using a power law to drive nodes' movement. We show that the model makes it possible to express key peer-to-peer properties such as inter-contact/contact time distributions. Leveraging on the expressive and modeling power of STEPS, we analyze how fundamental structural properties can emerge from the combination of elementary node's mobility behavior. Specifically, we show that highly mobile nodes are at the origin of the emergence of small-world structures in opportunistic networks.

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## 1. INTRODUCTION

Opportunistic networks are dynamic networks based on nodes' intermittent contacts. This type of network was shown to be the sole communication means in many extreme situations, especially when an infrastructure-based communication is not possible, for instance, deep space communications, disaster recovery networks, battlefield networks. Moreover, the ever increasing density of mobile wireless devices and sensors that populate the edge of the Internet raises the question of the efficient cooperative use of these vast space of resources by leveraging on the spontaneous communication capacity offered for free by the "mobile cloud" of edge devices. Therefore, opportunistic networks pave the way to a pervasive and universal communication environment in which opportunistic communication can play an important

role by its capacity to free users from infrastructure dependence.

Human mobility was known to have a significant impact on performance of opportunistic networks. Unfortunately, for the moment, there is no model that is able to capture all the characteristics of human mobility due to its high complexity. We introduce Spatio-TEmporal Parametric Stepping (STEPS) – a powerful formal model for human mobility or mobility inside social/interaction networks. The introduction of this new model is justified by the lack of modeling and expressive power, in the currently used models, for the spatio-temporal correlation usually observed in human mobility.

We show that preferential location attachment and location attractors are invariants properties, at the origin of the spatio-temporal correlation of mobility. Indeed, as observed in several real mobility traces, while few people

have a highly nomadic mobility behavior the majority has a more sedentary one.

We assess the expressive and modeling power of STEPS by showing that this model succeeds in expressing easily several fundamental human mobility properties observed in real traces of dynamic network:

- The distribution of human traveled distance follows a truncated power law.
- The distribution of pause time between travels follows a truncated power law.
- The distribution of inter-contact/contact time follow a truncated power law.

On the other hand, mobility models often fail in expressing basic structural properties of opportunistic networks. This raises the issue of the capacity of these models to represent and reproduce the structural properties observed in real traces of dynamic networks. We address this issue by showing that STEPS is capable of capturing not only the elementary mobility behaviors but also the structural characteristics of opportunistic networks. We show in this paper how fundamental global structural properties can emerge from specific behavior of dynamic network nodes. Specifically, we transpose in the framework of opportunistic networks the notion of small-world structure.

In his famous experiment, Milgram showed that the human acquaintance network has a diameter in the order of six, leading to the small-world qualification. Watts and Strogatz later introduced a model of small-world phenomenon for static graphs [1]. They proposed a random rewiring procedure for interpolating between a regular ring lattice and a random graph. Between these two extrema, the graph exhibits an exponential decay of the average shortest path length contrasting with a slow decay of the average clustering coefficient. Interestingly, numerous real static networks exhibit such property. From a communication perspective, Watts and Strogatz also pointed out that a small-world network behaves as random network in terms of information diffusion capacity.

However, the great majority of studies on small-world networks properties and behaviors focused on static graphs and ignored the dynamics of real mobile networks. For example, in a static graph, an epidemic cannot break out if the initial infected node is in a disconnected component of the network; conversely in a mobile network, nodes

movements can ensure the temporal connectivity of the underlying dynamic graph. Moreover, an epidemic can take off or die out depending not only on the network structure and the initial carrier, but also on the time when the disease begins to spread. These aspects cannot be captured by a static small-world model.

In order to formalize the dynamic small-world phenomenon, we extend to dynamics networks the notions of dynamic clustering coefficient and shortest dynamic path. By studying the evolution of these metrics from our rewiring process, we show the emergence of a class of dynamic small-world networks with high dynamic clustering coefficients and low shortest dynamic path length. We then demonstrate the capacity of STEPS to capture these structural characteristics of mobile opportunistic networks by showing that, when increasing progressively the dynamicity of a network from an initial stable state, then this rewiring process entails the emergence of a small-world structure.

The rest of this chapter is structured as follows. After an overview of the related works in Section 2, Section 3 formally introduces STEPS and Section 4 shows its capacity to capture salient features observed in real opportunistic networks. In Section 5, after having formally defined the notions of dynamic clustering coefficient and shortest dynamic path length, we analyze various real opportunistic network traces and show the intrinsic properties of opportunistic networks that induce the small-world phenomenon. We show how STEPS can capture these properties and how to explain the emergence of these properties in opportunistic networks in Section 6. Finally we conclude the paper in Section 7.

## 2. RELATED WORKS

Human mobility has attracted a lot of attention of not only by computer scientists but also epidemiologists, physicists, etc because its deep understanding may help to explain many important issues in these different fields. The lack of large scale real mobility traces made that research initially based on simple abstract models, e.g., Random Waypoint, Random Walk (see [2] for a survey). These models whose parameters are usually drawn from a uniform distribution, although making simulations simple, can not reflect the

reality and even are considered counterproductive in some cases [3].

Recently, available real mobility traces allowed researchers to understand deeper the nature of human mobility. The power law distribution of the traveled distance was initially reported in [4] in which the authors study the spatial distribution of human movement based on bank note traces. The power law distribution of the inter-contact time was initially studied by Chaintreau et al. in [5]. In [6], Karagiannis et al. confirm this and also suggest that the inter-contact time follows a power law up to a characteristic time (about 12 hours) and then cut-off by an exponential decay.

In [7], the authors show that people have a significant probability to return to a few highly frequented locations. Another study [8] shows that humans show significant propensity to return to the locations they visited frequently before, like home or workplace. These two intrinsic human mobility characteristics, i.e., location preference and attractor, are implemented in our model.

Some more sophisticated mobility models have been proposed. In [9], the authors have proposed an universal model being able to capture many characteristics of human daily mobility by combining different sub-models. With a lot of parameters to configure, the complexity of this type of model makes them hard to use.

In [10], the authors propose SLAW – a Random Direction like model – except that the traveled distance and the pause time distributions are ruled by a power law. An algorithm for trajectory planning was added to mimic the human behavior for always choosing the optimal path. Although being able to capture statistical characteristics like inter-contact, contact time distribution, the notion of spatio-temporal preferential attachment is not expressed.

Another modeling stream aims to integrate social behaviors. In [11], a community based model was proposed in which the movement depends on the relationship between nodes. The network area is divided in zones and the social attractivity of a zone is based on the number of friends in the same zone. The comparisons of this model with real traces show a difference for the contact time distribution.

Time Varying Community [12] is another interesting model in which the authors try to model the location preference and periodical re-appearance of human mobility by

creating community zones. Nodes have different probabilities to jump in different communities to capture the location preference. Time structure was build on the basis of night/day and days in a week to capture the periodical re-appearance. However, fundamental features of human trajectories such as traveled distance distribution and inter-contact/contact time distributions were not highlighted.

Regarding the fundamental structural properties of network, in [1], Watts and Strogatz introduce a model of small-world phenomenon in static graphs. From a regular ring lattice, they rewire randomly edges in this graph with a probability varying from 0 (i.e. leading to a regular network) to 1 (i.e. leading a random graph). During this process they observed an abrupt decrease of the average shortest path length, leading to short path of the same order of magnitude as observed in random graphs, while the clustering coefficient is still of the same order of magnitude than the one of a regular graph. This features suggested the emergence of the small-world phenomenon. The authors also demonstrate that this graph structure, observed in many real static networks, allows information to diffuse as fast as in a random graph.

Kleinberg [13] extended the model to 2-d lattices and introduced a new rewiring process. This time, the edges are not uniformly rewired but follow a power law  $\frac{1}{d^\alpha}$  where  $d$  is the distance on the lattice from the starting node of the edge and  $\alpha$  is the parameter of the model. Newman [14] proposed another definition of the clustering coefficient which has a simple interpretation and is easier to process. The authors argue that the definition in [1] favors vertices with low degree and introduces a bias towards networks with a significant number of such vertices.

Although research pays much attention to the small-world phenomenon in static networks, either through modeling or analytical analysis, the small-world phenomenon in dynamic networks like opportunistic networks is still not well understood. This is partly due to the lack of models and metrics for dynamic graphs. Recently, J.Tang et al. [15] defined several metrics for time varying graphs, including temporal path length, temporal clustering coefficient and temporal efficiency. They showed that these metrics are useful to capture temporal characteristics of dynamic networks that cannot be captured by traditional static graph metrics. The definition of dynamic path, introduced in this paper, is close to their definition (we had the dual metric of the number of hops). We also introduce

a new definition of dynamic clustering coefficient which captures more accurately the dynamics of opportunistic networks.

In [16], the authors highlight the existence of the small-world behavior in real dynamic network traces. Using the definition of temporal correlation introduced in [17], they show that real dynamic networks have a high temporal correlation and low temporal shortest path, suggesting a dynamic small-world structure. In this modeling work, we extend consistently to dynamic networks the initial small-world metrics defined in [1] (i.e., shortest path length and clustering coefficient).

### 3. CHARACTERIZING & MODELING HUMAN MOBILITY

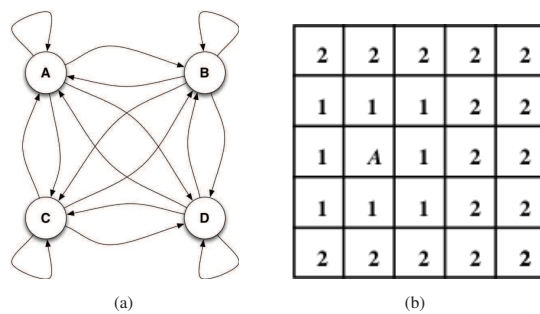
STEPS is inspired by observable characteristics of the human mobility behavior, specifically the spatio-temporal correlation of human movements. Indeed, people share their daily time between some specific locations at some specific time, e.g., home/office, night/day. This spatio-temporal pattern repeats at different scales and has been recently observed on real traces [7, 8].

On a short time basis, i.e., a day or a week, we can assume that one have a finite space of locations of interest between which peoples' movements are ruled by two fundamental mobility principles:

- Preferential attachment: the probability for a node to move to a location is inversely proportional to the distance between this location and the node's preferential location.
- Attractor: when a node is out of his preferential location, he has a higher probability to move closer to this location than moving farther.

From this point of view, the human mobility can be modeled as a finite state space Markov chain in which the transition probability distribution expresses a movement pattern. Figure 1(a) illustrates a Markov chain of 4 states which correspond to 4 locations of interest.

In STEPS, a location is modeled as a zone which corresponds to a Markov chain state. Inside a zone, nodes can move freely according to a random mobility model such as Random Waypoint. The displacement between zones is drawn from a power law distribution whose the



**Figure 1.** (a) Human mobility modeling under a markovian view: States represent different localities, e.g., House, Office, Shop and Other places, and transitions represent the mobility pattern. (b)  $5 \times 5$  torus representing the metric distances from location A to other locations.

exponent value dictates a more or less nomadic behavior. By simply tuning the power law exponent, STEPS can cover a large spectrum of human mobility patterns from purely random ones to highly localized ones. Besides, complex heterogeneity can be described by combining nodes with different mobility patterns as defined by their preferential zones and their related attraction power. Group mobility is also supported on our implementation. Hereafter, we give the details of this model.

#### 3.1. STEPS

Assume that the network area is a square torus\* divided in  $N$  square zones. The distance between zones is defined according to a metric. In this case, we use Chebyshev distance for its simplicity. Figure 1(b) illustrates an example of a  $5 \times 5$  torus with the distances from the zone A. One can imagine a zone as a geographic location (e.g., home, school, supermarket) or a logical location (i.e., a topic of interest such as football, music, philosophy, etc). Therefore, we can use this model to study both human geographic mobility and human social behaviors. In this paper, for our purpose of studying opportunistic networks, we deal only with the first case.

In such structured space, each mobile node is associated with a preferential zone  $z_{pref}$ . For the sake of simplicity, we assume that each node is attached to one zone. However, this model can be extended by associating a node with several preferential zones. The node movement between zones is driven by a power law satisfying two mobility

\*The choice of a torus allows to have a homogeneous area

principles described above. The probability mass function of this power law is given by

$$P[D = d] = \frac{\beta}{(1 + d)^\alpha}, \quad (1)$$

where  $D$  is a discrete random variable representing the distance from  $z_{\text{pref}}$ ,  $\alpha$  is the power law exponent that represents the attractor power of  $z_{\text{pref}}$  and  $\beta$  is a normalizing constant.

From Equation (1) we can see that, the farther a zone is from the preferential zone, the less probability the node to move in. This is the principle of preferential attachment. On the other hand, when a node is outside of its preferred zone, it has a higher probability to move closer to this one than moving farther. This is the principle of attraction. In consequence, with a power law, the model is able to capture two basic characteristics of human mobility.

This small set of modeling parameters allows the model to cover the full spectrum of human mobility behaviors. Indeed, according to the value of the  $\alpha$  exponent a node can have a more or less nomadic behavior. For instance,

- when  $\alpha < 0$ , nodes have a higher probability to choose a long distance than a short one and so the preferential zone plays the repulsion role instead of an attraction one;
- when  $\alpha > 0$ , nodes are more localized, hence tend to stay in their preferential zones;
- when  $\alpha = 0$ , nodes roam the network area.

We summarize the details of STEPS in Algorithm 1. A MATLAB implementation of STEPS can be downloaded at [18].

### 3.2. The Underlying Markov Chain

In this section, we give the details and the properties of the Markovian model underlying STEPS. Wherever node's preferential zones are, the torus structure gives different nodes the same spatial structure, i.e., they have the same number of zones with a given distance from their preferential zones. More specifically, for a distance  $d$ , we have  $8d$  zones with equal distances from  $z_{\text{pref}}$ . Consequently, the probability for a node to choose one among these zones is

$$P[z_i, d_{z_i z_{\text{pref}}} = d] = \frac{1}{8d} P[D = d] = \frac{\beta}{8d(1 + d)^\alpha}. \quad (2)$$

```

Input: Initial zone  $\leftarrow z_{\text{pref}}$ 
1 repeat
2   Choose a random distance  $d$  from the probability
   distribution (1);
3   Select uniformly at random a zone  $z_i$  among all
   zones that are  $d$  distance units away from  $z_{\text{pref}}$ ;
4   Choose uniformly at random a point in  $z_i$ ;
5   Go linearly to this point with a speed chosen
   uniformly at random from
    $[v_{\min}, v_{\max}]$ ,  $0 < v_{\min} \leq v_{\max} < +\infty$ ;
6   Choose uniformly at random a staying time  $t$ 
   from  $[t_{\min}, t_{\max}]$ ,  $0 \leq t_{\min} \leq t_{\max} < +\infty$ ;
7   while  $t$  has not elapsed do
8     Perform Random Waypoint movement in  $z_i$ ;
9 until End of simulation;

```

**Algorithm 1:** STEPS algorithm for a node

Because the probability for a node to select a destination zone  $z_i$  depends only on the distance from  $z_i$  to  $z_{\text{pref}}$ , wherever the node is residing, it has the same probability to select  $z_i$ . If we define the transition probabilities of the Markov chain as a stochastic matrix, this one will have identical rows. The matrix is then idempotent, i.e., the multiplication by itself gives the same matrix. This matrix is given by

$$\begin{bmatrix} P(z_0) & P(z_1) & \dots & P(z_{N-1}) \\ \vdots & \vdots & \ddots & \vdots \\ P(z_0) & P(z_1) & \dots & P(z_{N-1}) \end{bmatrix}. \quad (3)$$

It is straightforward to deduce the stationary state of the Markov chain which is

$$\Pi = \left( P(z_0) \quad P(z_1) \quad \dots \quad P(z_{N-1}) \right). \quad (4)$$

From this result, it is interesting to characterize the inter-contact time<sup>†</sup> of STEPS because this network property was shown to have important impacts on forwarding algorithm in opportunistic networks. To simplify the problem, let assume that a contact occurs if and only if two nodes are in the same zone and node's movement is limited to jumping between zones. Let two nodes  $A$  and  $B$  move according to the STEPS model, starting initially from the same zone. The probability that the two nodes are in the same zone at

<sup>†</sup>The time interval between two consecutive contacts of the same node pair.

a given time is

$$\begin{aligned}
 p_{\text{contact}} &= P_A(z_0)P_B(z_0) + \dots + P_A(z_{n-1})P_B(z_{n-1}) \\
 &= \sum_{i=0}^{N-1} P(z_i)^2 = \sum_{d=0}^{d_{\max}} \frac{1}{8d} \left[ \frac{\beta}{(d+1)^\alpha} \right]^2,
 \end{aligned} \tag{5}$$

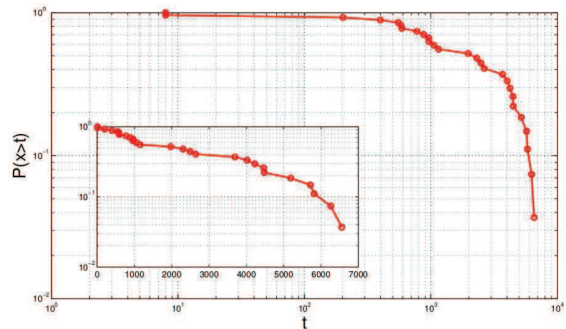
where  $d_{\max} = \lfloor \frac{\sqrt{N}}{2} \rfloor$  is the maximum distance between zones in the torus.

Let  $ICT$  be the discrete random variable which represents the time elapsed before  $A$  and  $B$  are in contact again. One can consider that  $ICT$  is the number of trials until the first success of an event with probability of success  $p_{\text{contact}}$ . Hence  $ICT$  follows a geometric distribution with the parameter  $p_{\text{contact}}$ . Therefore, the probability mass function of  $ICT$  is given by

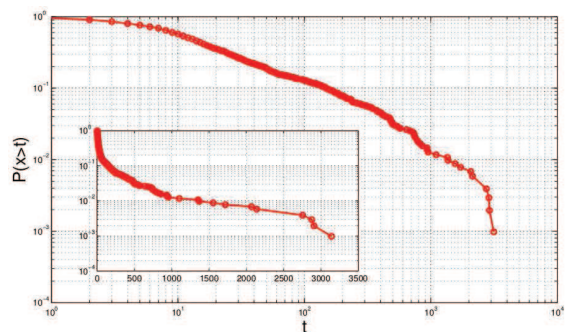
$$P[ICT = t] = (1 - p_{\text{contact}})^{t-1} p_{\text{contact}}. \tag{6}$$

It is well known that the continuous analog of a geometric distribution is an exponential distribution. Therefore, the inter-contact time distribution for i.i.d. nodes can be approximated by an exponential distribution. This is true when the attractor power  $\alpha$  is equals to 0, i.e., when nodes move uniformly, because there is no spatio-temporal correlation between nodes. But when  $\alpha \neq 0$ , there is a higher correlation in their movement and in consequence the exponential distribution is not a good approximation. Indeed, in [19], the authors report this feature for the Correlated Random Walk model where the correlation of nodes induces the emergence of a power law in the inter-contact time distribution. We provide simulation results related to this feature for STEPS.

Figure 2 gives the log-log and linear-log plots of the complementary cumulative distribution function or CCDF of the inter-contact time that results from a simulation of the Markov chain described above when  $\alpha = 0$  and  $\alpha > 0$ . In the first case, the inter-contact time distribution fits an exponential distribution (i.e., is represented by a linear function in the linear-log plot) while in the second case it fits a power law distribution (i.e., is represented by a linear function in the log-log plot) with an exponential decay tail. These results confirm the relationship between the spatio-temporal correlation of nodes and the emergence of a power law in inter-contact time distribution.



(a)  $\alpha = 0$



(b)  $\alpha > 0$

Figure 2. Theoretical inter-contact time distribution of STEPS

## 4. FUNDAMENTAL HUMAN MOBILITY FEATURES IN STEPS

It is worth mentioning that a mobility model should express the fundamental properties observed in real opportunistic networks. In this section, we show that STEPS can, indeed, capture the salient characteristics of human mobility.

### 4.1. Inter-Contact Time Distribution

The inter-contact time is defined as the delay between two encounters of a pair of nodes. Real traces analysis suggest that the distribution of inter-contact time can be approximated by a power law up to a characteristic time (i.e., about 12 hours) followed by an exponential decay [6]. In the following we will use the set of traces presented by Chaintreau et al. in [5] as base of comparison with STEPS mobility simulations. Figure 3(a) shows the aggregate CCDF of the inter-contact time<sup>‡</sup> for different traces. In

<sup>‡</sup>The CCDF of inter-contact time samples over all distinct pairs of nodes

order to demonstrate the capacity of STEPS to reproduce this feature, we configured STEPS to exhibit the results observed in the Infocom 2006 conference trace which is the largest trace in the dataset. Table I summarizes the characteristics of this trace.

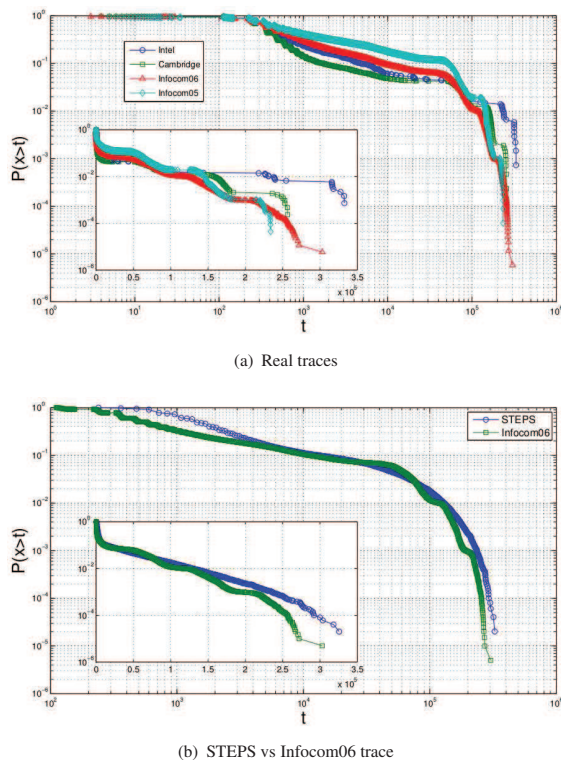


Figure 3. CCDF of Inter-Contact Time

Characteristic	Value
Number of nodes	98
Duration	4 days
Connectivity	Bluetooth
Average inter-contact time	1.9 hours
Average contact duration	6 minutes

Table I. Infocom 2006 trace

To simulate the conference environment, we create a  $10 \times 10$  torus of size  $120 \times 120m^2$  that mimics rooms in the conference. The radio range is set to  $10m$  which corresponds to Bluetooth technology. The node speed is chosen as human walking speed which ranges from  $[3, 5]$  km/h. Figure 3(b) shows the CCDF of inter-contact time in log-log and lin-log plots. We observe that the resulting inter-contact time distribution given by the STEPS simulations fits with the one given by the real trace.

Mobility degree	RWP pause time range (s)	Number of nodes
Very high	[0, 60]	65
High	[60, 900]	15
Low	[900, 3600]	10
Very low	[3600, 43200]	8

Table II. Node categories for the contact-time measure

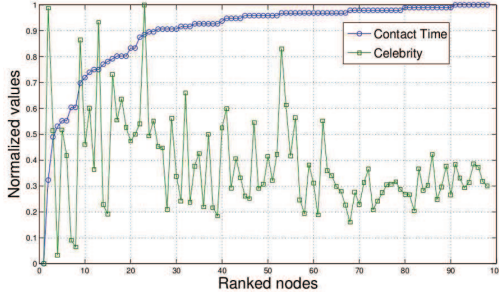
## 4.2. Contact Time Distribution

Because of the potential diversity of nodes behaviors, it is more complicated to reproduce the contact duration given by real traces. Indeed, the average time spent for each contact depends on the person. For instance, some people spend a lot of time to talk while the others just check hands. We measured the average contact duration and the average node degree, i.e., the global number of neighbor nodes, of the Infocom06 nodes and ranked them according to their average contact duration. The result is reported in Figure 4(a). According to this classification, it appears that the more (resp. less) popular the person is, the less (resp. more) time he spends for each contact. Because the contact duration of STEPS depends principally on the pause time of the movement inside zone (i.e., the pause time of RWP movement), to mimic this behavior, we divided nodes in four groups. Each group corresponds to a category of mobility behavior: highly mobile, mobile, slightly mobile and rarely mobile. The pause time for each groups is summarized in Table II.

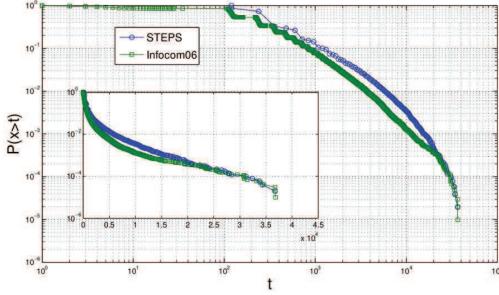
With this configuration, we succeeded to mimic the behavior observed in Infocom06 trace where a large percentage of nodes have short contacts and a few nodes have long to very long contacts. The CCDFs of contact time of STEPS and Infocom06 trace as shown in Figure 4(b) show that STEPS can also capture with high accuracy this mobility behavior.

## 5. CHARACTERIZING OPPORTUNISTIC NETWORK STRUCTURE

A good mobility model should allow not only to express faithfully peer-to-peer interaction properties such as inter-contact time and contact time, but also to reproduce the fundamental structure of the underlying interaction dynamic graph, i.e., a graph with time varying edges and links. The structural properties of static interaction graphs



(a) Social characteristic observed in Infocom06 trace



(b) CCDF of contact time of STEPS vs Infocom06 trace

**Figure 4.** Contact time behavior of STEPS vs real trace

have been studied leading to the observation of numerous instances of real interaction graph with a high clustering coefficient and a low shortest path length [1]. Such a structure of graph is called small-world. With respect to routing, the small world structure induces fast message spreading in the underlying network.

In this section, we formalize the notion of small-world phenomenon in dynamic networks by introducing two metrics used for qualifying such phenomenon: shortest dynamic path length and dynamic clustering coefficient. Then by analyzing extensively real opportunistic network traces, we show fundamental characteristics which are at the origin of the dynamic small-world phenomenon.

## 5.1. Dynamic Small-world Metrics

### 5.1.1. Shortest Dynamic Path Length

Basically, the shortest path problem in static graphs consists in finding a path such that the sum of the weights of its constituent links is minimized. From a graph theory point of view a dynamic networks can be described by a temporal graph, i.e., a temporal sequence of graphs that describe the discrete evolution of the network according to nodes and links creation and destruction events. A path in a dynamic network can be seen as an ordered set of temporal

links that allow a message to be transferred using the store-move-forward paradigm between two nodes. Formally, let  $l_{ij}^t$  be a link between node  $i$  and node  $j$  at instant  $t$ . A dynamic path from node  $u$  to node  $v$  from time  $t_0$  to time  $t$  is described by a time ordered set  $p_{uv}(t_0, t) = \{l_{ui}^{t_0}, l_{ij}^{t_1}, \dots, l_{wv}^t\}$  where  $t_{k+1} > t_k$ . We consider two metrics of dynamic paths:

- Delay : the sum of the inter-contact times between consecutive links which constitutes the path.
- Number of hops : the number of temporal links which constitutes the path.

This leads to the following definition of shortest dynamic path length.

#### Definition 1

*The shortest dynamic path is the path giving the minimum amount of delay<sup>§</sup>. If there are several paths giving the same delay, then we select the one giving the minimum number of hops. Formally, the shortest dynamic path length between  $i$  and  $j$  from time  $t_0$  is*

$$\mathcal{L}_{ij}^{t_0} = \inf \{t - t_0 | \exists p_{ij}(t_0, t)\} . \quad (7)$$

*The shortest dynamic path length of a network of  $N$  nodes from time  $t_0$  is the average of the shortest dynamic path lengths of all pairs of nodes in the network*

$$\mathcal{L}^{t_0} = \frac{\sum_{ij} \mathcal{L}_{ij}^{t_0}}{N(N-1)} . \quad (8)$$

To find the shortest dynamic path length of all pairs of nodes, we propose an algorithm leveraging on the following interesting property of adjacency matrix in static graphs.

The adjacency matrix  $A$  is defined as the matrix in which the element  $(A)_{i,j} \in \{0, 1\}$  at row  $i$  and column  $j$  denotes the existence of a link between node  $i$  and node  $j$ . If we process the power  $n$  of such matrix, then its element  $(A^n)_{i,j}$  gives the number of paths of length  $n$  between  $i$  and  $j$ . Indeed, for example, when  $n = 2$ ,  $(A^2)_{i,j} = \sum_k (A)_{i,k} \times (A)_{k,j}$  sums all the possibilities to go from  $i$  to  $j$  through an intermediate node  $k$ . We extend this property to dynamic networks. Let  $A_t, t = 0, 1, \dots, n$  be the adjacency matrix of a dynamic network at time  $t$ . The

<sup>§</sup>we can also have another definition for minimizing the number of hops. In this work, we focus only on delay constrained path.

matrix  $C_t$  obtained as follows

$$C_t = \mathbf{A}_t \vee \mathbf{A}_t^2 \vee \dots \vee \mathbf{A}_t^n, \quad (9)$$

where  $\mathbf{A}_t^i$  denotes the binary version of the matrix  $A_t^i$  (i.e. the element  $(\mathbf{A}_t^i)_{i,j}$  equals to 1 if  $(A_t^i)_{i,j} > 0$  and 0 otherwise) has its elements  $(C_t)_{i,j}$  which indicate if there is a direct or indirect link (up to  $n$  hops) between  $i$  and  $j$  at time  $t$ . Indeed,  $(C_t)_{i,j}$  is the logical sum of all possibilities to have a direct or indirect link (up to  $n$  hops) between  $i$  and  $j$  at time  $t$ . In consequence, the product

$$D_t = C_0 C_1 \dots C_t \quad (10)$$

results in a matrix in which the element  $(D_t)_{i,j}$  specifies, when not null, that there is dynamic path of delay  $t$  between  $i$  and  $j$ . Therefore the shortest dynamic path length from node  $i$  to node  $j$  is given by the smallest value of  $t$  such as  $(D_t)_{i,j}$  equals to 1.

It is straight-forward to demonstrate that if a node  $k$  belongs to a shortest path between node  $i$  and node  $j$  then the  $i$  to  $k$  sub-path gives the shortest path between  $i$  and  $k$ . Therefore the shortest path between two nodes  $i$  and  $j$  can be easily backwardly reconstructed. Note that at time  $t$  two nodes can be connected to each other via a multiple hops path. To find the complete spatio-temporal path with all the intermediate nodes, we simply apply a breath first search each time we find a spatial multiple hops link. In practice, as it's unlikely to have a large number of nodes connected to each other at a given moment, we can optimize the algorithm by limiting the number of iterations  $n$  in Equation 9 to an upper bound of the network diameter. Finally, this algorithm is more efficient (time complexity  $O(n^3)$ ) than the depth first search approach as proposed in [15] (time complexity  $O(n^4)$ ).

We provide a MATLAB implementation of this algorithm in [20].

### 5.1.2. Dynamic Clustering Coefficient

As defined in [1], the clustering coefficient measures the cliquishness of a typical friend circle. The clustering coefficient of a node is calculated as the fraction of actual existing links between its neighbors and the number of possible links between them. The clustering coefficient of a network is calculated by averaging the clustering coefficients of all the nodes in the network. In [14],

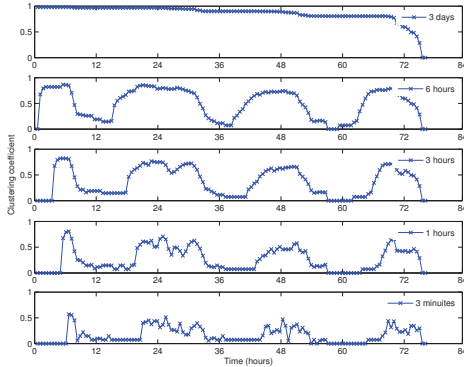
Newman defines the clustering coefficient in term of transitivity. The connection between nodes  $u, v, w$  is said to be transitive if  $u$  connected to  $v$  and  $v$  connected to  $w$  implies that  $u$  is connected to  $w$ . The clustering coefficient of a network is then calculated as the fraction of the number of closed path of length two over the number of path of length two, where a path of length two is said to be closed if it is a transitive path. This definition is simple to interpret and easy to calculate. Considering that, the initial definition gives more weight to nodes with low degree and introduces a bias towards graph composed of several of these nodes, in this work, we favor Newman's definition and extend it to dynamic networks.

In [15], Tang et al. first introduced a generalization of Watts and Strogatz's definition for temporal graph. The temporal clustering coefficient of a node during a time interval  $t$  is the fraction of existing opportunistic contacts (multiple contacts count once) between the neighbors of the node over the number of possible contacts between them during  $t$ . The clustering coefficient of the network is the average of the clustering coefficients of all the nodes. This is simply the application of Watts and Strogatz's definition on a time snapshot of the network. While this definition was shown to better capture temporal characteristics of time varying graph, it depends strongly on the length of the chosen time interval. If this interval tends to infinity, the temporal clustering coefficient tends to 1 as all the nodes meet each other with a high probability. On the other hand, if the interval tends to 0, then conversely the temporal clustering coefficient tends to 0. Figure 5 illustrates the influence of the time window size on measures of the clustering coefficient on a real mobility trace.

In order to avoid this temporal bias, we propose a new definition of dynamic clustering coefficient which captures the dynamics of the degree of transitivity and is independent of the measuring time interval.

#### Definition 2

*A dynamic path from node  $i$  to node  $j$  is transitive if there exists a node  $k$  and time  $t_1, t_2, t_3$  so that  $i$  is connected to  $k$  at  $t_1$ ,  $k$  is connected to  $j$  at  $t_2$ ,  $i$  is connected to  $j$  at  $t_3$  and  $t_1 \leq t_2 \leq t_3$ . The dynamic clustering coefficient of node  $i$  from time  $t_0$  is measured by the inverse of the time  $t - t_0$  where  $t$  is the first instant from time  $t_0$  when the transitive path from  $i$  to  $j$  is formed, that is  $C_i^{t_0} = \frac{1}{t - t_0}$ . The dynamic clustering coefficient of a network of*



**Figure 5.** Time window size effect on measure of temporal clustering coefficient (as defined in [11])

Trace	Intel	Cambridge	Infocom05	Infocom06
Number of nodes	9	12	41	98
Duration (days)	6	6	4	4
Granularity (seconds)	120	120	120	120
Connectivity	Bluetooth	Bluetooth	Bluetooth	Bluetooth
Environment	Office	Office	Conference	Conference

**Table III.** Dataset of real opportunistic network traces

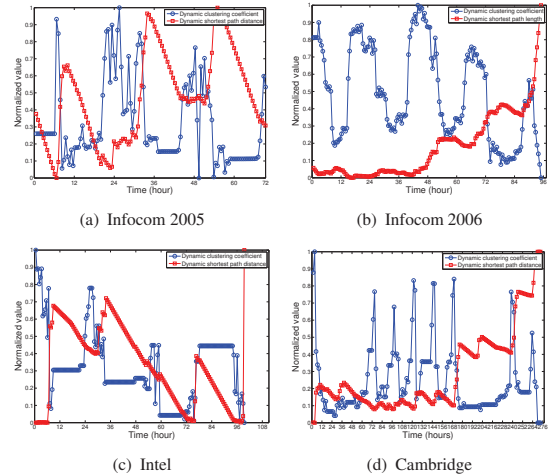
$N$  nodes is then calculated by averaging over the dynamic clustering coefficient of all the nodes from time  $t_0$

$$C = \frac{1}{N} \sum_i C_i . \quad (11)$$

## 5.2. Opportunistic Network Traces Analysis

In this section, we analyze extensively real opportunistic network traces to understand how small-world behavior emerges in dynamic networks. We first apply the above definitions to highlight the existence of dynamic small-world phenomenon on these traces. For that, we use the data sets from the Haggie project [5, 21] which consists of the recording of opportunistic bluetooth contacts between users in conference or office environments. The settings of these data sets are summarized in Table III.

For each trace, we measure the shortest dynamic path length and the dynamic clustering coefficient every 2000 seconds to see the evolution of these metrics over time. The obtained values are then normalized and plotted in Figure 6. We can observe a periodic pattern of both metrics with a typical period of 24 hours and a phase change every 12 hours. This can be easily explained by the fact that human daily activity is periodic with night/day phases. Indeed, people are more nomadic during day while they



**Figure 6.** Small world phenomenon observed in real mobility traces

are mostly sedentary at night. Besides, it is interesting to note that the dynamic clustering coefficient and the shortest dynamic path length evolve in opposite phase. Despite of a slight diversity in different traces due to differences in nodes number and density, traces durations, etc, during the dynamic phase (i.e., day, for instance, the period around 24 hours in Infocom2005 trace), these networks always exhibit high dynamic clustering coefficients and low shortest dynamic path lengths, suggesting the existence of a dynamic small-world phenomenon.

To explain the emergence of this phenomenon, let us focus on and analyze the structure of these networks during the dynamic phases. In the Watts and Strogatz model, the small-world phenomenon emerges when shortcut edges are randomly added to a regular graph. These shortcuts allow the average shortest path length to be reduced significantly while conserving network nodes's cliquishness. We argue that in dynamic networks, mobile nodes are implicitly at the origin of these shortcuts. Indeed, it is known that people spend their daily life among different social communities at specific locations at different times (e.g., colleagues at office in the morning, family at home in the evening). A community can be disconnected from the others in space and/or in time. Besides, some people are more “mobile” than other, they have contacts in many communities and move often between these communities or areas. These “nomadic” nodes contribute to reduce significantly the shortest dynamic path length from nodes in a disconnected

component to the rest of network and hence contribute to the emergence of the dynamic small-world phenomenon.

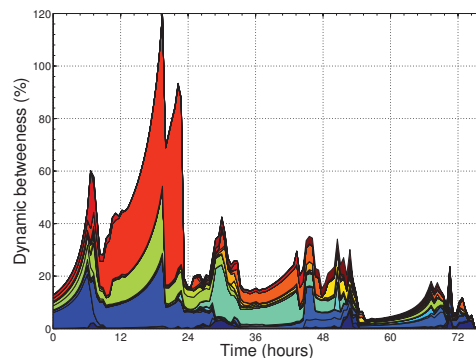
To identify the spatio-temporal shortcuts in dynamic networks, we introduce a metric that measures the influence a node has on the characteristic dynamic path length of the network. The nodes with highest influence are the ones whose removal from the network increases the most the average shortest dynamic path length of the network. To identify these nodes one may adapt to dynamic networks the notion of betweenness centrality already introduced for static networks. In the context of dynamic networks, we call it *dynamic betweenness centrality*. Consider a node  $i$ , first of all, we measure the average of the shortest dynamic path length between all pairs of nodes  $s, t$  except paths from and to  $i$ . Then, we remove  $i$  from the network and perform the same measure. The dynamic betweenness centrality of  $i$  is defined as the ratio between these two measures. Formally, that is

$$x_i = \frac{\sum_{st} \mathcal{L}'_{st}}{\sum_{st} \mathcal{L}_{st}}, \quad (12)$$

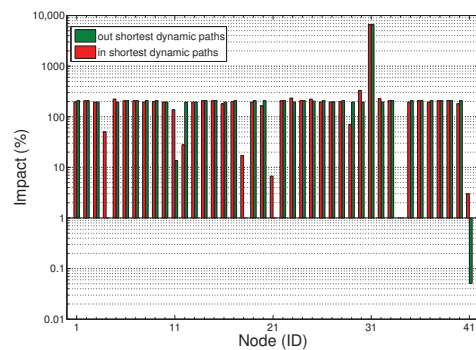
where  $\mathcal{L}'_{st}$  and  $\mathcal{L}_{st}$  are respectively the shortest dynamic path lengths from  $s$  to  $t$  after and before removing  $i$ .

We measure the dynamic betweenness of all nodes at different times on the traces. Figure 7 shows the temporal evolution of the dynamic betweenness for the Infocom05 trace. On the figure, the different areas represent the measured metric (in %) of different nodes. We can observe that the dynamic betweenness of a nodes changes over time and that there are some nodes with very high influence whose removal would dramatically increase the dynamic characteristic path length of the network. Indeed, at the time of the highest pick, redrawing the most influential node would result in an 70% increase of the average shortest dynamic path length of the network. We can also see the abrupt decrease of the average shortest dynamic path length at time 24 hours on Figure 6(a). The time average of the dynamic betweenness centrality of each network node allows one to rank the influence of each node during a time window. For instance in Figure 7 the highest value for the daytime period corresponds to node with ID 34.

Now let us look at the highest pick to see what happened in the network at that moment. We measure the impact of node 34 on the shortest dynamic paths from and to each other node (respectively denoted out/in shortest dynamic

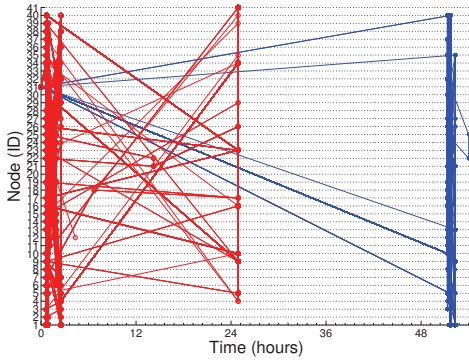


**Figure 7.** Evolution of dynamic betweenness centrality of nodes in Infocom05 trace

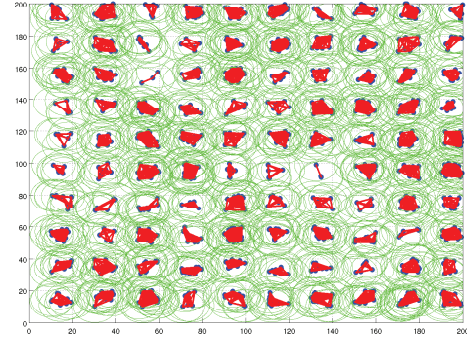


**Figure 8.** Impact of node 34 on the shortest dynamic paths from and to the other nodes at  $t = 22h$  (Infocom05 trace)

path on Figure 8). Figure 8 shows that node 34 has very high influence on node 31. We then apply our all-pairs-shortest-dynamic-path algorithm to find all the shortest dynamic paths from node 31 to others before and after removing node 34. Figure 9 shows that node 34 is crucial for node 31 to efficiently communicate with other nodes at that instant. Therefore node 34 plays the role of a spatio-temporal shortcut between node 31 and the other nodes. This result can be observed for any node with a high dynamic betweenness. Indeed, if the so disconnected network part is a giant component, then the impact of the removal of a dynamic shortcut can dramatically increase the characteristic dynamic path length of the network.



**Figure 9.** Shortest dynamic paths from node 31 at  $t = 22\text{h}$  in Infocom05 trace, before (in red) and after (in blue) removal of node 34



**Figure 10.** Small-world network configuration

## 6. MODELING OPPORTUNISTIC SMALL-WORLD STRUCTURE WITH STEPS

The previous section showed that the dynamic small world phenomenon is intrinsic to a great diversity of opportunistic network traces. Therefore, the definition of a model that abstracts this phenomenon in order to study the impact of its emergence on dynamic networks communications performances is a significant issue. In this section, we show the modeling and expressive capacity of STEPS for capturing the dynamic small-world structure in opportunistic networks. As evoked previously, the dynamic small-world phenomenon results from human mobility behaviors:

- People move between communities
- Some people are nomad while the others are more sedentary. These nomadic nodes move from zone to zone, contributing to reduce the network diameter.

Consider an opportunistic network modeled by STEPS in which each node belongs to a preferential attachment zone. We introduce two types of nodes: sedentary nodes which move only inside their preferential zone and nomadic nodes which can move between zones. Nodes moving in two different zones cannot be connected and therefore nodes in different zones can communicate only through the movement of nomadic nodes. Initially, nomadic nodes are uniformly distributed over all zones. We introduce another parameter of STEPS  $p$  which is the fraction of nomadic nodes.

Obviously, when  $p$  equals to 0, there is no possible communication between nodes in different zones and hence the network is totally partitioned in disconnected zones. On the contrary, when  $p$  equals to 1, all the nodes are nomadic and hence there are dynamic paths between clusters and in consequence the network is highly connected. In consequence, the *rewiring process* consists in varying  $p$  from 0 to 1. We are interested in the properties of networks which are formed between these two extrema.

We simulate in MATLAB an opportunistic network of 1000 nodes. The simulated network area of size  $200 \times 200 \text{ m}^2$  divided into  $20 \times 20$  zones as shown in Figure 10 gives a density of  $25000 \text{ nodes/km}^2$  which corresponds to the population density of a large city like Paris. We distribute uniformly nodes over zones and set the radio range to 10 m which corresponds to bluetooth technology. We set a very high value of the power law exponent for sedentary nodes and 0 for nomadic nodes. While varying the fraction of nomadic nodes from 0 to 1, we measure the dynamic clustering coefficient and shortest dynamic path length of resulting networks.

Figure 11 plots the resulting average over 10 simulations with the corresponding 95% confidence intervals. We observe that the shortest dynamic path length drops rapidly as soon as we introduce a small percentage of nomadic nodes (i.e. less than 10 %) into the network while the clustering coefficient remains very high. This result is consistent with the original static small-world model described in [1] and show how the small-world phenomenon can emerge in opportunistic networks.

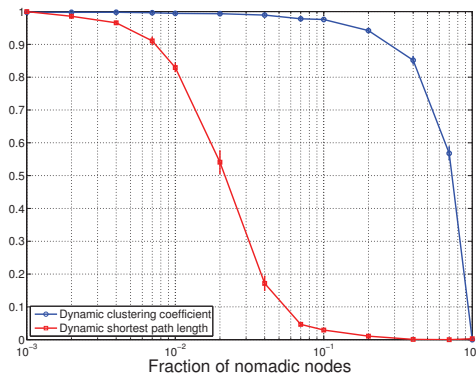


Figure 11. Small-world phenomenon in dynamic networks

## 7. CONCLUSION

In this paper, we have introduced STEPS, a generic and simple modeling framework for opportunistic networks which abstracts the spatio-temporal correlation of human mobility. Based on the principles of preferential attachment and location attractor, this model can cover a large spectrum of human mobility patterns by tuning only a small set of parameters. Via simulations, the model is shown to be able to capture different characteristics observed on top of real mobility traces. Moreover, STEPS is also able to capture the structural properties of opportunistic network's underlying dynamic graphs. Finally, the formal Markovian basis of our model make it possible to derive analytical results that comply with properties observed in real traces of opportunistic networks.

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