Modeling Human Mobility and its Applications in Routing in Delay-Tolerant Networks: a Short Survey

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ABSTRACT

Human mobility patterns are complex and distinct from one person to another. Nevertheless, motivated by tremendous potential benefits of modeling such patterns in enabling new mobile services and technologies, researchers have attempted to capture salient characteristics of human mobility. In this short survey paper, we review some of the major techniques for modeling humans’ co-location, as well as predicting human location and trajectory. Further, we review one of the most important application areas of such models, namely, routing in delay-tolerant networks.

Keywords
Human mobility, delay-tolerant networks, routing

1. INTRODUCTION

The ability to model human mobility is key to developing various mobile technologies such as context-aware services, e-health, cloud computing, and delay-tolerant networking, to name a few. In this survey, we review the state-of-the-art research on modeling humans’ collocation and predicting people’s locations and trajectories ([2]). Then we focus on the applications of these models in the specific area of routing in delay tolerant networks ([4])—sparse wireless networks with limited connection opportunities. The choice of delay tolerant networks as the application area is not random: mobile networks have been shown to be a vehicle for both collecting a wealth of information on human mobility and applying new services enabled by human mobility models.

We deliberately avoid discussing technical details in order to provide an overview of the area. The interested reader is referred to the references for further details. It is worth noting that a number of human mobility datasets are available in CRAWDAD [1], which is an online collection of many networking-related datasets and analysis tools.

2. HUMAN MOBILITY

In this section, we review the literature on human mobility models in three related categories: inter-contact time (i.e., measuring how often two people are co-located) in §2.1, location prediction (i.e., predicting where a person will be at time t and for how long) in §2.2, and human mobility models (i.e., modeling the trajectory of a person) in §2.3.

2.1 Inter-Contact Time

Inter-contact time is the duration between two consecutive times when a given pair of mobile devices are co-located (i.e., they are near each other). Chaintreau et al. [5] observed that the distribution of the inter-contact times in a mobility dataset exhibits a heavy tail such as that of a power law distribution. This observation has played a key role in advancing the future research. Delving more into statistical properties of inter-contact times, Karagiannis et al. [18] showed that before a certain time threshold, the CCDF (i.e., Complementary CDF given by \( P(X > x) \)) of inter-contact times follows the power law and after the threshold the CCDF resembles the exponential distribution. This observation was based on studying a number of GPS, GSM, WiFi, and Bluetooth datasets. Recently, these statistical characteristics of inter-contact times have been reconfirmed [15].

2.2 Location Prediction

Lee and Hou [19] used a dataset of users’ associations with access points (APs) and applied transient analysis of a semi-Markov model to design a timed and location prediction algorithm that can predict the future location of a user including both the future access points she is going to be associated with and her future associations’ durations. Technically, a state in this model represents an AP that the user is associated with at a given time instant. The input to the algorithm is the history of user-AP associations, and the output is \( \phi_{ij}(k) \), which is the probability of the event that the user will be in state j after k time intervals if she is currently in state i.

WhereNext [23] is a classification-based scheme to learn the trajectory of a moving object based on the history of its movements. The performance of the classifier is evaluated over a dataset of 17,000 cars equipped with GPS. In contrast to the previous work that can only predict the next location of a user but not his/her arrival time and residency time (i.e., the interval of time spent at a location), NextPlace [29] tries to estimate the duration of a visit to any given location and the time interval between two subsequent visits to that location.

There are two classes of mobility models [6]. The basic assumption of a location-dependent model (e.g., [19]) is that people tend to remain at the same place for similar durations on each visit. A location-independent model (e.g., [29]), on the other hand, uses temporal features without location...
information. Chon et al. [6] analyzed these two classes of mobility models using fine-grained mobility data. They deployed LifeMap, a mobility learning system to collect real user traces over a two-month period. LifeMap monitors the user’s mobility every two minutes, using GSM, WiFi, and GPS. The system automatically recognizes visited places with room-level accuracy using WiFi fingerprinting. The basic idea is that radio signals from surrounding WiFi access points (APs) are similar when a user is stationary at the same location. The authors have drawn several conclusions on the advantages of each of the two approaches to modeling mobility. Perhaps most notably, their experiments showed that location-dependent models tend to have a higher accuracy in predicting human’s temporal behavior.

2.3 Modeling Human Trajectory

Motivated by the fact that a realistic human trajectory (also referred to as human mobility) model can be useful in networking-related simulation studies, Lee et al. [20] developed a human mobility model. Past research had shown that human mobility has certain statistical characteristics, namely:

- **Truncated power-law flights and pause times**: where a (human) flight is a straight line trip without any directional change or pause.
- **Heterogeneously bounded mobility areas**: people mostly move within their own confined areas of mobility, and different people may have widely different mobility areas.
- **Truncated power-law inter-contact times**: where a flight is a straight line trip without any directional change or pause.
- **Fractal waypoints**: people are always more attracted to more popular places.

Building on these characteristics, Slaw [20] presents a mobility model for mobile networks that can produce synthetic human mobility traces that possess all these statistical features.

Rhee et al. [28], in their seminal work, argued that despite certain well-understood characteristics of human mobility, no empirical evidence existed to prove the accuracy of the models founded on them. They studied the mobility patterns of humans up to the scales of meters and seconds using mobility track logs obtained from over 100 participants carrying GPS receivers in five sites. They concluded that human walk patterns involve statistically similar features to those observed in Levy walks. These features include heavy-tail flights and pause-time distributions and the superdiffusive nature of mobility. Gonzalez et al. [12] studied the trajectories of 100,000 mobile phone users whose positions were tracked for a 6-month period. They found that the travel patterns of individual users could be approximated by a Levy flight up to a certain threshold distance. Moreover, they observed that the individual trajectories are bounded beyond the threshold distance; thus, large displacements, which are the source of the distinct and anomalous nature of Levy flights, are statistically absent. As a result, human trajectories were found to show a high degree of temporal and spatial regularity.

A related question is to what extent human mobility is predictable? Song et al. [30] studied a 3-month-long record capturing the mobility patterns of 50,000 individuals. By measuring the entropy of each individual’s trajectory, they found a 93% potential predictability in user mobility.

Pu et al. [24] took a different approach to analyzing mobility of mobile phone users. They analyzed phone call records of three million mobile phone users in a city over a span of one year. Each phone call record usually contains the caller and callee IDs, date and time, and the base station where the phone calls are made. Using visualization techniques, they classified users into distinct groups based on their mobility patterns.

Tournoux et al. [33] studied the motion of a population of rollerbladers and observed a behavior called **accordion phenomenon**, which basically means people get close to and far from each other with some harmonic delay. The authors made use of this observation to tune the spray-and-wait [31] routing protocol (see §3.1).

3. ROUTING IN DELAY-TOLERANT NETWORKS

A Delay-Tolerant Network (DTN) is a sparse wireless network in which most of the time there does not exist a complete path from a given source to its destination. Thus, conventional routing schemes fail in DTNs. There is a considerable body of literature devoted to developing efficient routing techniques in DTNs, some of which utilize the properties of human mobility.

3.1 Opportunistic Forwarding

Opportunistic forwarding methods are characterized by forwarding messages greedily or based on contact prediction as nodes encounter each other. An initial attempt for routing in DTNs was Epidemic Routing [34] using which a node copies the message to every other node it encounters that does not already have a copy of the message. Message copies time out. The hope is that at some point the destination node receives the message. Spray-and-wait [31] departs from the epidemic method in that it controls the number of copies of each message in the network. In particular, a number $L$ of logical tickets are associated with each message. Node $i$ copies a message to node $j$ that it encounters only if the message owns $L > 1$ tickets or $j$ is the destination. The new copy in $j$ will have $L_j = \lfloor \frac{L}{2} \rfloor$ tickets and $L_i = L - L_j$ tickets will remain with the message in $i$. MaxProp [4] is based on prioritizing both the schedule of packets transmitted to other peers and the schedule of packets to be dropped. It uses several mechanisms to define the priority based on which packets are transmitted and deleted. MaxProp protocol uses a ranked list of the node’s stored packets based on a cost assigned to each destination. The cost is an estimate of delivery likelihood. In addition, MaxProp uses acknowledg-
ments sent to all nodes to notify them of packet deliveries to prevent further transmission attempts.

More recently proposed routing schemes account for node resource constraints. RAPID [2] makes the case that a contact may be too short to transmit all packets, so it is important to determine in what order packets should be forwarded. RAPID considers the DTN routing problem as a resource management problem in which various performance criteria such as average delay, delivery deadline, and maximum delay can be incorporated. Delegation Forwarding [8] exploits optimal stopping theory to decide whether an encountered node would be a good relay at the moment of encounter. Similarly, optimal probabilistic forwarding (OPF) [22] was designed under the assumption of long-term regularity of nodes mobility patterns as well as the assumption that each node knows the mean inter-meeting times of all pairs of nodes mobility patterns. The forwarding rule (i.e., the decision on whether to forward) depends on whether replacing the copy in node $i$ (the current node that contains the message) with two new copies in node $i$ and node $j$ (a neighboring node) will increase the overall delivery probability. Therefore, given a certain set of constraints on the maximum number of forwarding attempts per message, OPF maximizes the delivery probability of each message.

Using predict and relay (PER) [37], nodes determine the probability distribution of future contact times and choose a proper next hop in order to improve the end-to-end delivery probabilities. The design is based on two observations and explicitly takes advantage of human mobility models. First, nodes in a network within a social environment usually move around a set of landmarks. Second, in some social environments the node trajectory in time is almost deterministic given the history of nodes mobility.

Spyropoulos et al. [32] studied routing in DTNs whose nodes are heterogeneous. Heterogeneity refers to the difference in nodes classes (e.g. handheld devices, vehicles, and sensors). The authors showed that heterogeneity would reduce the routing performance when a typical routing scheme is used. Consequently, they introduced the notion of utility for each network node that represents its capabilities that matter to the routing strategy such as Most-Mobile-First (MMF), Spraying or Most-Social-First (MSF) Spraying, etc. Crafting appropriate utility functions in designing utility-based protocols is effective in improving routing performance.

Encounter-based routing (EBR) [25] is based on the observation that the future rate of a node’s encounters can be roughly predicted by past data. This property is useful because nodes that experience a large number of encounters are more likely to successfully pass the message along to the final destination than those nodes who only infrequently encounter others.

Time-sensitive Opportunistic Utility-based Routing (TOUR) [36] considers time value of messages: each message has a certain initial value that diminished with time. The goal is to maximize the remained time values of the messages when they get to their destinations.

A common assumption in most DTN routing schemes is that network nodes know their neighboring nodes. If there is no infrastructure and devices must probe their environment to discover other devices, an energy-aware contact probing mechanism is required. If devices probe very infrequently, they might miss many of their contacts. On the other hand, frequent contact probing might be energy inefficient. Wang et al. [33] study the problem of finding the optimal probing time interval.

### 3.2 Social-based Forwarding

Research on social networks has been beneficial in designing DTN routing protocols. SimBet [7] is a routing scheme that assesses similarity to detect nodes that are part of the same community, and betweenness centrality to identify bridging nodes that could carry a message from one community to another. The decision to forward a message depends on the similarity and centrality values of the newly encountered node, relative to the current one: If the former node has a higher similarity with the destination, the message is forwarded to it; otherwise, the message stays with the most central node. The goal is to first make use of more central nodes to carry the message between communities, and then use similarity to deliver it to the destination’s community. BubbleRap [16] is essentially similar to SimBet in that betweenness centrality is used to find bridging nodes until the message reaches the destination community. In contrast to SimBet, BubbleRap explicitly identifies communities by a community detection algorithm rather than doing so implicitly using similarity. Once arrived at the destination community (i.e., the community in which the destination node is located), the message is only forwarded to other nodes of that community: a local centrality metric is used to find increasingly better relay nodes within the community.

PeopleRank [24] is another social-based routing scheme based on PageRank [8]. The intuition behind it is that socially well-connected nodes tend to be more effective in message forwarding, simply because they meet more nodes. In PeopleRank, node $i$ forwards data to node $j$, which it has just met, if the rank of $j$ is higher than the rank of $i$. Nikolopoulos et al. [26] challenged the suitability of using centrality metrics in routing by conducting simulations. They presented three reasons behind the observed inefficiency: lack of destination awareness, use of estimated centrality metrics due to practical limitations, and making over-simplifying assumptions in building the contact graph.

Gao et al. [11] presented the first attempt toward understanding and formulating the problem of multicasting...

\[^{1}\text{Similarity of two nodes is defined as the number of neighbors these nodes have in common.}\]

\[^{2}\text{Betweenness centrality of a node is defined as the fraction of shortest paths between each possible pair of nodes going through this node.}\]
in DTNs. They utilized social networks concepts, including centrality and social community, to improve the cost-effectiveness of multicast in DTNs as compared to the case of using unicast schemes to carry out multicasting. By modeling the problem using the unified knapsack problem, they developed forwarding schemes that involve the forwarding probabilities to multiple destinations simultaneously.

Gao and Cao [10] considered forwarding data only to the nodes that are interested in the data (called interesters). The interesters of a data item are typically unknown in advance at the data source because it is difficult for the data source to acquire knowledge about the interests of other nodes in the network a priori. Therefore, the problem is different from multi-casting and unicasting. They proposed a technique to relay selectively based on node centrality values, and ensure that data items are disseminated based on their popularities.

Hossmann et al. [14] argued that the prevalent pairwise statistics (e.g., contact and inter-contact time distributions) could not appropriately define a mobility model since a mobility model should also reflect the macroscopic community structure of who meets whom. The authors observed that communities are often connected by a few bridging links between nodes who socialize outside of the context and location of their home communities. They showed that it is the social nature of bridges that makes them differ from intra-community links. They argued that this observation should be accounted for in the future schemes.

The social graph that represents frequency of contacts between pairs of users and is used in social-based schemes is typically an aggregation of contacts during a long time span. Hossmann et al. [13] argued that in social-based methods the mapping from the mobility process generating contacts to the aggregated social graph is more important than the routing algorithm in terms of their respective effects on routing performance. The claim is verified by their study of SimBet [7] and BubbleRap [16]. Then, they designed an online learning-based algorithm to infer the right level of aggregation in building the contact graph. In a related work, Gao and Cao [9] observed that the transient contact characteristics of mobile nodes during short time periods in DTNs differ from their cumulative contact characteristics.

3.3 Getting Selfish Nodes to Cooperate in Packet Forwarding

To conclude the topic of DTN routing, we note that all the reviewed schemes (perhaps implicitly) make the assumption that network nodes are willing to cooperate in forwarding the packets. However, without any incentives, selfish nodes would rather not collaborate and only take advantage of other cooperative nodes. Therefore, it appears an incentive-based mechanism should be an integral part of any realistic DTN routing technique. We are not going to focus on this issue and refer the interested reader to [59] as an early attempt to tackle this problem. Another related scheme has been proposed by Li et al. [21]. They made the case that most people are socially selfish; i.e., they are willing to forward packets for nodes with whom they have social ties but not others, and such willingness varies with the strength of social ties. They proposed the Social Selfishness Aware Routing (SSAR) algorithm in which a forwarding node is selected by considering both users’ willingness to forward and their contact opportunity, resulting in a better forwarding strategy than purely contact-based approaches. Despite these few related works, it is somewhat surprising that providing cooperation incentives has been ignored in a majority of proposed DTN routing protocols.

4. CONCLUSIONS

First, we reviewed the state-of-the-art methods of modeling human mobility. Even though human mobility is inherently complicated to capture, even relatively simple models that incorporate a few of its key characteristics have been useful in advancing research on mobile networking, among other fields. Then, we summarized the existing methods of routing in DTNs, which significantly benefit from human mobility models.

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