Rethinking Network Mobility in Pervasive Markets: Model and Trust

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Abstract. With recent advances of wireless ad hoc networking, especially opportunistic forwarding and cognitive radio, there is an increasing concern that existing mobility models are insufficient to represent network mobility in real world settings. In this paper, we discuss our proposal for a more realistic mobility model which captures key features of human movements in pervasive markets. Our findings lead to a non-traditional mobility model which can be used to reconstruct the statistical patterns commonly observed in the literature, and facilitate the study of mobile communication and software engineering design problems under the context of pervasive computing for markets.

1 Introduction

The communication environment surrounding our daily experience is increasingly characterized by mobile devices that can exchange information and provide access to various services of complex nature. The trend is clear that future personal computing experience would be more and more based on pervasive communication devices and services, and the underlying mobile networks are becoming cooperative as mobile devices are increasingly rely on nearby nodes to maintain connectivity or relay messages.

In the future scenarios of wireless ad hoc networking like above, local connections and user mobility are as important as infrastructure access today for delivering data [9], but those mobility issues are not well studied in the past. As mobile devices are often attached to users, understanding their mobility patterns would lead to more *realistic* network simulation and better software and communication system design in general. However, existing mobility models are either too simplistic or do not represent the key characteristics of user mobility [10]. In the literature, most commonly used mobility models can be categorized into two types: individual mobility model and group mobility model.

Individual mobility models address the movement at individual node level, where each node is assumed to be independent from others: the Random Walk model [11] is the *de facto* mobility model for most mobile network simulations, which is a direct implementation of Brownian motion. The Random Waypoint model [12, 13] is also widely used in mobile network simulations, where nodes travel between randomly chosen locations. The Gauss-Markov model [14] was designed to adapt to different levels of randomness, where nodes updates their speed and direction at each time step, taking previous values into account.

In a group mobility model, the movement of a node is calculated relatively to the movement of a reference point in the group it belongs to: the Reference Point Group model [15] was based on the observation that mobile nodes in real world tend to coordinate their movement (e.g., in battlefield, a number of soldiers may move together in a group or platoon; or during disaster relief, various rescue crews form different groups and work cooperatively), where nodes are assumed to be in groups of one leader and a number of members. The movement of the group leader determines the mobility behavior of the entire group. The Social Network and Community model [16, 17] is a recent approach to deriving mobility traces based on the analysis of community structure in social networks, which further considers the group dynamics and clustering techniques in the node movement calculations.

Observing that above approaches are all *top-down*: they try to define the real characteristics that a mobility model should capture and then build the model accordingly, we take a reversed thinking *down-top* that mobility models should be inferred from observations made in real world networks, due to two facts: (1) real characteristics are actually hard to define; (2) node mobility characteristics in real world are very application specific.

The rest of paper is organized as follows. Section 2 provides background information and data collection techniques. Section 3 presents a novel approach to mobility model for real-life networks. Section 4 validates our hypothesis about this model and a trust-biased refinement is proposed in Section 5. We conclude the paper in Section 6.

2 Data collection

Camden market was chosen for collecting user mobility traces. Camden market is a large craft and clothing market in Camden town and the fourth most popular visitor attraction in London, attracting approximately 100,000 people each weekend [18]. HP GPS rx5730 handheld receiver is used for data collection, with a position accuracy of better than 3 meters most of the time. Users were supposed to keep the GPS receiver with them for as much of their visiting time as possible, with most carrying the GPS receiver in pockets. Occasionally, tracking information has discontinuity mainly when users move inside the indoor part of Camden market where GPS signals cannot be received.

The GPS receiver takes reading of the user's position every second and records it into a trace log. The trace log contains at least the following data:

`Latitude;Longitude;Altitude;Speed;Date;Heading` (**1**)

For the preliminary study, we collected traces of 4 market visitors (2 male and 2 female) over two month period. The assumption we taken here is that every visitor in the Camden market has the same statistical mobility tendency, and we believe it is reasonable to analyze the aggregative statistical patterns instead of individual statistical patterns. This assumption is also found in [1-4, 7]. Therefore we believe it is reasonable to use this assumption in our analysis.

From those traces, we extract the following information: movement length, stay time, direction, and speed. Since we are mainly interested in two dimensional mobility models, we map the raw data from GPS reading into two dimensional ones. Other treatments of the raw dataset are similar to [19]. Figure 1 shows a sample GPS trace visualized in the Google earth.

Fig. 1. Sample GPS trace from Camden market

3 A Levy Walk Mobility Model

Many recent studies [1-8] have found, in various areas of real world mobility ranging from physical particles, biology, human behaviors, to computer networks, some fascinating common features pervade them: the once abstract notions of *fractal* space and time appear naturally and inevitably in dynamical systems like above [8], which are not present in traditional random process models.

More specifically, what all these movements have in common is that their mobility patterns are shown to strongly resemble the Levy walk [5] process. A Levy walk is comprised of random sequences of movement-segments, with length l, drawn from a probability distribution function having a power-law tail:

$$p(l) \propto l^{-\gamma} \qquad (\mathbf{2})$$

where $\gamma \in (1,3]$. Such a distribution is said to have a heavy-tail [4] because large-length values are more prevalent than would be present within other random distributions, such as Poisson or Gaussian.

Levy walk was used to model animal foraging patterns [1]. According to the foraging theory, animals are presumed to search for nutrients and obtain them in a way to maximize the ratio of energy intake over the time spent for foraging. Levy walk is a commonly observed searching strategy in animal foraging, and it is proved that Levy walk strategy minimizes the mean distance traveled and presumably the mean energy expended before encountering a target [5]. Recent literature demonstrated that the Levy walk system is also very similar to the way that humans shop [1, 3, 4].

Figure 2 shows an abstract model of market visitors' traces: (1) a visitor's directions of successive steps are uncorrelated; (2) the distribution of the lengths of the steps (called flights) is characterized by a long tail.

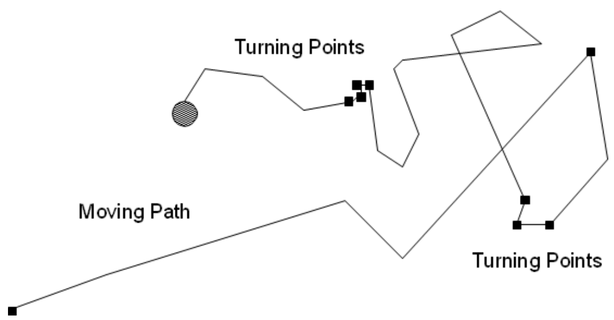

Fig. 2. Abstract graphical model of human shopper

4 Experimental Confirmation

It is confirmed from our measurement that Camden market visitor's trace also statistically resembles the Levy walk model: the flight distance l, which is defined as the longest possible straight line between locations without a directional change or pause, follows a power-law distribution.

4.1 Flight Distance

A power-low distribution of flight distances is the defining feature of Levy walk. We first show a statistical result from our measurement in the Camden market, and then use curve-fitting techniques to extract the scale parameter from the measurement.

We used a similar statistical method as [1]. For market visitors' movements, we first do a spectrum analysis as Figure 3, which already shows some evidences of an intermittent structure of longer flights. Using the frequency counts from the spectrum, we can normalize the distance distribution and derive a distance probability density graph as Figure 4.

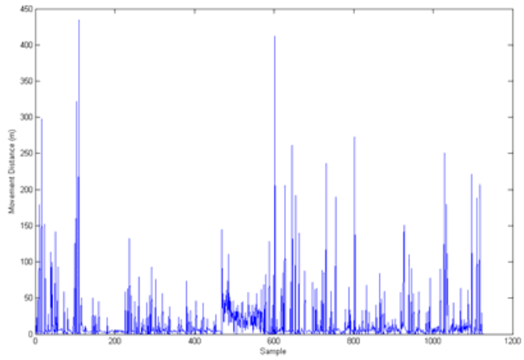

Fig. 3. Spectrum analysis of market visitors' movements

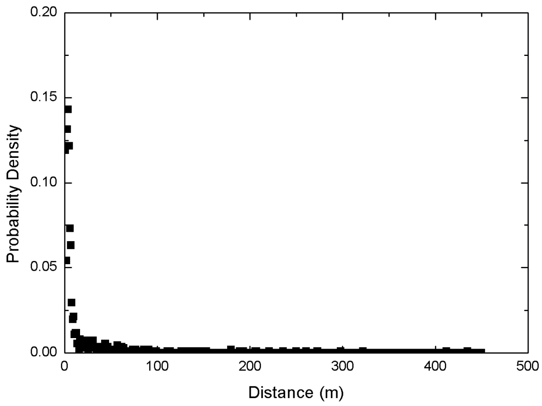

Fig. 4. Normalized distance distribution based on frequency

Figure 4 already exhibits the long tail characteristic of the visitor's movements, but we can show it more clearly in a log-log plot refinement as Figure 5, where the levy characteristic is highlighted as a red line. Though the levy tendency is evident in Figure 5, we still need to quantitatively validate the Levy model with a scale parameter.

We used the maximum likelihood estimation (MLE) to estimate the scale parameter:

$$\gamma = 1 + n[\sum_{i=1}^{n} \ln \frac{x_i}{x_{\min}}]^{-1} \tag{3}$$

where γ is the estimated scale parameter and x_i is the data sample. With this estimated scale parameter γ, we are already able to reconstruct a levy distribution curve. But at this point, we are not yet sure if the reconstructed curve is really a good fit of the original dataset. Thus a goodness-of-fit test is needed, and we used Kolmogorov-Smirnov statistic to validate the fitness:

$$f = \max_{x \geq x_{\min}} \left| S(x) - P(x) \right| \tag{4}$$

where f is the goodness-of-fit, $S(x)$ is the cumulative distribution function (CDF) of the data, and $P(x)$ is the CDF from our reconstructed curve.

Figure 6 shows the quantitative analysis result with an estimated scale parameter $\gamma = 1.8790$ and its goodness-of-fit $f = 0.0421$.

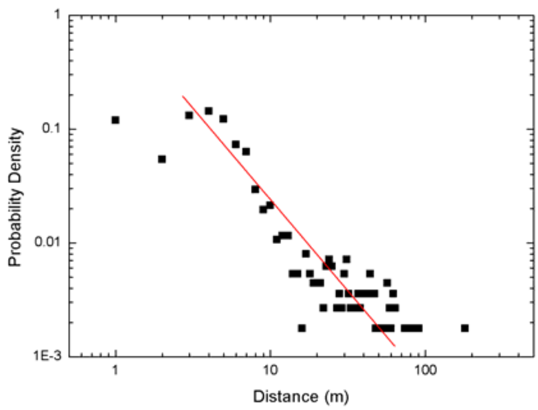

Fig. 5. Log-log plot refinement of Figure 4.

4.2 Stay Time and Turning Angle

The definition of Levy work *does not* require a power-law distribution of the stay time Δt, which is defined as the pause time in a location. However, surprisingly, we also observed a levy distribution of stay time from the Camden market visitor's traces. Using the same techniques developed in Section 4.1, we can derive a quantitative result with $\gamma = 1.8700$ and $f = 0.0849$ as shown in Figure 7. However, a goodness-of-fit value $f = 0.0849$ implies that Levy tendency in stay time distribution is not as strong as that in distance distribution.

Though power-law distribution of stay time is not necessary in the Levy work definition, it would be interesting to further investigate whether this phenomenon is a pure coincidence or a common feature.

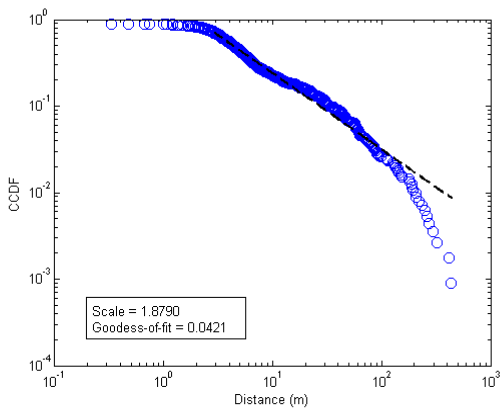

Fig. 6. Quantitative analysis of distance

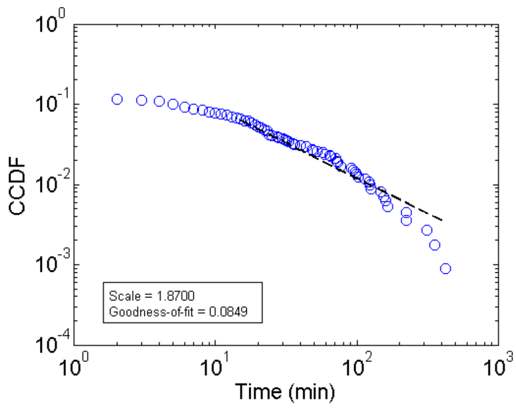

Fig. 7. Quantitative analysis of time

The turning angle θ, which measures the directional changes, not surprisingly, does not follow a power-law distribution. One reasonable assumption can be made here is that turning angles may be influenced by the geographical characteristics since shop placements in the Camden market must follow the geographical and council regulations, a quadrimodal distribution is expected here since urban architecture is dominated by right angles.

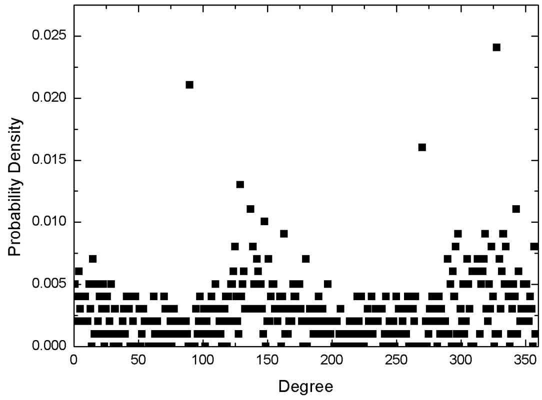

Fig. 8. Turning angle distribution

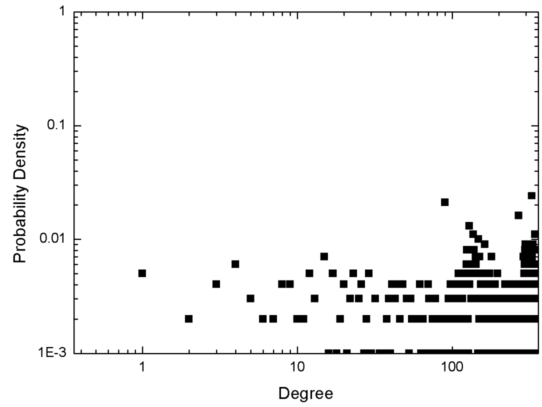

Fig. 9. Log-log plot of turning angle distribution

However, the observed distribution in Figure 8 does not exhibit a strong quadrimodal tendency. This distribution has no Levy tendency either, as shown in Figure 9. If we plot this distribution in a cumulative manner, we may observe a linear tendency in Figure 10. Therefore we believe uniform distribution may be a good fit here, though the bias from quadrimodal distribution needs further investigation in this case.

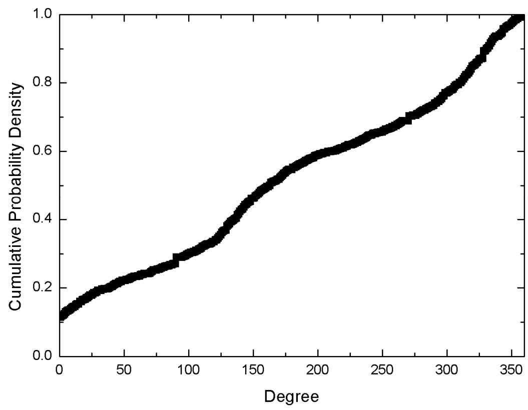

Fig. 10. Cumulative distribution of turning angle

4.3 Reconstruction

Now we are ready to reconstruct the user mobility traces in Camden market with a Levy walk model. The feature of each movement tuple M is captured by three variables:

$$M = (l, \Delta t, \theta) \tag{5}$$

where l, Δt, and θ are flight distance, stay time, and turning angle respectively. When reconstructing the mobility traces, our model would calculate M_t at time t and randomly generate l_t and $(\Delta t)_t$ with the Levy distribution; while θ_t follows a uniform distribution. We use the following probability density function to calculate the Levy walk [20]:

$$f(x,c) = \sqrt{\frac{c}{2\pi}} \frac{e^{-\frac{c}{2x}}}{x^{\frac{3}{2}}} \tag{6}$$

where c is the scale parameter and needs fine-tuning in the reconstruction process. Figure 11 shows a comparison of reconstructed sample mobility traces with the random walk model, the random waypoint model, and the Levy walk model respectively.

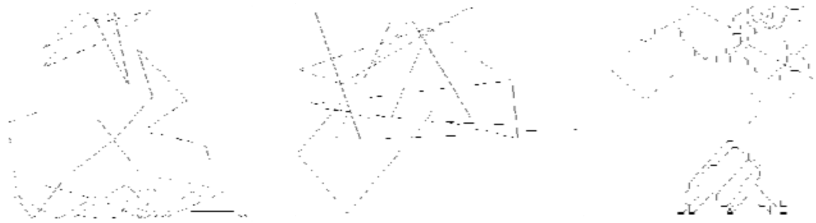

Fig. 11. Reconstructed sample mobility traces with **a.** the random walk model, **b.** the random waypoint model, and **c.** the Levy walk model; (from left to right).

5 A Trust-biased Refinement

Though it is shown in Section 4 that the Levy walk model is better in modeling user mobility traces in real world pervasive markets, this model can still be further refined for improvements: the Levy walk model is built on the uniform distribution assumption that the precise location of the targets is not known *a priori* but their spatial distribution is uniform. Our experimental data in Section 2 were also collected in line with this assumption: the visitors had no prior information on trust [21, 22], defined in the broad sense, of shops in Camden market.

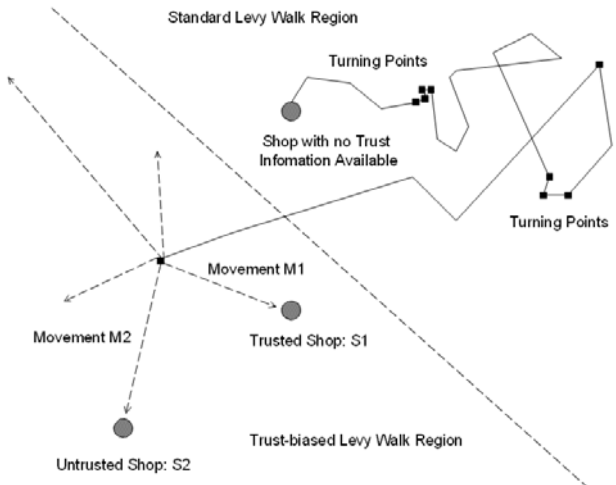

Fig. 12. Abstract graphical model of trust-biased human shopper

However, for a refined approach, with the vision provided by our pervasive computing for markets project [23], there is often presumptive knowledge of trust on shops available to visitors via pervasive computing technology, and visitors are subsequently supposed to best use this additional trust information provided by pervasive computing. Thus, the uniform distribution assumption is not necessarily true in this case.

Figure 12 illustrates an abstract model of visitor traces in presence of trust, where we label that the trust value $s_1 \geq s_2$. If we denote a trust-biased probability distribution function of movements m as $D(m)$, it should satisfy the following condition:

$$\forall s_1 \geq s_2 : \exists D : D(m_1) \geq D(m_2) \text{ and } D \in \mathrm{P}(Levy) \tag{7}$$

It is our hypothesis that this new probability distribution function $D(m)$ based trust and Levy walk should capture the key features of user mobility traces in presence of trust under the context of pervasive markets.

6 Concluding Remarks

Network mobility is an important research area in pervasive computing. Understanding user mobility is critical for simulations of mobile devices in a wireless network, but current mobility models often do not reflect real user movements.

This paper presented a non-traditional phenomenological approach to user mobility modeling in pervasive markets. We introduced the Levy walk model to the user mobility patterns, based on the assumption of no prior trust information. The preliminary study in Camden market confirmed that market visitor's trace statistically resembles the Levy walk model.

We then relaxed the uniform distribution assumption and proposed a trust biased refinement to the Levy walk model. It is our hypothesis that user mobility patterns in presence of trust follow a trust-biased Levy walk distribution as Equation 7. However, we still need real world measurement date in pervasive markets to validate our hypothesis, which can be one of the future works in this research.

Because of resource constraints, the experimental data collected in our preliminary study in the Camden market is relatively limited. Our model presented in this paper mainly captures the features of individual movements at node level. It would be interesting to study both individual and group movements with and without trust information in various types of pervasive markets [24].

Acknowledgment

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