Introspection-based Periodicity Awareness Model for Intermittently Connected Mobile Networks

Okan Turkes, Hans Scholten, and Paul Havinga

Dept. of Computer Engineering, Pervasive Systems
University of Twente, PO-Box 217, 7500 AE
Enschede, The Netherlands
{o.turkes,hans.scholten,p.j.m.havinga}@utwente.nl
http://ps.ewi.utwente.nl

Abstract. Recently, context awareness in Intermittently Connected Mobile Networks (ICMNs) has gained popularity in order to discover social similarities among mobile entities. Nevertheless, most of the contextual methods depend on network knowledge obtained with unrealistic scenarios. Mobile entities should have a self-knowledge determination in order to estimate their activity routines in a group of communities. This paper presents a periodicity awareness model which relies on introspective spatiotemporal observations. In this model, hourly, daily, and weekly locations of mobile entities are being tracked to predict future trajectories and periodicities within a targeted time period. Realistic simulations are utilized to analyze the predictions in weekly observation sets. The results show that a reasonable accuracy with an increasing level of determination can be obtained which does not require global network knowledge. In this regard, the presented model can give insights for any type of ICMN objectives.

Keywords: Intermittently-connected mobile networks; social networks; context-awareness; periodicity awareness model; spatiotemporal correlations

1 Introduction

Opportunistic way of communications has become feasible with the idea of forming circumstantial networks such as Intermittently Connected Mobile Networks (ICMNs), with ubiquitous mobile- and smart-phone carriers [1]. ICMNs provide flexibility and scalability for information sharing, especially in case of overloaded or inoperable wired/wireless infrastructures during emergencies. Unlike conventional wireless networking approaches, ICMNs focus on exploiting the advantages and obviating the disadvantages of ever-changing mobility dynamics for data routing and dissemination. In order to form collaborative/cooperative node clusters for communicating with high efficiency in communities or connecting dispersed vicinities with suitable intermediary nodes, research motivations for ICMNs converge on context-awareness (CA) to eliminate forecast uncertainty due to unpredictable nature of mobile entities [2].

For CA, ICMNs can exploit either self-knowledge (K_S), or vicinity-knowledge (K_V), or both to a certain extent. Most of the routing strategies rely on a full K_V, in which global network properties are known beforehand or provided routinely. Approaches, which exploit relative significance values among node locations and meas-

adfa, p. 1, 2013.

ure several graph metrics such as centrality and closeness, initially obtain a partial or full K_V as well. Such unreasonable scenarios may substantially cause an unexpected level of dissemination in reality [3]. With more realistic scenarios, methods such as social labeling, ranking, and temporal-based comparisons mostly rely on an encounter-based K_V. However, determining socially (in)coherent nodes among contacts may not necessarily provide a high efficiency and scalability in information sharing, since spatiotemporal node behaviors and relationships are especially evaluated for only small-scale vicinities. There are self-aware methods which focus more on K_S to determine social similarities over large-scale ICMNs [4-6]. However, they do not observe mobility routines for longer period of times. To the best of our knowledge, spatiotemporal periodicities in ICMNs have still not been investigated thoroughly.

This study presents a periodicity awareness model for ICMNs which relies on introspective reasoning of spatiotemporal trajectories. Only utilizing K_S, locations of network entities are being tracked for long period of time. Hourly, daily, and weekly sets are formed in order to record and determine regions of all of the mobile nodes at specific time intervals. Then, these spatiotemporal regions are analyzed to build a prediction set for future locations and trajectories within a targeted time. On the contrary, K_V is completely ignored, such that the level of network dependency is attained at its lowest. With an efficient and realistic introspection, simulation results indicate that a reasonable awareness can be achieved for any kind of objective in ICMNs.
The rest of the paper is organized as follows: Section 2 explains our periodicity awareness model. Section 3 demonstrates our experimental setup. Section 4 gives the performance analysis. Section 5 gives the conclusion and outlines the future work.

2 Introspection-based Periodicity Awareness Model

The proposed periodicity awareness model relies on location and time context. We use K_S of mobile spatiotemporal periodicity data for two basic reasons: 1)Mobile nodes must have selective message switching mechanisms to decide on when to relay the information to the other network entities. 2)Message sharing methods must investigate mobile message carriers' attitude to project future trajectories or contacts.

We define two dynamic buffers, $L = \{l_1, l_2,\ldots, l_k\}$ and $T = \{t_1, t_2, \ldots, t_k\}$, to keep track of the locations and the corresponding times, respectively. The number of measurements, denoted by k, can be adjusted according to the application necessities. We define an ordered pair, $s_i=(l_i, t_i) \mid 1 \leq i \leq k,\ l_i \in L,\ t_i \in T$ to form a general spatiotemporal set $S = \{s_1, s_2,\ldots, s_k\}$. A weekly record set, $W = \{S_1,\ldots, S_7\}$, contains all recordings of a specific day (S_d) of the previous week. Every week, recordings in the sets are updated. Analogically, we define an identical instance of W, as $\overline{W}$, to investigate the generality of the weekly recordings. According to that, average spatiotemporal pair set, that is $\bar{s}_i=(\bar{l}_i, t_i)$, is recorded in $\overline{W}$ and is also updated every week as given in Equation 1, where c demonstrates the number of observation weeks.

$$\bar{s}_i = \begin{cases} \dfrac{c \times \bar{s}_i + s_i}{c+1}, & if\ W \neq \emptyset \\ s_i, & if\ W = \emptyset \end{cases} \tag{1}$$

Spatiotemporal data are recorded to project trajectories and, therefore, to estimate total distances (x) and displacements (ΔR) for a targeted time t_g. Starting from the current time t_c, until t_c+ t_g, pairs of s_{c+n} and $\bar{s}_{c+n}$ ($1 \le n \le g, n \in \mathbb{N}$) are obtained from the sets of the same day, S_d and $\bar{S}_d$. For t_c, we have the location from the preceding week ($l_c \in S_d$) and the average location for the weeks observed ($\bar{l}_c \in \bar{S}_d$), where the Euclidean center of them is μ_c. Then, we find the Euclidean vector v which is from μ_c to the real current location. For each subsequent s_{c+n} and $\bar{s}_{c+n}$, we find μ_{c+n}. We have the set $M = \{\mu_c, \mu_{c+1}, \dots, \mu_{c+g} \mid c, g \in \mathbb{N}\}$ at t_c+ t_g. For each two consecutive elements of M, we update the ratio ϕ_n between μ_{c+n} and μ_{c+n+1}. The terminal point of the vector ϕv gives us the projected location at that time, which is θ_{c+n}. We have the set $\Theta = \{\theta_c, \dots, \theta_{c+g} \mid c, g \in \mathbb{N}\}$ for the projected locations at t_c+ t_g. As Equations 2 and 3 show, we then calculate the estimated x and ΔR between t_c and t_g.

$$\tilde{x} = \sum_{n=1}^{g} \sqrt{(\theta_{c+n} - \theta_{c+n-1})^2} \tag{2}$$

$$\Delta\tilde{R} = \sqrt{(\theta_{c+g} - \theta_c)^2} \tag{3}$$

We also check the distance between the estimated locations $l_{c+g} \in W$and $\bar{l}_{c+g} \in \bar{W}$ of a mobile node. As given in Equation 4, if it is shorter or longer than a threshold distance (τ), we set the periodicity degree ($°\rho$) of that node to high or low, respectively.

$$°\rho = \{\, Low, if \left| l_{c+g} \in W - l_{c+g} \in \bar{W} \right| < \tau, \text{or } High, if\ otherwise \tag{4}$$

This periodicity awareness model gives an insight for any type of ICMN objective by estimating future locations, trajectories, and displacements. As shown in Figure 1, when two nodes meet at t_c, they calculate their own $\tilde{x}$, $\Delta\tilde{R}$, and $°\rho$ for t_c+ t_g. If the objective is the collaboration for an event detection, they can compare their $\Delta\tilde{R}$ whether to see they stay in the same region, or not. If the objective is data dissemination over large regions, they can compare their $\tilde{x}$ to understand which one is more dynamic to carry the message to the other regions. If the objective is creating social-coherent clusters, they can check their $°\rho$ and decide to involve in that community, or not. In this model, nodes utilize K_S with their own observations and do not require K_V.

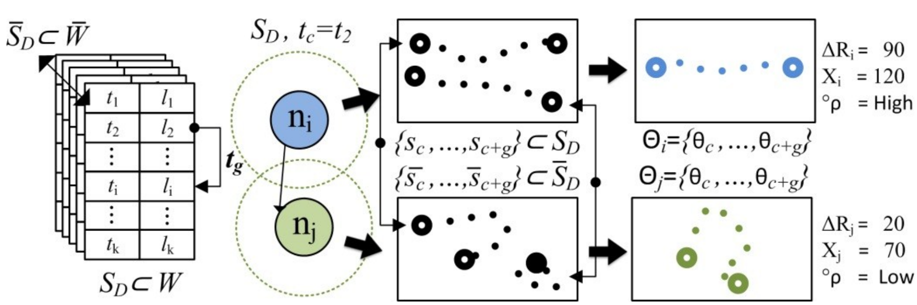

Fig. 1. The periodicity awareness model

3 Experimental Setup

The Opportunistic Networking Environment simulator [7] with the shortest path map-based movement model is used to evaluate our proposed model. In the experiments, a virtual city of approximately 5000m by 5000m is generated to analyze 500 individuals as mobile entities under 4 different groups, as shown in Table 1. In the city map, 5 different points-of-interests (POIs) types are defined with several locations. For instance, residential and commercial POIs are dispersed over the city map whereas marketplace POIs are located near to the city center. Several range of POI probabilities are assigned for each group. In the simulation, a worker can drop over places such as his/her house, office, and restaurant whereas a student can shuttle between places such as his/her house, school, and library. A housewife spends most of her time at home and usually goes for shopping. Thus, these 3 groups generally move with a purpose. Besides, a tourist is a random-stroller in the simulation.

With this scenario, we draw a parallel between the real world and the simulation setup for daily city activities. In addition, by assigning varying characteristics to the mobile entity groups, we define 5 different settings with random seed numbers in order to represent each workday of a week. Random seed numbers in the simulation create different trajectories for one-day-long activities of the mobile entities, meaning that the individuals have appraised POIs with varying schedules. Spatiotemporal data are tracked to create the sets W and $\overline{W}$, which are utilized to predict the periodicities.

Table 1. POI probabilities for different mobile entity groups in the simulation

Groups/POIs	**Residential**	**Commercial**	**Educational**	**Recreational**	**Marketplace**
Workers (125)	0.20-0.25	0.35-0.40	0.00-0.05	0.05-0.15	0.10-0.15
H.wives (125)	0.35-0.40	0.00-0.00	0.05-0.10	0.10-0.15	0.30-0.35
Students (125)	0.25-0.30	0.00-0.00	0.30-0.35	0.20-0.25	0.05-0.10
Tourists (125)	0.00-0.20	0.00-0.20	0.00-0.20	0.00-0.20	0.00-0.20

4 Performance Analysis

The soundness of the presented model is investigated by analyzing the spatiotemporal periodicities, estimated distances ($\tilde{x}$), and displacements ($\Delta\tilde{R}$) of mobile entities. For each entity, spatiotemporal data is recorded for 40 different experiments, which form 8 weekly observation sets by each of 5 weekday tests. The sensing interval differs between 300sec and 3600sec. Figure 2(a) shows the difference between the real and estimated displacements ($|\Delta R$- $\Delta\tilde{R}|$) with regard to number of weeks (c) and sensing interval, where t_g is twice of the sensing interval. It is evident that sensing frequency has a positive effect on the ΔR estimation, however, to a certain extent. Besides, an increase in c does not substantially improve the accuracy of ΔR estimation. As Figure 2(b) depicts, if mobile entities are investigated separately, the effect of periodicity on x estimation can be seen clearly. Strict periodicities generate accurate x estimations. This means that the presented periodicity model is also suitable for determining trajectories of vehicles and people with predetermined routes carrying wireless modules.

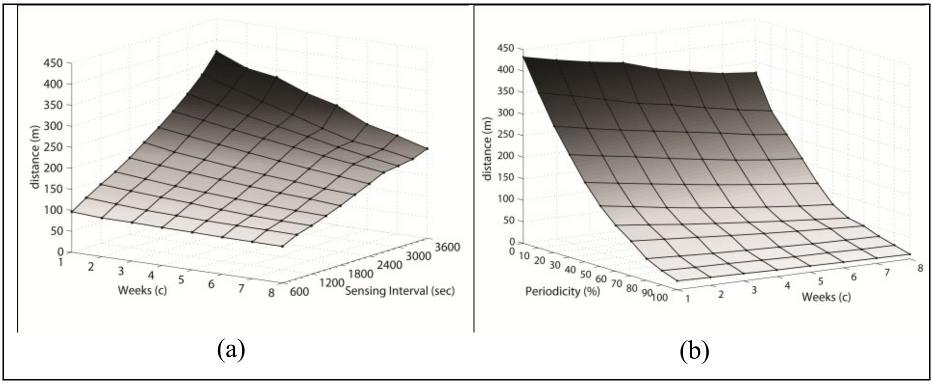

Fig. 2. The effect of sensing interval and periodicity on estimated distances

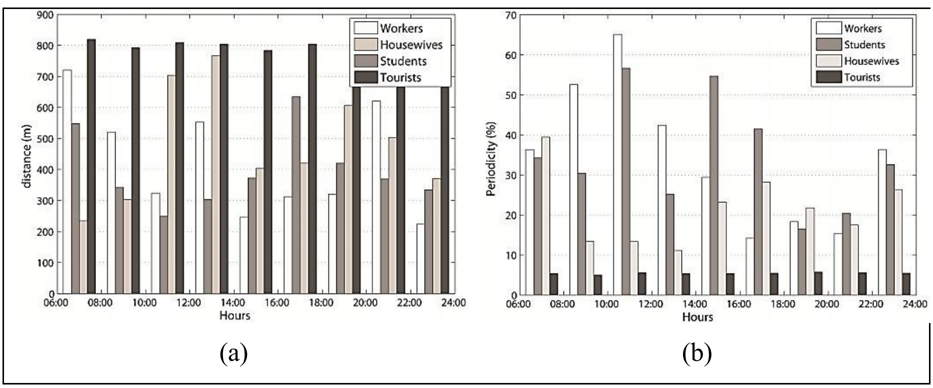

Fig. 3. Periodicities of mobile groups with respect to time and distance traveled

Figure 3(a) shows $\tilde{x}$ results for each entity groups according to different day hours when t_g=1800sec. In addition, the hourly changes in periodicities for each group are shown in Figure 3(b), by calculating the percentage of entities which stay in the same POI region within t_g among all group entities ($°\rho = High, \tau = 500m$). By analyzing $\tilde{x}$ and $°\rho$ results together, we can compare the social routines of the entities. Thus, our model can be suitable to fulfill any ICMN objective such as collaboration, dissemination, and clustering which are the tasks T_1, T_2, and T_3 defined in Table 2, respectively.

Table 2. Number of appropriate nodes selected at specific POIs and times for the defined tasks

Tasks/Regions (t_g=30min)	**Residential**	**Commercial**	**Educational**	**Recreational**	**Marketplace**
T_1: $\tilde{x} \le 100$m $\wedge$ $°\rho$ = High	11 (04:00) 6 (20:00)	9 (11:00) 3 (16:00)	10 (11:00) 5 (16:00)	6 (09:00) 6 (17:00)	3 (09:00) 5 (17:00)
T_2: $\Delta\tilde{R} \ge 100$m $\wedge$ $°\rho$ = Low	2 (04:00) 5 (20:00)	4 (11:00) 9 (16:00)	5 (11:00) 7 (16:00)	14 (09:00) 22 (17:00)	11 (09:00) 32 (17:00)
T_3: $\tilde{x} \le 1000$m $\wedge$ $\Delta\tilde{R} \le 500$m	16 (04:00) 8 (04:00)	13 (11:00) 4 (16:00)	10 (11:00) 6 (16:00)	8 (09:00) 7 (17:00)	10 (09:00) 9 (17:00)

The number of appropriate nodes for T_1 is high for the POIs which are visited at least for once by each mobile group. For example, all of the mobile groups stay at residential areas during night. Similarly, student and worker groups provide better results for T_3 during work hours. Besides, recreational and marketplace POIs are suitable For T_2.

5 Conclusion & Future Work

In this paper, we propose a periodicity awareness model for ICMNs with introspective spatiotemporal observations. We record the locations of mobile entities with different time intervals to discover daily and weekly movement routines. We present an estimation model to predict trajectories and periodicities. The model projects the future locations in a targeted time period by utilizing weekly observation sets. Realistic simulations show that we can obtain reasonable accuracy with an increasing level of determination without global network knowledge. The proposed model gives insights for any kind of ICMN objective. As future work, the model should utilize more precision controls and knowledge for periodicity awareness. The model will be used as basis for an efficient data dissemination protocol in a network of mobile phones.

Acknowledgments

This study is supported by the SenSafety project in the Dutch Commit program.

References

1. M. Khabbaz, C. Assi, andW. Fawaz, “Disruption-tolerant networking: A comprehensive survey on recent developments and persisting challenges,” Communications Surveys Tutorials, IEEE, vol. 14, no. 2, pp. 607 –640, quarter 2012.
2. P. Bellavista, A. Corradi, M. Fanelli, and L. Foschini, “A survey of context data distribution for mobile ubiquitous systems,” ACM Comput. Surv., vol. 44, no. 4, pp. 24:1–24:45, Sep. 2012.
3. Y. Zhu, B. Xu, X. Shi, and Y. Wang, “A survey of social-based routing in delay tolerant networks: Positive and negative social effects,” Communications Surveys Tutorials, IEEE, vol. 15, no. 1, pp. 387 –401, quarter 2013.
4. W.-J. Hsu, D. Dutta, and A. Helmy, “Profile-cast: Behavior-aware mobile networking,” in Wireless Communications and Networking Conference, 2008. WCNC 2008. IEEE, 31 2008-april 3 2008, pp. 3033 –3038.
5. G. S. Thakur, A. Helmy, and W.-J. Hsu, “Similarity analysis and modeling in mobile societies: the missing link,” in Proceedings of the 5th ACM workshop on Challenged networks, ser. CHANTS ’10. New York, NY, USA: ACM, 2010, pp. 13–20.
6. S. Moon and A. Helmy, “Understanding periodicity and regularity of nodal encounters in mobile networks: A spectral analysis,” in Global Telecommunications Conference (GLOBECOM 2010), 2010 IEEE, dec. 2010, pp. 1 –5.
7. A. Keränen, J. Ott, and T. Kärkkäinen, “The ONE Simulator for DTN Protocol Evaluation,” in SIMUTools ’09: Proceedings of the 2nd International Conference on Simulation Tools and Techniques. New York, NY, USA: ICST, 2009.