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Analyzing temporal scale behaviour of connectivity properties of node encounters

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Abstract

Nowadays the growing popularity of wireless networks, combined with a wide availability of personal wireless devices, make the role of human mobility modeling more prominent in wireless networks, particularly in infrastructure-less networks such as Delay Tolerant Networks and Opportunistic Networks. The knowledge about encounters' patterns among mobile nodes will be helpful for understanding the role and potential of mobile devices as relaying nodes. Data about the usage of Wi-Fi networks can be exploited to analyze the patterns of encounters between pairs of mobile devices and then be extrapolated for other contexts. Since human mobility occurs in different spatial and temporal scales, the role of scale in mobility modeling is crucial. Although spatial properties of mobility have been studied in different scales, by our knowledge there is no fundamental perspective about human mobility properties at different temporal scales. In this paper we evaluate the connectivity properties of node encounters at different temporal durations. We observed that connectivity properties of node encounters follow almost the same trends in different time intervals, although slopes and exponential decaying rates may be different. Our observations illustrate that networks formed from encounters of nodes extracted from Wi-Fi traces do not exhibit a scale free behaviour.

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1. Introduction

The majority of portable wireless devices such as Wi-Fi devices are carried by humans, so these devices form networking nodes that exhibit movement behavior of their human carriers and such movement strongly impacts the network operation and performance. Movement patterns of roaming users can be captured, in

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statistical terms, up to some extent. Hence, by analyzing and attempting to model mobility patterns that relate to human behavior, it may be possible to apply those models in many application domains such as urban planning, social science, epidemiology and network communications [1]. The analysis of Wi-Fi data traces can provide significant information about human mobility patterns and regularities. Moreover, knowledge about the usage of Wi-Fi networks can be used to perform an analysis of encounters between pairs of devices, and then be extrapolated for other contexts. Mobility and nodal encounters are utilized to deliver messages in intermittently connected Delay Tolerant Networks (DTN) and Opportunistic Networks. Understanding of nodal encounter patterns and their characteristics are critical for the success of protocols and deployments in DTNs because delivery mechanism depends on nodal encounters. Also human mobility occurs on a variety of spatial and temporal scales, ranging from short distance pedestrian motion within buildings to long range trips by airplanes, and involves different modes of transportation. So scale in modeling mobility is crucial due to deviations in patterns and properties that may be observed at each layer of scale and also the driving forces of mobility can also differ on different scales [2]. Although human spatial mobility properties have been studied in different scales, continent and country scale [3], city scale [4], regional scale [1,5] and much finer scale such as campus and buildings [6,7] fundamental studies about mobility models on different temporal scales are still missing. In this paper we study the characteristics of connectivity properties of node encounters [2] on different temporal dimensions. Although some researchers may argue that human behavior should be scale free in different dimensions [1], we need more study for further verification.

The performance of message dissemination and delivery in opportunistic and DTN networks is greatly influenced by Connectivity Properties of human mobility [2] such as Contact Time (CT - the time period while two mobile nodes are in communication range of each other and can communicate directly or indirectly) and Inter Contact Time (ICT - the time elapsed between two consecutive contact of the same pair of nodes), especially ICT that can be used to estimate the delay.

Node Degree (the number of distinct encounter events per each node) and Encounter Counts are two connectivity properties of node encounters, which have important influence on diffusion of messages in Opportunistic Networks, will be analyzed on different temporal scales.

The main contribution of this paper is in assessing the behaviors of the connectivity properties of node encounters on different temporal scales. Although human spatial mobility have been studied at different scales [1,3,4,5,6,7,8], to our knowledge no specific studies exist on the behavior of node encounters on temporal dimensions.

In this paper we use the terms station, mobile node and also mobile device as being equivalent to each other.

The remaining of the paper is organized as follows: in section 2 we discuss the concept of encounter among mobile devices. In section 3 we discuss the most prominent connectivity properties of node encounters, and the statistics and trends of the connectivity properties of encounters are presented in section 4. In section 5 we discuss related work and finally, in section 6, conclusion and future work are drawn.

2. Pair Encounters

An encounter event in the real world means meeting face to face, which implies physical proximity among involving objects. The extent of this physical proximity is not always exactly clear and may be different on different scenarios, applications and domains. For instance, in the biological field and in disease spreading, physical proximity or distances between involving objects are short and even can be considered as direct touching, while in wireless networks this proximity (or distances) can be limited by the coverage areas of mobile devices or wireless network infrastructures. Nowadays the majority of short-range wireless devices, such as Wi-Fi devices, are carried by humans. So these devices can be used to observe human mobility behaviors and also to extract physical proximity among human carried mobile devices in the real world and, as a result, encounter events among humans. Therefore in a communication perspective, an encounter between

two mobile devices occurs when they are in communication range of each other or within the coverage area of WLAN infrastructures that devices are associated to. Therefore, extracting encounters among people through their portable wireless devices is constrained by the coverage area of devices or infrastructures. In wireless networks, two kinds of encounters are defined: Direct and Indirect. Bluetooth traces track direct encounters between mobile nodes. In this case an encounter occurs when devices come into the radio communication range of each other. WLAN traces record associations between mobile nodes and APs (Access Points). Even though APs are stationary, they can link mobile nodes that never directly encounter. Therefore, in this case we have indirect encounters, since communication opportunity between nodes is established through APs.

Most researchers [9,10] define an encounter event occurrence in a WLAN when two or more nodes are associated to the same AP during an overlap time interval, and named this as an encounter of indirect type. This definition may not always reflect proper and exact realistic physical encounters among nodes due to some challenges. For instance, nodes might be physically close to each other but associated to different APs, or they are out of coverage area of APs, or they are involved in ping-pong events [11]. Discussing about these challenges is out of scope of this paper and here we try to analyze characteristics of extracted node encounters (for extracting node encounters we have used the common mentioned definition of encounters by considering some of these challenges). Despite some challenges and limitations, if collected data traces are used carefully (i.e. accounting for the effects of ping-pong events, overlap in coverage areas and missed encounters) it would appear to be a good source of empirically-derived data on human encounters since large amount of data can be gathered easily at low cost, allowing large scale analysis of encounter patterns.

3. Connectivity Properties of Node Encounters

Connectivity properties of mobility include the contact (CT) time, i.e. the duration of a contact between the same pair of nodes (when they are in communication range of each other), and the inter-contact time (ICT), i.e. the amount of time between two successive contacts of the same pair of nodes [2]. Since the behavior of human-carried mobile devices can be considered as a proxy of human movements, a contact between two devices implies that the corresponding users are close to each other. Thus, by extension, ICT and CT can be considered as measures of how frequent and how long two users spend time together. Also given that messages can be exchanged only when nodes are in radio range of each other, the longer the contact, the more messages can be exchanged. In addition, considering the necessity of injecting messages in the network at any time, a single sporadic contact cannot be enough for delivering messages. Thus, the distribution of ICT is very important: more frequent contact between nodes means that nodes have more opportunities for exchanging messages. The ICT has a great influence on performance of the message dissemination and delivery in opportunistic networks. In particular, ICT can be used to estimate the delay. Among those two metrics, ICT is considered to be the most important one. Many experiments have been conducted in order to specify the nature of ICT and there is now a general agreement on the fact that the Aggregate ICT distribution which is aggregated over all pairs of nodes (AICT) for pedestrians follows a power law with a final exponential cut-off over a wide range of values, from few minutes to half a day [12,13,14]. Hui et al. [15] has shown that the duration of ACT follows an approximate power-law distribution.

Other properties that can be considered are Unique Encounter Count and Total Encounter Count. Unique Encounter Count is defined as the number of times that two specific nodes are in communication range of each other at a specific location (AP), whereas Total Encounter Count is the number of times that two specific nodes meet each other regardless of the location. The distributions of Aggregate Unique and Total Encounter Counts (which are aggregated over all pair of nodes) are shown in Figure 1 (for 3 months long trace collected at a university campus). They almost follow a power law and are almost coincident, implying that most pairs of nodes meet each other in the same locations. This is compatible with the location preference property of human mobility [10].

Table 1. Encounter statistics

| Trace | Porto University | Minho University |
|---|------------------|------------------|
| Duration | 5 months | one year |
| Number of distinct Stations in Wi-Fi trace | 18 137 | 21 746 |
| Number of Stations involved in encounters with other Stations | 15 701 | 20 120 |
| Total number of encounters | 4 495 617 | 18 042 678 |
| Number of distinct encounters | 804 271 | 1 845 594 |

Node Degree (the number of distinct encounters per each node) is another connectivity property that is used in data forwarding and routing in DTN and Opportunistic Networks. A node with high node degree value keeps contacts with numerous other nodes. Such nodes are popular nodes with large number of links to other nodes (Hubs). In data forwarding, nodes with higher node degree (centrality) values have a more important role in relaying data than nodes with low centrality. Centrality is a good measure for path finding in intermittently connected networks [16].

4. Encounters' Statistics

In this section we introduce our Wi-Fi dataset and discuss distribution of connectivity properties of node encounters on different temporal intervals.

4.1. The Dataset

In our experiment we used two Wi-Fi traces, extracted from logs of the RADIUS service, one of them from two separate campuses of Minho University and another from one campus of Porto University in Portugal. Whenever a station (smartphone, tablet or laptop computer) associates or disassociates with an AP, a syslog message is recorded. Each record contains a time stamp in seconds, the MAC addresses of the AP and Station, the Access Session Time in seconds, and the Access Session Status (Start - association), or Stop - disassociation). The analyzed Minho trace is one year long, from 1 Jan 2011 to 31 Dec 2011 and Porto trace 5 months long from 1 Jan 2011 to 31 May 2011. The Minho trace contains references to 3035 distinct APs and 21746 stations and Porto trace contains references to 1381 distinct APs and 18137 stations. The Wi-Fi data traces do not include any information about the geographical coordinates of the APs and their spatial distributions.

4.2. Statistics and Trends

Table 1 shows the number of nodes in each one of Minho and Porto traces. We also observed that 15701 (87%) out of 18137 stations in Porto trace and 20120 (93%) out of 21746 stations in Minho trace get involved in encounters with other stations. One interesting observation is that the average number of encounters per pair of nodes in the Minho trace is almost two times more than in the Porto trace. It means that, on average, people in Minho campus meet each other more frequently than people in Porto campus.

As we can see in Figure 2, the cumulative number of nodes involved in encounter events) in both traces grows continuously. These encounter networks are open and they form by the continuous addition of new nodes to the system, thus the number of nodes increases throughout the lifetime of the network. A common feature of these systems is that the network continuously expands by the addition of new nodes that are connected to the nodes already present in the system.

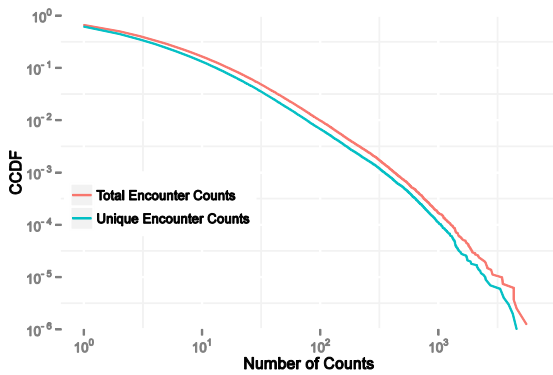


Fig. 1. Distribution of Unique and Total Encounter Counts

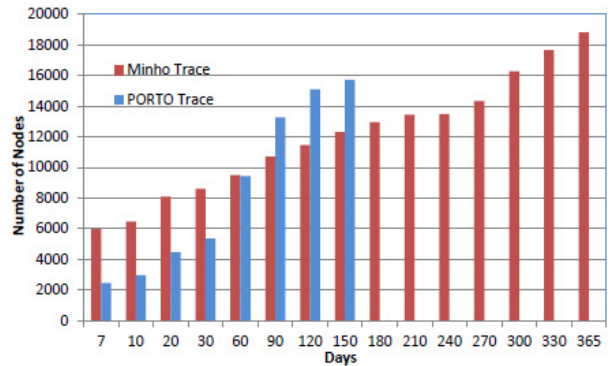


Fig. 2. Growth on the cumulative number of nodes involved in encounter events over time.

The distributions of connectivity properties of encounter events are important to understand the structure of the relationship among mobile nodes. The understanding of the distribution of encounters aids in assessing the opportunities for message dissemination, prediction of information transmission and message delivery and estimation of delay.

Figures 3a and 3b depict the distributions of Node Degree for different observation periods for Minho and Porto traces, respectively. The distributions could be fitted best with Log-Normal 3 or Log-Pearson 3 for both traces, over different observation duration periods.

This implies that in these WLAN networks a few nodes act as highly connected hubs, while most nodes are not well connected. In other words, over time a few devices collect an extremely large number of encounters and form hubs, while the vast majority of devices have a small number of encounters.

Although authors in [17] declare that Power Law and Log-normal distributions are intrinsically connected and very similar and that basic generative models can lead to either power law or lognormal distributions depending on seemingly trivial variations, we cannot conclude that Node Degree is scale free in these two campus traces because distributions do not follow a Power Law. According to [18,19] two mechanisms, growth and preferential attachment, are sufficient conditions for the appearance of scale free networks (Power Law distribution). Although the first condition is satisfied here according to Figure 2, the second condition, preferential attachment (The probability that a new node is connected to one of the available nodes in network is proportional to the Node Degree of those nodes), does not seem to be satisfied here. Therefore, from the Node Degree perspective, these networks do not show scale free (self-similarity) behavior.

On the other hand, the results in Figures 3a and 3b can be interpreted as a centrality distribution of the nodes that suggest the heterogeneity of the centrality of nodes. Centrality is a good measure for path finding in intermittently connected networks. In data forwarding, nodes with higher centrality values have a more important role in relaying data than nodes with low centrality. Heterogeneity in centrality implies heterogeneity in popularity of mobile nodes to help design more efficient forwarding strategies. The above distributions depict very wide heterogeneity in centrality levels. This clearly shows that a small number of nodes have extreme centrality and thus high relaying ability and large number of nodes have moderate or low centrality across all above traces durations.

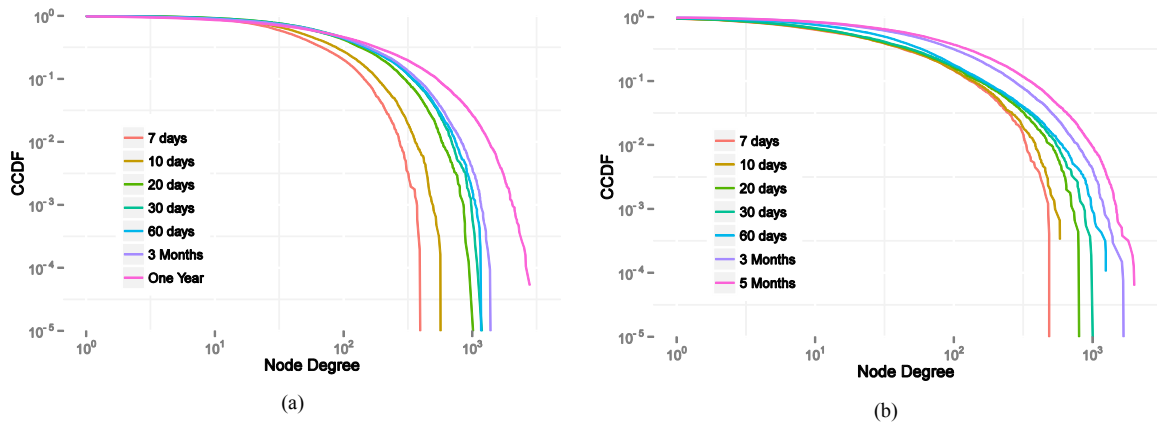


Fig. 3. Distribution of Node Degree for different observation periods: (a) Minho trace; (b) Porto trace.

As we mentioned before, CT and ICT are two important connectivity properties of human mobility [2] that have prominent role in protocol performance in opportunistic networks. Here we look into the distributions AICT, which is aggregated over all pairs of nodes, and also the distribution of ACT (Aggregate Contact Time) over different temporal intervals for both Wi-Fi traces.

Figures 4a and 4b show the distributions of ACT of Minho and Porto traces respectively. ACT distributions of both traces on different time intervals, from one week to one year, in Minho trace and from one week to 5 months in Porto trace are best fitted with Pareto distributions. We observe that these distributions almost overlap each other over different time intervals. So even in this case we cannot conclude that ACT behavior is scale free, since it does not follow linear power law, although over different observation duration distribution trends are similar.

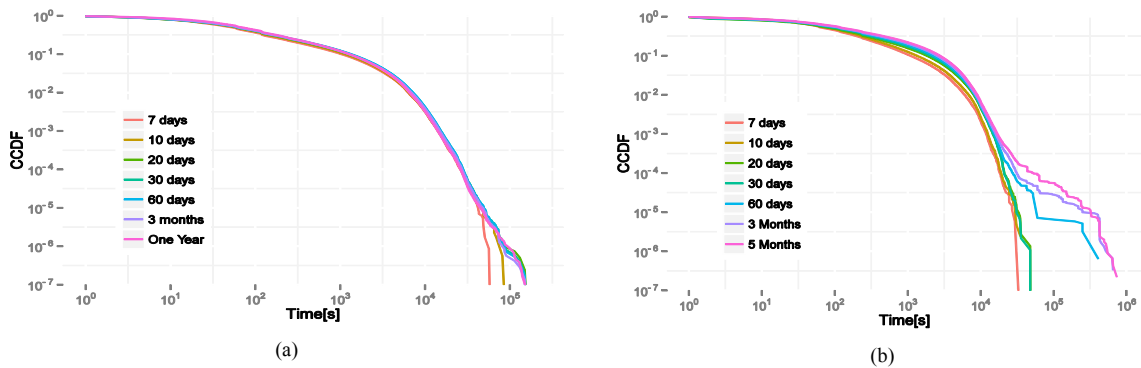


Fig. 4. Behaviour of ACT on different temporal dimensions: (a) Minho trace; (b) Porto trace.

Figures 5a and 5b depict distributions of AICT for the Minho and Porto traces, respectively. The distributions obtained from different observation durations show similar trends. For instance, AICT distributions of different time durations have different power law slopes and exponential decaying rates, but all of them follow truncated power law trend with almost same characteristic time of 24 hours (characteristic time, is the time that distribution changes from power law to exponential truncating mode). By ignoring short values

of ICT (less than 100 seconds), the power law part of these distributions can be fitted with a straight line with a slope that increases by increasing observation intervals. Thus AICT, although follow same trend on different observation duration, do not show scale free behaviour on temporal scale because of its truncated tail.

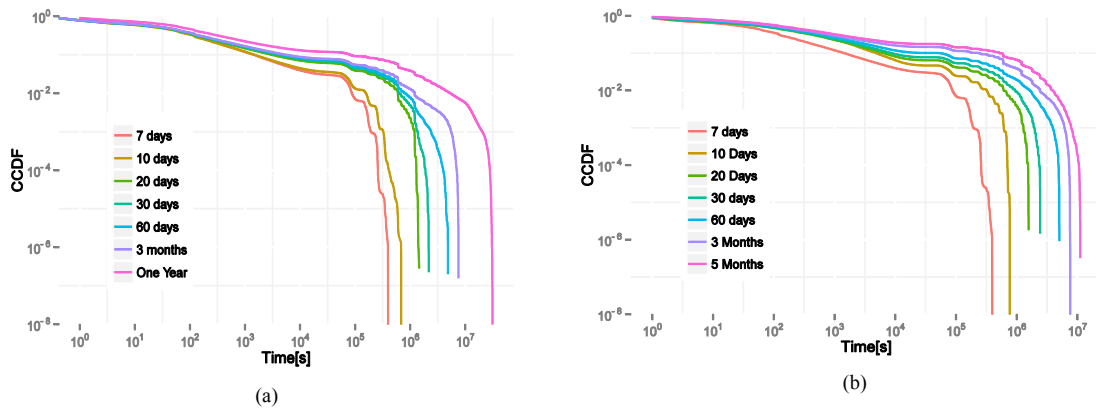


Fig. 5. Behaviour of AICT on temporal dimension: (a) Minho trace; (b) Porto trace.

Also, the Pareto and truncated power law trends in ACT and AICT distributions, respectively, confirm the heterogeneity in the encounters among mobile nodes. It means that the majority of the encounters have short duration, while a few encounters have long duration. In the case of AICT, the truncated power law distribution indicates that the majority of pairs of nodes meet each other frequently while some pairs of nodes meet each other very rarely and after long time intervals.

We also observed that Aggregate Total Encounter Count distributions (Minho trace in Figure 6a and Porto trace in Figure 6b) exhibit almost a power law distribution (scale free behavior) on different temporal intervals, meaning that distributions follow almost skewed trend [10] on different observation intervals (up to one year in Minho trace and up to 5 months in Porto trace). Similar behavior was observed for Aggregate Unique Encounter Count distributions. Also our observed characteristic, trend and behaviour of each connectivity property on both Minho and Porto traces are similar. For instance in both traces AICT follow truncated Power law and depicts similar trends over different observation periods.

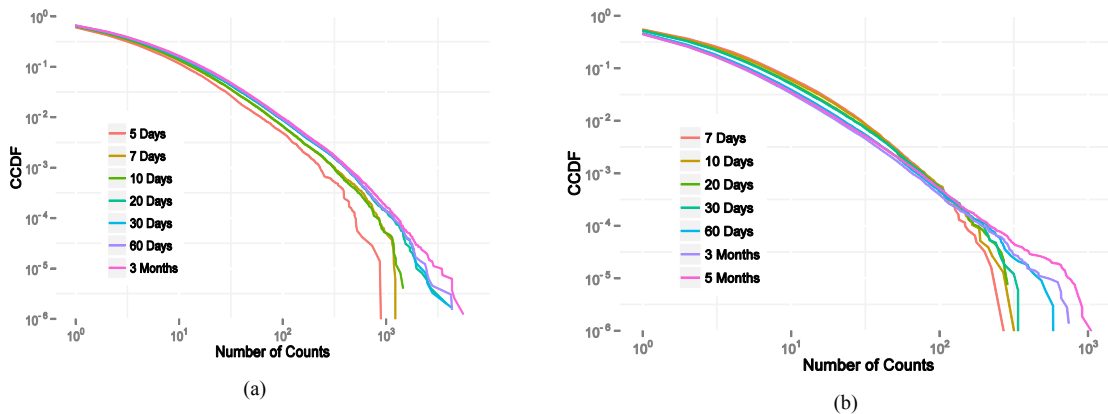


Fig. 6. Distribution of Total Encounter Counts for different observation periods: (a) Minho trace; (b) Porto trace.

5. Related Work

Mobile devices have become more and more ubiquitous and popular, and analyzing wireless networks formed over these devices is becoming an important research field. Since encounters between nodes provide communication opportunities in DTN and opportunistic networks, knowledge about node encounters' patterns, their characteristics extracted from collected data traces is important for designing DTNs. These patterns can be uncovered by analyzing trends and statistics of encounters. The majority of works on empirical analysis of node encounters [9,10] are focused on extracting patterns and regularity of encounters without fundamental analyzing the role of spatio-temporal scale behavior of these encounters. Human mobility occurs on variety of spatio-temporal scales, ranging from short distance to long-range travel by airplanes and involves different mode of transportation. Human spatial mobility properties have been studied in different scales, continent and country scale [3,20], city scale [4], regional scale [1,5] and much finer scale such as campus and building scale [6,7]. For instance, Bin Jiang in [20] explores human mobility patterns based on massive tracking data of US flights. He found that travel length exhibits an exponential distribution rather than a power law with exponential cut off. This result indicates that the distribution is exponential for travel lengths less than 9000 km, whereas it is a power law for travel lengths greater than 9000 km. Although we see various studies of spatial properties of human mobility over wide range, as far as we know there isn't fundamental study to propose connectivity properties of human mobility model on different temporal scales.

Hui et al. [15] has shown that the duration of contact times among pedestrians follows an approximate power-law distribution. Also in several studies [12,13,14] it has been observed that AICT for pedestrians are distributed according to a power law with a final exponential cut-off over a range of values from a few minutes to half a day. Comparing these works and our extracted results, we can say that AICT distributions follow truncated power law distributions over a very wider range (up to several months).

In this paper we studied the characteristics of connectivity properties of node encounters on different temporal scales. By our knowledge this is the first study of behaviours of connectivity properties of node encounters over different and wide temporal scales with such large number of mobile nodes. Our observations depict that most of connectivity properties of node encounters do not show scale free (self-similarity) behaviour except Unique and Total Encounter counts.

6. Conclusions and Future Work

In this paper we discussed connectivity properties of node encounters extracted from Wi-Fi traces. We observed that although the distributions of different connectivity properties of node encounters over different time intervals follow the same trends (although slopes and exponential decaying rates may be different in different time intervals), except Unique and Total Encounter Counts, others do not show scale free behaviors over different observation intervals. It suggests that connectivity properties of node encounters are not scale free (self-similar) on the temporal dimension. Also observed characteristic and behavior of each connectivity property in both Minho and Porto traces are similar.

One reason for this non-scale free behavior may be is that CT and ICT aren't stationary process and are non-stationary process and as result are time variant. Definitely CT and ICT among mobile nodes in different times of the day are different. We don't expect to have long CT during night hours while ICT is longer during night and we expect that be shorter during day hours since during day this is more probable that people meet each other more frequently. In this sense may be diffusion of date in opportunistic network can be considered as non-stationary process.

As future work, due to the importance of individual pair ICT among encounters for estimation of message delivery in opportunistic networks, and knowing that in heterogeneous network AICT is not representative of pairwise ICT [21], we plan to study the connectivity properties of encounters at pairwise level over different

temporal scales. Also as future work, perhaps, it may be interesting to investigate whether periodic node encounters forms/maintains a small-world structure [10].

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References

- [1] M. Gonzalez, C. Hidalgo, A. Barabasi, “Understanding individual human mobility patterns”, in *Nature* 453 (7196)-2008.
- [2] A. Chaintreau, P. Hui, J. Crowcroft, C. Diot, R. Gass, J. Scott, “Impact of human mobility on opportunistic forwarding algorithms,” in *IEEE Transactions on Mobile Computing* , 2007.
- [3] Duygu Balcan, Vittoria Colizza et al, “Multiscale mobility networks and the spatial spreading of infectious diseases,” *PNAS*, 2009.
- [4] Richard A. Becker et al. “Human mobility characterization from cellular network data,” *Communications of the ACM*, January 2013.
- [5] Amos Maritan Albert-Laszlo Barabasi, Marta C. Gonzalez, Filippo Simini, “A universal model for mobility and migration patterns,” *Nature*, 2012.
- [6] Ming Zhao et al, “Empirical study on human mobility for mobile wireless networks,” *Military Communications Conference, MILCOM IEEE*, November 2008.
- [7] Franck Legendre Thrasyvoulos Spyropoulos, Theus Hossmann, “A complex network analysis of human mobility,” 3rd *IEEE International Workshop on Network Science for Communication Networks*, April 2011.
- [8] Nicola Scafetta, “Understanding the complexity of the Levy –Walk nature of human mobility with a multi-scale cost/benefit model,” in *Chaos ,an interdisciplinary Journal of Nonlinear Science*, 2011.
- [9] Wei-jen Hsu and Ahmed Helmy, “On Nodal Encounter Patterns in Wireless LAN Traces”, in *IEEE Transaction on Mobile Computing* , Vol 9, No.11, Nov 2010.
- [10] Gautam S. Thakur, Udayan Kumar, Ahmed Helmy, Wei-Jen Hsu, “Analysis of Spatio-Temporal Preferences and Encounter Statistics for DTN Performance”, 7th *International Wireless Communications and Mobile Computing Conference, Istanbul, Turkey*, 2011.
- [11] Minkyong Kim, David Kotz, Songkuk Kim, “Extracting a mobility model from real user traces”, *INFOCOM 2006, 25th IEEE Conference on Computer Communications, Spain*, 2006.
- [12] Andrea Passarella and Marco Conti, “Characterizing aggregate inter-contact times in heterogeneous opportunistic networks”, in *Proceedings of the 10th International IFIP TC 6 conference on networking*, 2011.
- [13] Dmytro Karamshuk, Chiara Boldrini, Marco Conti and Andrea Passarella, “Human Mobility Models in Opportunistic Networks”, in *IEEE Communications Magazine*, December 2011.
- [14] Karagiannis, T., Le Boudec, J. Y. and Vojnovic, M, “Power Law and Exponential Decay of Inter-contact Times between Mobile Devices,” in *IEEE Transactions on Mobile Computing* , Vol. 9, 2010.
- [15] A. Chaintreau, P. Hui, J. Crowcroft, C. Diot, R. Gass, J. Scott, “Impact of human mobility on opportunistic forwarding algorithms,” in *IEEE Transactions on Mobile Computing* , 2007.
- [16] Elizabeth M.Daly and Mads Haar, “Social Network Analysis for information flow in disconnected Delay-Tolerant Manets,” *IEEE TRANSACTIONS ON MOBILE COMPUTING*, May 2009.
- [17] Michael Mitzenmacher, “A Brief History of Generative Models for Power Law and Lognormal Distributions ,” in *Internet Mathematics*.
- [18] Network Science, BarabásiLab, <http://barabasilab.neu.edu/networksciencebook/downloadPDF.html> (visited July 2014).
- [19] Albert Barabasi and Eric Bonabeau, “Scale Free Networks”, *Scientific American*, 2003
- [20] Bin Jiang and Tao Jia, “Exploring Human Mobility Patterns Based on Location Information of US flights,” In *Proceedings of CoRR*. 2011.
- [21] Vania Conan, Jeremie Leguay, Timur Fridman, “Characterizing Pairwise Inter-Contact Patterns in Delay Tolerant Networks,” in *Proceedings of the 1st international conference on Autonomic computing and communication systems, Belgium*, 2007.