On Investigating Social Dynamics in Tactical Opportunistic Mobile Networks

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ABSTRACT

The efficiency of military mobile network operations at the tactical edge is challenging due to the practical Disconnected, Intermittent, and Limited (DIL) environments at the tactical edge which make it hard to maintain persistent end-to-end wireless network connectivity. Opportunistic mobile networks are hence devised to depict such tactical networking scenarios. Social relations among warfighters in tactical opportunistic mobile networks are implicitly represented by their opportunistic contacts via short-range radios, but were inappropriately considered as stationary over time by the conventional wisdom. In this paper, we develop analytical models to probabilistically investigate the temporal dynamics of this social relationship, which is critical to efficient mobile communication in the battlespace. We propose to formulate such dynamics by developing various sociological metrics, including centrality and community, with respect to the opportunistic mobile network contexts. These metrics investigate social dynamics based on the experimentally validated skewness of users' transient contact distributions over time.

1. INTRODUCTION

While mobile networking at the tactical edge have received much attention, such as the Army's Warfighter Information Network - Tactical (WIN-T)[2] and DARPA's Content-Based Mobile Edge Networking (CBMEN) program,[1] they are based on the traditional Mobile Ad-Hoc Networks (MANETs) and assume end-to-end wireless connectivity between warfighters. Such connectivity, however, is usually not the case in practical Disconnected, Intermittent, and Limited (DIL) environments at the tactical edge.[37,38] The environmental dynamics and warfighter mobility in such environments lead to opportunistic and intermittent network disconnection, and warfighters can only communicate when they move into the communication range of others' wireless radios, referred to as *contact*. The delay for MANET reconfiguration against these disconnections would be seriously amplified and MANET routing protocols would even fail due to the unavailability of end-to-end routes.

Opportunistic Mobile Networks, also known as Delay/Disruption Tolerant Networks (DTNs),[16] consist of mobile devices which are connected only intermittently when they opportunistically contact each other, i.e., move into the communication range of their short-range radios (e.g., Bluetooth, WiFi). Such intermittent network connectivity can be a result of mobility, device sparsity or power outage. Opportunistic mobile networks, therefore, reflect the actual DIL network scenarios of military operations at the tactical edge.[37,38] To deal with the lack of end-to-end network connectivity, researchers adopt the idea of "carry-and-forward":[33] a node carries data when no route to the destination exists, and later forwards data to another node (relay) upon contacts. However, they are limited to fixed relay selection strategies according to the offline network configurations. When warfighters in the theater encounter dynamic situational changes, they fail to adapt accordingly and impair the situational awareness.

The key to realize such adaptability is that the mobile communication networks and human social networks in DIL environments are closely coupled, and the network communication opportunities and network design choices are determined by the warfighters' behavior patterns, i.e., their contact processes. Such patterns need to be timely and precisely investigated, so as to predict warfighters' communication needs in the future and adapt accordingly. Traditional solutions have been myopic in that they predict warfighters' contacts from their physical mobility patterns, which are random and inaccurate. They have minimal explorations into the social behavior patterns of warfighters, which are more accurate and essential to understanding their contact processes. A social-aware perspective of mobile networking at the tactical edge, therefore, is much more than simply eliminating the randomness of warfighters' physical mobility, but to fundamentally improve our understanding about how we could adapt the military communication strategies to better support the tactical operations.

In this paper, we propose to consider the social relationship between warfighters as dynamic and implicitly represented by their contact processes, and develop algorithms investigating and exploiting the characteristics of such social dynamics among warfighters in opportunistic mobile networks. More specifically, we investigate such social dynamics via formulation and calculation of various sociological metrics in mobile network scenarios. These concepts include: i) *centrality*: the social importance of users' facilitating communication among other users; ii) *community*: users are formed into groups according to their social relations.

The rest of this paper is organized as follows. Section 2 briefly reviews the related work. Section 3 presents our experimental investigation results of the transient contact patterns among mobile users during different short time periods. Section 4 and 5 then present details about our proposed approach to investigation of social dynamics among mobile users. Section 6 concludes the paper.

2. RELATED WORK

The research on data forwarding in opportunistic mobile networks originates from Epidemic routing[42] which floods the entire network. Later studies develop data forwarding strategies to approach the performance of Epidemic routing with lower forwarding cost, which is measured by the number of data copies created in the network. While the most conservative approach[40] always keeps a single data copy and Spray-and-Wait[41] holds a fixed number of data copies, most schemes leave such numbers as dynamic and make data forwarding decision by comparing the nodes' utility functions. Representative strategies include Compare-and-Forward,[11,13] Delegation[14] and Spray-and-Focus,[39] which were exploited when studying forwarding redundancy in this paper.

The utility functions of mobile nodes, which measure the nodes' contact capabilities, are generally independent from the data forwarding strategies mentioned above. Various utility functions can be applied to the same forwarding strategy for different performance requirements. Some schemes predict node contact capability by estimating their co-location probabilities in different ways, such as the Kalman filter[8] and semi-Markov chains.[43] In some other schemes, node contact pattern is exploited as abstraction of node mobility pattern for better prediction accuracy, based on the experimental[5,23] and theoretical[4] analysis on the node contact characteristics. The nodes' capability of contacting others in the future can be predicted based on their cumulative contact records in the past. MaxProp[3] estimates the node contact likelihood based on the contact counts in the past, and PodNet[25] forwards data to nodes based on their received data queries in the past.

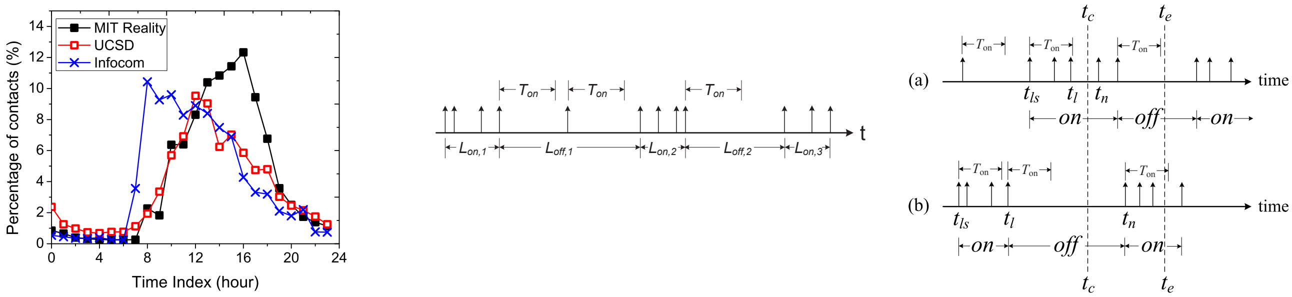
Social properties of human mobility including centrality and community structures are also exploited for forwarding messages.[18,21] SimBet[9] uses ego-centric betweenness as relay selection metric, and BUBBLE Rap[21] considers node centrality hierarchically in social community structures. Gao et al.[18] exploited both centrality and social communities for multicasting, and proposed Cumulative Contact Probability (CCP) as the utility function for data forwarding based on the cumulative node contact rates and the assumption of exponential distribution of pairwise node inter-contact time. Such CCP metric was also used in this paper.[17] furthermore extends CCP to the multi-hop network scope.

Social community structure in opportunistic mobile networks, on the other hand, is usually used to determine the network scope for evaluating node centrality, and can be detected in a fully distributed manner in various ways.[22] k-clique-based[32] method enables the detection of overlapping communities, and modularity-based method[29] works on weighted network contact graph. Based on such community detection techniques, BUBBLE Rap[21] exploited social community structures for data forwarding in opportunistic mobile networks based on the cumulative node contact characteristics. Node centrality is evaluated at various network scopes according to the community boundary of the destination, and data is hence forwarded in a hierarchical manner.

3. TRANSIENT CONTACT PATTERNS

Our investigation of social dynamics in opportunistic mobile networks is mainly motivated by the temporal heterogeneity of user contact patterns over time. Conventional wisdom suggests that user contacts are homogeneously distributed over time and the contact characteristics can be depicted by the cumulative distribution of pairwise inter-contact times (ICTs), which is either exponential or power-law.[4,5,23,44] A user could simply predict its contacts with another user in the future by estimating their next ICT, based on their maintained contact history in the past.

However, our studies over realistic opportunistic mobile network traces collected at university campus (MIT Reality,[12] UCSD[28]) and conference site (Infocom[5]) observe that the characteristics of user contacts are practically heterogeneous



(a) Skewed contact distributions over time (b) Alternative appearance of on-periods and off-periods (c) Cases of contact prediction

Figure 1. Transient user contact patterns

over time and differentiated by their occurrence *time* and *location*. For example, as shown by Figure 1(a), over 50% of user contacts in the MIT Reality trace happen between 12PM to 4PM at a daily basis, while only 7% of contacts are observed between 10PM to 7AM.

The accuracy of contact prediction builds on appropriate formulation of transient user contact patterns. We formulate users' daily contact processes as alternative appearance of "on-periods" and "off-periods". As shown in Figure 1(b) where each arrow indicates a contact and $L_{\text{on},i}(L_{\text{off},i})$ denotes the length of the i-th on-period (off-period), on-periods and off-periods are divided based a ICT threshold (T_{on}), and an ICT longer than T_{on} indicates the beginning of an off-period. This formulation considers that most of contacts happens during on-periods with short ICTs, and only few contacts can be found during off-periods at random. We experimentally verified that the lengths of on-periods and off-periods follow Gaussian distribution, and are able to update the parameters of these distributions online.

Therefore, as shown in Figure 1(c), the next contact between two mobile users could only happen before the delay constraint t_e of data dissemination in one of the following two cases: *a)* the current time t_c is within an ongoing on-period, and *b)* t_c is within an ongoing off-period but the next on-period will start before t_e. The contact probability during the transient time period $[t_c, t_e)$ can then be computed based on the distributions of the on-period and off-period lengths, which are described by their Probability Density Functions (PDFs) $f_{\text{on}}(t)$ and $f_{\text{off}}(t)$, as follows:

$$\mathbb{P}(t_n \leq t_e) = \int_0^T p_t(t) f_{\text{on}}(t + t_c - t_{ls})dt + \int_0^T p_t(T - t) f_{\text{off}}(t + t_c - t_l)dt, \quad (1)$$

where t_n is the time when the next contact happens, $p_t(t)$ is the transient PDF of the ICT distribution during on-periods, and t_{ls} and t_l are the starting and ending times of the last on-period before t_c. The two terms in Eq. (1) correspond to the two cases of user contacts shown in Figure 1(c), respectively.

4. TRANSIENT CENTRALITY

Built on the above method of transient contact prediction, we first develop analytical centrality metrics which vary over time and describe the importance of a specific mobile user in facilitating communication among other users.

4.1 Problem Formulation

We formulate opportunistic contacts as a ***network contact graph (NCG)*** $G = (V, E)$, where the stochastic contact process between any two warfighters $i, j \in V$ is modeled as an edge $e_{ij} \in E$, named an *opportunistic link*. We define warfighters i, j as ***k-hop contacted neighbors*** if the length of the shortest path between i and j on NCG is $L(i, j) = k$, and the ***k-hop contacted neighborhood*** of a warfighter i on NCG as $\mathcal{N}_i^{(k)} = \{j | L(i, j) \leq k\}$. Note that, any user $i \in V$ can only obtain information about contacts within $\mathcal{N}_i^{(1)}$ via its own short-range radios, but can obtain such information in a larger scope by exchanging information with other users upon contacts.

4.2 Multi-hop Opportunistic Connectivity

We first formulate the multi-hop opportunistic communication between the contacted neighbors of a warfighter, by aggregating his contact characteristics over multiple opportunistic links. Existing research has been focused on formally exploring the topological features of NCG,[6,34,36] but has not explicitly investigated multi-hop communication through opportunistic links.

We defined a k-hop path on the NCG as an "opportunistic path", and the weight of a k-hop opportunistic path P_{AB} connecting users A and B with linkwise contact rates $\{\lambda_1, \lambda_2, ..., \lambda_k\}$ as the probability that data is transmitted from $A$to B via P_{AB} within time T. By assuming the ICTs on all opportunistic links as exponentially distributed, we computed such weight in[19] from the PDF convolutions of random variables indicating linkwise ICTs as

$$p_{AB}(T) = \int_0^T \sum_{i=1}^k a_i^{(k)} p_i(x)dx = \sum_{i=1}^k a_i^{(k)} \cdot (1 - e^{-\lambda_i T}), \tag{2}$$

where $p_i(x) = \lambda_i e^{-\lambda_i x}$ is the exponential PDF, and $a_i^{(k)} = \prod_{j=1, j\neq i}^k \frac{\lambda_j}{\lambda_j - \lambda_i}$.

We further take the transient user contact patterns into account. Intuitively, the temporal heterogeneity of contact patterns reduces an opportunistic path's communication capability, because data can only be transmitted through consecutive opportunistic links during the overlapping part of their on-periods. The more their on-periods overlap, the more likely the weight of an opportunistic path can still be evaluated using Eq. (2).

To determine such overlap, we will take the distribution of starting times of on-periods into account. For a k-hop opportunistic path with random variables t_s^i and L_i indicating the starting time and length of the on-period of its i-th opportunistic link, the cumulative on-period over all the k opportunistic links is $[X, Y]$, where $X = \max_i\{t_s^i\}$ and $Y = \min_i\{t_s^i + L_i\}$. The characteristics of X and Y are described by their PDFs as $f_X(x) = \prod_{i=1}^k f_s^{(i)}(x)$ and $f_Y(y) = 1 - \prod_{i=1}^k (1 - f_s^{(i)}(x) \otimes f_L^{(i)}(x))$, where $f_s^{(i)}(x)$ and $f_L^{(i)}(x)$ are the PDFs of t_s^i and L_i, and $\otimes$ indicates convolution between functions. We then convert $f_X(x)$ and $f_Y(y)$ to truncated distributions[10] within the given time period $[t_c, t_e)$ for data access.

Next, we convert the linkwise contact rates of an opportunistic path with respect to $[X, Y]$, so as to compute a lower bound of the communication capability provided by this path following Eq. (2). For an opportunistic link with an on-period $[x_o, y_o]$ and contact rate λ_o within $[x_o, y_o]$, its converted contact rate λ_c is determined by the difference between $[x_o, y_o]$ and $[X, Y]$. This difference could be efficiently measured in various ways, for example, the Kullback-Leibler (KL) divergence.[24]Since both x_o and y_o are random variables, we measure such difference using the Kullback-Leibler (KL) divergence, i.e., $\lambda_c = \lambda_o \cdot \exp(-(D_{KL}(f_X(x), f_{xo}(x)) + D_{KL}(f_Y(y), f_{yo}(y)))$, where $f_{xo}(x)$ and $f_{yo}(y)$ are the PDFs of x_o and y_o respectively, and

$$D_{KL}(f_X(x), f_{xo}(x)) = \int_{-\infty}^{\infty} \ln\left(\frac{f_X(x)}{f_{xo}(x)}\right) f_X(x)dx.$$

4.3 Centrality Metric Design

We develop a centrality metric in a probabilistic manner, such that the centrality value of a user i at time t is defined as

$$C_i^{(k)}(t) = \sum_{j \in \mathcal{N}_i^{(k)}} P_{ij}(t), \tag{3}$$

where the user i maintains the information about opportunistic paths to its k-hop contacted neighbors within $\mathcal{N}_i^{(k)}$, and $P_{ij}(t)$ indicates the weight of the opportunistic path between i and j. $C_i^{(k)}(t)$ hence indicates the expected number of warfighters within $\mathcal{N}_i^{(k)}$ whose communication would be facilitated by i at time t.

To verify the advantage of our centrality metric design, we compare our proposed metric with two baselines: *i)* the ego-centric betweenness metric,[15] and *ii)* the CCP centrality metric developed in our previous work[18] based on cumulative contact patterns. The evaluation is conducted through experiments of opportunistic data forwarding between random sources and destinations over the Infocom trace,[5] using Compare-and-Forward[11] as the relay selection strategy and different centrality metrics to evaluate the relays' utilities. Figure 2 shows that our proposed centrality metric significantly improves the data delivery ratio.

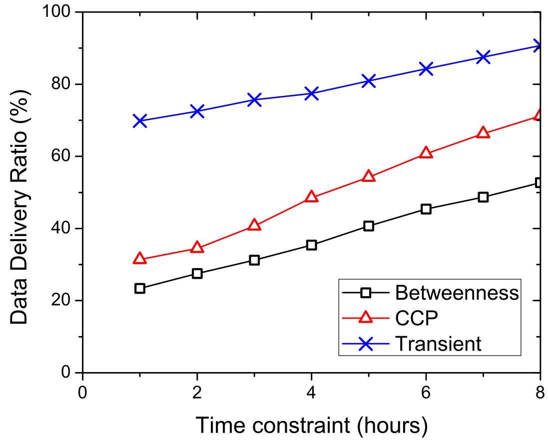
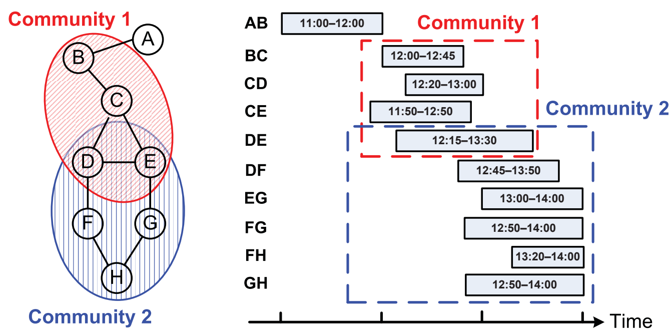


Figure 2. Comparison of data forwarding performance using different centrality metric designs



(a) (b)

Figure 3. Transient community characterization: (a) local view of the NCG, (b) community characterization based on similarity of on-periods.

Scope of centrality calculation. Centrality calculation in a larger network scope increases the effectiveness of characterizing the warfighters' social dynamics, at the cost of higher overhead of maintaining their contact information. As the future work, we propose to analytically study such tradeoff, and hence provide the military network operators with the flexibility to balance between them according to the specific network requirements. In particular, our proposed formal analysis will build on the spectral graph theory.[7] When the scope of centrality calculation increases from k to $k+1$, let T_k be the time needed for the k-hop contacted neighbors of a warfighter i to contact another $(k+1)$-hop contacted neighbor of i, we have

$$\mathbb{P}(T_k \leq t) \geq (1 - e^{sh_G t}), \tag{4}$$

where $s = |\mathcal{S}| = |\mathcal{N}_i^{(k+1)} \setminus \mathcal{N}_i^{(k)}|$, and h_G is the edge expansion[20] of $\mathcal{S}$. We will further substantiate this analysis by applying Eq. (4) to derive the lower bounds of centrality fluctuations and maintenance overhead when k changes. The tightness of these bounds will also be analytically investigated.

5. TRANSIENT COMMUNITY

Social dynamics among mobile users can also be characterized by their social communities, each of which consist of users that frequently contact each other. In this section, we investigate the impact of transient contact patterns on the social community structure among users, and further propose methods to analytically characterize such transient communities.

Conventional wisdom detected communities in weighted[29] and unweighted networks,[32,35] and considers communities as fixed over time. However, the communities in practical DIL environments is usually dynamic due to the heterogeneity of

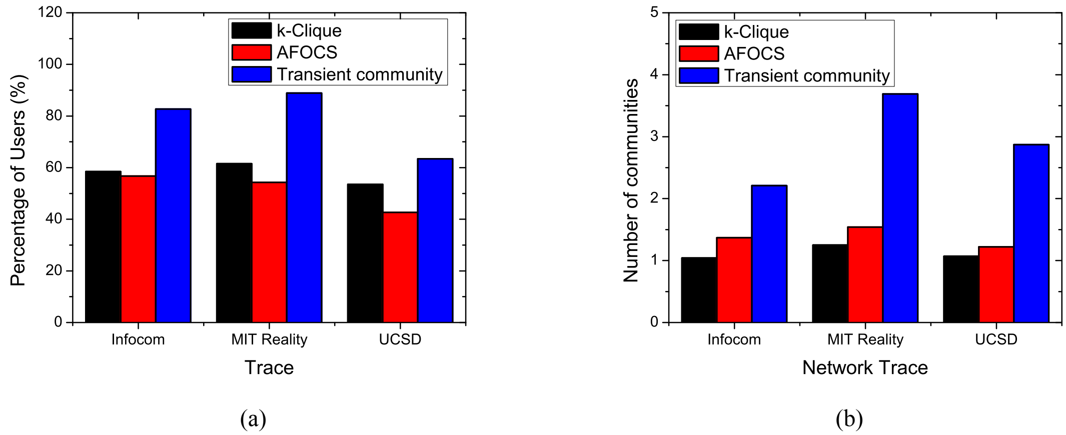


Figure 4. Evaluation of transient community characterization: (a) percentage of users involved in communities; (b) number of associated communities for each user

users' transient contact patterns, and a user may belong to different communities during different time periods. For example, a user may switch between multiple squads when executing different tactical missions. Ignorance of such community dynamics leads to *false mixture* and *false separation* of transient communities. First, two transient communities may be incorrectly mixed when their cumulative contact patterns are similar. Second, a transient community may be incorrectly divided if the NCG within the community is weakly connected. Recent research efforts[30,31] strive to capture the temporal community changes in mobile environments, but are only based on unweighted network snapshots and did not associate the community evolution with its time and location contexts. They are hence incapable of addressing the above problems.

Our developed approach, instead, aims to classify warfighters with the similar transient contact patterns together. For two pairs of warfighters with on-periods $\mathcal{T}_1 = [t_1^1, t_2^1]$ and $\mathcal{T}_2 = [t_1^2, t_2^2]$ respectively, we define their similarity using Jaccard index as

$$S(\mathcal{T}_1, \mathcal{T}_2) = \frac{|\mathcal{T}_1 \bigcap \mathcal{T}_2|}{|\mathcal{T}_1 \bigcup \mathcal{T}_2|}, \tag{5}$$

where $|\mathcal{T}|$ measures the length of a time period $\mathcal{T}$. Transient communities are then characterized by classifying pairs of warfighters with the distance measure specified in Eq. (5). In practice, since the starting and ending times of on-periods are random variables, it is non-trivial to calculate the similarity in Eq. (5). An intuitive calculation is to replace these random variables with deterministic values of their means, and we propose to further develop analytical methods to compute such similarity with respect to the probabilistic properties of $\mathcal{T}_1$ and $\mathcal{T}_2$. A viable approach is to study the probabilities of $t \in \mathcal{T}_1$ and $t \in \mathcal{T}_2$, where t is a random sample drawn from a uniform population.

Figure 4 demonstrated that our proposed approach could efficiently address the problems of false mixture and false separation. First, the two transient communities in Figure 4 could be correctly identified from their differences of transient contact patterns. Second, although user B is weakly connected to D and E only via C, our approach avoids the separation of Community 1 into two parts. To further evaluate the effectiveness of transient community characterization, we evaluate our approach against the existing community detection methods: k-clique[32] and AFOCS.[31] The results in Figure 4 show that our proposed method incorporates the majority of users into transient communities, and is also efficient to detect overlapping communities. Therefore, warfighters' transient associations to multiple communities can be precisely characterized.

Based on these results, we plan to further improve the effectiveness of transient community characterization by adopting the Bayesian non-parametric approach to the above classification algorithm, so as to address the over- and under-fitting problems of traditional parametric unsupervised learning algorithms such as k-means[26] or k-nearest-neighbor.[27]

6. CONCLUSIONS

In this paper, we present analytical algorithms and methods investigating the social dynamics among mobile users in tactical opportunistic mobile networks, which are implicitly represented by the opportunistic contact patterns among mobile users.

We develop quantitatively metrics formulating various sociological metrics including centrality and community, and in particular, their dynamic fluctuations over time. The effectiveness of such investigations has been validated via extensive trace-driven experiments. In the future, we plan to further develop adaptive mobile networking techniques based on such investigation and formulation of social dynamics in opportunistic mobile networks.

REFERENCES

[1] Darpa content-based mobile edge networking (cbmen). http://www.darpa.mil/Our_Work/STO/Programs/Content-Based_Mobile_Edge_Networking_(CBMEN).aspx.

[2] M. Acriche, C. Holsinger, A. Staikos, J. Dimarogonas, and R. Sonalkar. Multi-dimensional, assured, robust communications for an on-the-move network. In *Proceedings of the Military Communications Conference (MILCOM)*, pages 2378–2383, 2005.

[3] J. Burgess, B. Gallagher, D. Jensen, and B. Levine. Maxprop: Routing for vehicle-based disruption-tolerant networks. *Proc. INFOCOM*, 2006.

[4] H. Cai and D. Y. Eun. Crossing over the bounded domain: from exponential to power-law inter-meeting time in manet. *Proceedings of the 13th Annual International Conference on Mobile Computing and Networking (MobiCom)*, pages 159–170, 2007.

[5] A. Chaintreau, P. Hui, J. Crowcroft, C. Diot, R. Gass, and J. Scott. Impact of Human Mobility on Opportunistic Forwarding Algorithms. *IEEE Transactions on Mobile Computing*, 6(6):606–620, 2007.

[6] A. Chaintreau, A. Mtibaa, L. Massoulie, and C. Diot. The diameter of opportunistic mobile networks. In *Proceedings of the 3rd ACM International Conference on Emerging Networking Experiments and Technologies (CoNEXT)*, 2007.

[7] F. R. K. Chung. *Spectral graph theory*. American Mathematical Society, 1997.

[8] P. Costa, C. Mascolo, M. Musolesi, and G. Picco. Socially Aware Routing for Publish-Subscribe in Delay-Tolerant Mobile Ad Hoc Networks. *IEEE Journal on Selected Areas in Communications*, 26(5):748–760, 2008.

[9] E. Daly and M. Haahr. Social network analysis for routing in disconnected delay-tolerant MANETs. *Proc. MobiHoc*, 2007.

[10] Y. Dodge. *The Oxford dictionary of statistical terms*. Oxford University Press, 2006.

[11] H. Dubois-Ferriere, M. Grossglauser, and M. Vetterli. Age matters: efficient route discovery in mobile ad hoc networks using encounter ages. *Proceedings the 4th ACM Interational Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc)*, pages 257–266, 2003.

[12] N. Eagle and A. Pentland. Reality Mining: Sensing Complex Social Systems. *Personal and Ubiquitous Computing*, 10(4):255–268, 2006.

[13] V. Erramilli, A. Chaintreau, M. Crovella, and C. Diot. Diversity of Forwarding Paths in Pocket Switched Networks. In *Proceedings of Internet Measurement Conference (IMC)*, pages 161–174. ACM, 2007.

[14] V. Erramilli, M. Crovella, A. Chaintreau, and C. Diot. Delegation forwarding. In *Proceedings the 9th ACM Interational Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc)*, pages 251–260, 2008.

[15] M. Everett and S. Borgatti. Ego network betweenness. *Social Networks*, 27(1):31–38, 2005.

[16] K. Fall. A Delay-Tolerant Network Architecture for Challenged Internets. *Proc. SIGCOMM*, pages 27–34, 2003.

[17] W. Gao and G. Cao. User-centric data dissemination in disruption tolerant networks. In *Proceedings of INFOCOM*, 2011.

[18] W. Gao, Q. Li, B. Zhao, and G. Cao. Multicasting in delay tolerant networks: a social network perspective. In *Proceedings the 10th ACM Interational Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc)*, pages 299–308, 2009.

[19] W. Gao, Q. Li, B. Zhao, and G. Cao. Social-aware multicast in disruption-tolerant networks. *IEEE/ACM Transactions on Networking*, 20(5):1553–1566, 2012.

[20] S. Hoory, N. Linial, and A. Wigderson. Expander graphs and their applications. *Bulletin-American Mathematical Society*, 43(4):439–561, 2006.

[21] P. Hui, J. Crowcroft, and E. Yoneki. Bubble rap: social-based forwarding in delay tolerant networks. *Proceedings the 9th ACM Interational Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc)*, 2008.

[22] P. Hui, E. Yoneki, S. Chan, and J. Crowcroft. Distributed community detection in delay tolerant networks. *Proc. MobiArch*, 2007.

[23] T. Karagiannis, J.-Y. Boudec, and M. Vojnovic. Power law and exponential decay of inter contact times between mobile devices. *Proceedings of the 13th Annual International Conference on Mobile Computing and Networking (MobiCom)*, pages 183–194, 2007.

[24] S. Kullback and R. A. Leibler. On information and sufficiency. *The Annals of Mathematical Statistics*, 22(1):79–86, 1951.

[25] V. Lenders, G. Karlsson, and M. May. Wireless Ad hoc Podcasting. In *Proceedings of SECON*, pages 273–283, 2007.

[26] D. MacKay. An example inference task: Clustering. *Information Theory, Inference and Learning Algorithms*, pages 284–292, 2003.

[27] G. McLachlan and J. Wiley. *Discriminant Analysis and Statistical Pattern Recognition*, volume 5. Wiley Online Library, 1992.

[28] M. McNett and G. M. Voelker. Access and Mobility of Wireless PDA Users. *ACM SIGMOBILE CCR*, 9(2):40–55, 2005.

[29] M. Newman. Analysis of weighted networks. *Physical Review E*, 70(5), 2004.

[30] N. Nguyen, T. Dinh, Y. Xuan, and M. Thai. Adaptive algorithms for detecting community structure in dynamic social networks. In *Proceedings of IEEE INFOCOM*, pages 2282–2290, 2011.

[31] N. P. Nguyen, T. N. Dinh, S. Tokala, and M. T. Thai. Overlapping communities in dynamic networks: Their detection and mobile applications. In *Proceedings of the 17th Annual International Conference on Mobile Computing and Networking (MobiCom)*, pages 85–96, 2011.

[32] G. Palla, I. Derényi, I. Farkas, and T. Vicsek. Uncovering the overlapping community structure of complex networks in nature and society. *Nature*, 435(7043):814–818, 2005.

[33] L. Pelusi, A. Passarella, and M. Conti. Opportunistic networking: Data forwarding in disconnected mobile ad hoc networks. *IEEE Communications Magazine*, 44(11):134–141, 2006.

[34] A. Picu and T. Spyropoulos. Distributed stochastic optimization in opportunistic networks: The case of optimal relay selection. In *Proceedings of the 5th ACM Workshop on Challenged Networks (CHANTS)*, pages 21–28, 2010.

[35] U. N. Raghavan, R. Albert, and S. Kumara. Near linear time algorithm to detect community structures in large-scale networks. *Physical Review E*, 76(3):036106, 2007.

[36] J. Reich and A. Chaintreau. The Age of Impatience: Optimal Replication Schemes for Opportunistic Networks. In *Proceedings of Proceedings of the 5th ACM International Conference on Emerging Networking Experiments and Technologies (CoNEXT)*, pages 85–96, 2009.

[37] K. Scott, T. Refaei, N. Trivedi, J. Trinh, and J. P. Macker. Robust communications for disconnected, intermittent, low-bandwidth (dil) environments. In *Proceedings of the Military Communications Conference*, pages 1009–1014, 2011.

[38] J. Sonnenberg. Disconnected, intermittent, limited (dil) communications management technical pattern. *Network Centric Operations Industry Consortium*, 2009.

[39] T. Spyropoulos, K. Psounis, and C. Raghavendra. Efficient routing in intermittently connected mobile networks: The multiple-copy case. *IEEE/ACM Transactions on Networking*, 16(1):77–90, 2008.

[40] T. Spyropoulos, K. Psounis, and C. Raghavendra. Efficient routing in intermittently connected mobile networks: The single-copy case. *IEEE/ACM Transactions on Networking*, 16(1):63–76, 2008.

[41] T. Spyropoulos, K. Psounis, and C. S. Raghavendra. Spray and wait: An efficient routing scheme for intermittently connected mobile networks. In *Proceedings of 2005 ACM SIGCOMM Workshop on Delay-Tolerant Networking*, pages 252–259, 2005.

[42] A. Vahdat and D. Becker. Epidemic routing for partially connected ad hoc networks. *Technical Report CS-200006, Duke University*, 2000.

[43] Q. Yuan, I. Cardei, and J. Wu. Predict and relay: an efficient routing in disruption-tolerant networks. In *Proceedings of the 10th ACM International Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc)*, pages 95–104, 2009.

[44] H. Zhu, L. Fu, G. Xue, Y. Zhu, M. Li, and L. M. Ni. Recognizing Exponential Inter-Contact Time in VANETs. In *Proceedings of INFOCOM*, 2010.