Exploiting Deployment Information for Social-Aware Contact Prediction At the Tactical Edge

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***Abstract*—In the practical Disconnected, Intermittent, and Limited-bandwidth (DIL) network environment at the tactical edge, warfighters have to be able to efficiently transmit data between each other to ensure rapid situational response to the surrounding environment. To tackle with the intermittent wireless network connectivity in the DIL environment, the "carry-and-forward" approach has been adopted to exploit warfighters' mobility and physically relay the data upon contacts with each other, but its performance relies on accurate prediction of warfighters' contacts with each other. In this paper, we present a novel probabilistic framework that is able to ensure accurate prediction of warfighters' contacts by considering both initial deployment information and in-situ contact patterns of warfighters at the tactical edge. Analytically models are developed to depict the characteristics of both aspects and are then integrated towards a Bayesian-based probabilistic inference framework. Evaluation results over practical DIL network traces show that our approach can dramatically increase the accuracy of contact prediction and further improve the performance of data forwarding in the DIL network environment at the tactical edge.**

I. Introduction

Mobile networking systems which do not rely on persistent wireless infrastructure are crucial for warfighters at the tactical edge to maintain their situational awareness and rapid response to the surrounding environments [2]. Being different from traditional tactical mobile networking systems such as the Army's Warfighter Information Network - Tactical (WIN-T) [3] and DARPA's Content-Based Mobile Edge Networking (CBMEN) program [1] that assume end-to-end wireless connectivity between warfighters [30], recent research efforts have been focusing on the practical Disconnected, Intermittent, and Limited-bandwidth (DIL) environments at the tactical edge [28], [27], which are also known as Disruption Tolerant Networks (DTNs) [10]. The environmental dynamics and warfighter mobility in such environments lead to opportunistic and intermittent network disconnection, and make it difficult to maintain end-to-end communication links or global network information. Instead, warfighters can only communicate when they move into the communication range of others' wireless radios, referred to as *contact*. More specifically, to forward data to a destination, researchers adopt the idea of "carry-and-forward" [26]: node mobility is exploited to let nodes physically carry data as relays, which forward data when they opportunistically contact others. The key problem is hence how to select the most appropriate relays with the best chance to contact the data destinations.

The key factor to ensuring the efficiency of data forwarding in the DIL tactical environment, therefore, is to accurately predict contacts between warfighters in the future. However, the accuracy of such contact prediction, in practice, could be affected by various factors such as irregularity of warfighter mobility and sporadic events in the theater. Instead, since social relations among warfighters are likely to have long-term characteristics and are less volatile than their mobility patterns, social-aware schemes have been proposed to improve the accuracy of contact prediction and performance of data forwarding. More specifically, various sociological metrics, including centrality [22] and community [19], have been formulated with respect to the DIL environments and then used as the metric for relay selection.

The major difficulty that impairs the accuracy of such social-aware contact prediction at the tactical edge, nevertheless, lies in the disconnection between the social relationship and contact patterns of warfighters. On one hand, social relationship among warfighters are initially assigned during the mission planning phase before their field deployment, in the form of tactical squads or mission teams. Such relationship, therefore, could be partially fixed at all times and independent from the warfighters' actual behaviors in the theater. On the other hand, after deployment, warfighters at the tactical edge may autonomously self-organize themselves in different ways, in response to the situational contexts in the battlefield. These dynamic changes of their social relationship, then, are implicitly reflected by their contact patterns and can be inferred with certain formalism of social network structures for contact prediction in the future. Existing social-aware contact prediction schemes [8], [15], [31], however, characterize the social relationship among warfighters solely from their in-situ contact patterns but ignore the prior knowledge of such social relationship before deployment. This ignorance will lead the results of contact prediction to deviate from the actual situation at the tactical edge, seriously impairing the performance of the mobile communication system.

In this paper, we propose to bridge this gap by proposing a probabilistic contact prediction framework that combines both deployment information about the initial social relationship among warfighters and the in-situ contact patterns of warfighters after deployment. Our basic approach is to combine these two aspects with a Bayesian-based probabilistic inference framework, and to depict the characteristics of both deployment information and contact patterns of warfighters using analytical models. In particular, both models will be developed in the temporal domain, and be able to reflect the temporal evolutions of the social relationship and contact patterns of warfighters over time. Our detailed contributions are listed as follows:

- We integrate the deployment information and in-situ contact patterns of warfighters at the tactical edge into a generic framework.
- Our framework quantitatively models the temporal evolution of the impact of the warfighters' deployment information on their social relationship over time.
- We implemented and evaluated our proposed framework of contact prediction over realistic DIL network traces, and demonstrated that it outperforms existing contact prediction schemes.

The rest of this paper is organized as follows. In Section II we review the existing work and motivates our proposed work. Section III provides a high-level overview of our proposed framework for contact prediction. Sections IV and V describe the technical details of our design on exploiting deployment information at the tactical edge. Section VI presents the results of performance evaluation over various DIL network traces. Section VII finally concludes the paper.

II. Related Work

In DTNs, the relay selection metrics generally evaluate the capability of a mobile node to forward data to the specified destinations by contacting these destinations. Some schemes predict such capability by estimating the co-location probabilities of mobile nodes based on their mobility patterns in different ways, such as the Kalman filter [7], semi-Markov chains [32], and Hidden Markov Models [12]. More specifically, [33] employs some nodes with desirable mobility patterns as message ferries, and [6] analyzes the performance of such mobility-assisted schemes theoretically.

Since node mobility patterns are highly volatile and difficult to characterize or predict, node contact process [18] is also exploited, as abstraction of node mobility, to calculate relay selection metrics. More specifically, the nodes' capability of contacting others in the future is predicted, based on their cumulative contact records from the past. Based on the experimental [6], [21] and theoretical [5] analysis of node contact characteristics, relay selection metrics have been proposed to estimate node contact probability in the future [4], [13]. However, these metrics provide only simple heuristics for selecting relays without performance guarantee. In addition, since the modeling of nodes' contact patterns may not be strictly followed in practice, the accuracy contact prediction based on such modeling will be seriously impaired in cases of highly dynamic behaviors of mobile nodes.

Node contact process can also be exploited for contact prediction from a social network perspective. Most schemes exploit sociological centrality metrics [22] for relay selections. Various metrics have been proposed to evaluate node centrality. In SimBet [8] and BUBBLE Rap [19], betweenness [11] is used as the centrality metric which measures the social importance of a node facilitating the communication among other nodes. [16] propose Cumulative Contact Probability (CCP) as the centrality metric based on the cumulative node contact rates and the assumption of exponential distribution of pairwise node inter-contact time. [14] furthermore extends CCP to the multi-hop network scope. Social community structure in DTNs, 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 [20]. k-clique-based [25] method enables the detection of overlapping communities, and modularity-based method [24] works on weighted network contact graph. Based on such community detection techniques, BUBBLE Rap [19] exploited social community structures for data forwarding in DTNs 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.

However, all the existing schemes above are limited to predicting node contacts based on their contact records in the past, and exclude the prior information about the social relationship among mobile nodes into account. As a result, the social-aware contact prediction can only be conducted following the predefined formulation of social network structure among mobile nodes in the theater, and would suffer serious degradation of accuracy when the actual social relationship among these nodes deviates from such formulation. On the other hand, when such social relationship is unexpectedly changed by sporadic events during the network execution, these existing schemes will be unable to adapt to such unexpected changes and will mostly likely fail.

III. A Bayesian Framework for Contact Prediction

In this section, we introduce the high-level design of our framework of contact prediction, which take both prior information about the social relationship among warfighters during the deployment phase and the in-situ contact patterns of warfighters into account. Generally speaking, two warfighters are more likely to contact each other in the theater if they are socially correlated, e.g., belonging to the same tactical squad. By the time of initial deployment, warfighters' social relationship are only determined by their tactical missions and are fixed. As time elapses afterwards, social dynamics among warfighters, which are resulted from the situational battlefield changes, become the dominant factor determining warfighters' contact patterns and should be used more for contact prediction.

Hence, our basic idea of incorporating the deployment information into the contact prediction process is to further extend the traditional contact prediction method towards a Bayesian framework, such that

$$\mathbb{P}(X_t|Y_t) = \frac{\mathbb{P}(Y_t|X_t) \cdot \mathbb{P}(X_t)}{\mathbb{P}(Y_t)}, \tag{1}$$

where X_t indicates the event that two warfighters contact each other at time t, and Y_t indicates that the two warfighters are socially correlated at time t. Based on this formulation, the posterior contact probability $\mathbb{P}(X_t|Y_t)$ is determined by the following three factors:

- The *prior contact probability* $\mathbb{P}(X_t)$. The prior contact probability is solely calculated from the recorded contact patterns between warfighters in the past. For example, by assuming that the pairwise inter-contact times (ICTs) between two warfighters follow a certain probabilistic distribution, such probability can be calculated by estimating the next ICT as a random variable. In this paper, we refer to the existing research literature to compute such probability.
- The *marginal likelihood* $\mathbb{P}(Y_t)$. The marginal likelihood evaluates the chance for two warfighters to be socially correlated with each other after their initial deployment, and is solely determined by the deployment information about warfighters' tactical missions, squad formations, cooperation plan, etc. We will develop models to further quantify the temporal variations of such marginal likelihood after initial deployment of warfighters.
- The *observational probability* $\mathbb{P}(Y_t|X_t)$. The observational probability evaluates the causality between contacts and social relationship among warfighters. More specifically, when two warfighters have been observed to contact each other, the chance for them to be socially related is determined by the social network structure. We will develop quantitative methods to depict such causality.

IV. Modeling of Deployment Information

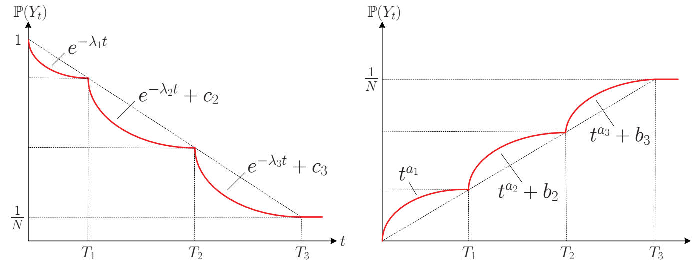
In this section, we present our models depicting the characteristics of warfighters' deployment information that determines their initial social relationship.

A. Temporal Evolution

Principally, we model the temporal evolution of $\mathbb{P}(Y_t)$ as a piecewise function that is segmented by the tactical missions being received by the warfighters before they are deployed to the tactical edge. By the time of initial deployment, whether two warfighters are socially correlated is solely determined by the tactical mission plan, no matter whether they will contact each other in the theater. Afterwards when time elapses, the impact of initial deployment on the social relationship between warfighters decreases over time, reflected by the change of the value of $\mathbb{P}(Y_t)$ over time.

Our modeling is illustrated in detail by Figure 1, where T_i indicates the starting time of the i-th tactical mission being assigned to warfighters, and N is the number of nodes in the network. When the deployment information indicates that two warfighters are socially related by the time of deployment, we have $\mathbb{P}(Y_0) = 1$. Afterwards, as shown in Figure 1(a), the probability for these two warfighters to retain such social relationship decreases over time, and converges to $1/N$ by the time when all the initial tactical missions have been completed. The specific characteristics of such decrease, then, vary during different missions and can be depicted by separate functions. More specifically, we adopt exponential distributions for describing these characteristics, such that

$$f_i(t) = e^{-\lambda_i t} + c_i, \tag{2}$$



(a) Deployment: socially related (b) Deployment: socially unrelated

Fig. 1. Temporal variation of the impact of deployment information on the social relationship between warfighters

whose parameters λ_i and c_i could be easily computed based on the fixed values of $f_i(t)$ at the boundary of the corresponding tactical mission.

Otherwise, when the two warfighters are not socially related by the time of deployment, we have $\mathbb{P}(Y_0) = 0$. Afterwards, as shown in Figure 1(b), $\mathbb{P}(Y_t)$ increases over time and converges at $1/N$ by the completion of tactical missions. Being similar with the previous case, we also depict the characteristics of such increase using stepwise functions, such that

$$g_i(t) = t_i^a + b_i. \tag{3}$$

Such modeling of deployment information, essentially, considers that the warfighters may encounter various types of situational dynamics and sporadic events after being deployed at the tactical edge, and the amount of such unexpected contexts in the battlefield may increase over time and have more significant impacts on the social relationship among warfighters. As a result, as time elapses, the impact of deployment information on the social relationship among warfighters diminishes, reflected by the value of $\mathbb{P}(Y_t)$ being deviated from its initial value.

B. In-field Mission Changes

Our model is also able to depict the in-field changes of tactical missions, which may be delivered to warfighters via long-haul wireless communication links or other communication vehicles during their operations. When a new tactical mission is assigned to squads at the tactical edge at time T ($T_{i-1} < T < T_i$), it will basically reset the value of $\mathbb{P}(Y_t)$ to one of its initial values (0 or 1), depending on the social relationship between warfighters being defined by the new mission. Afterwards, the temporal variation of $\mathbb{P}(Y_t)$ will be recomputed with the new set of tactical missions, following the same method that we have described in Section IV-A.

V. Causality Analysis

In this section, we present our formulation on the observational probability $\mathbb{P}(Y_t|X_t)$, which indicates the causality between the social relationship and contact patterns of warfighters and play a vital role in contact prediction as described in Eq. (1). Our basic idea of this formulation is to exploit the existing sociological concepts, including centrality and community, to quantify the probability for two warfighters who contact each other to be socially correlated. More specifically, when both centrality values and community structures of warfighters are inferred from their contact patterns [17], [19], [15], we observe that two warfighters with high centrality are more likely to be socially correlated if they are at the same community. On the other hand, two warfighters are unlikely to be socially correlated if they are in different communities.

Based on this observation, when two warfighters A and B are at the same community, we define the observation probability between these two warfighters as

$$\mathbb{P}(Y_t|X_t) = \frac{C_A}{N} \cdot \frac{C_B}{N}, \tag{4}$$

where N is the number of nodes in the community where A and B belong to, and C_A and C_B are the centrality values of A and B, respectively. In practice, the centrality value of a warfighter is usually proportional to the size of the community it belongs to. For example, betweenness measures the number of geodesic paths connecting other nodes in the community that have to pass through the specific warfighter, and hence has a higher value in a large community. Similarly, CCP [17] evaluates the average probability for other nodes to contact the specific warfighter. On the other hand, we simply define $\mathbb{P}(Y_t|X_t) = 0$ if warfighters belong to different communities.

In practice, the knowledge about social community structure among warfighters can be efficiently obtained from the deployment information, in form of tactical squad formation or warfighter locations in a specific target area. Based on such knowledge, we are able to efficiently identify warfighters community membership at real-time and then measure their centrality values within the appropriate scope. Hence, we ensure that the observational probability is correctly calculated.

VI. Performance Evaluation

In this section, we evaluate the performance of our proposed contact prediction framework over multiple sets realistic DIL network traces. As described by Table I, these traces collect contacts among mobile users at university campus (MIT Reality [9], UCSD [23]) and conference site (Infocom [6]). We will compare the accuracy of our contact prediction framework with multiple existing schemes in different application settings over these traces.

TABLE I
Trace summary

Trace	MIT Reality	UCSD	Infocom
Network type	Bluetooth	WiFi	Bluetooth
Number of devices	97	275	78
Number of internal contacts	114,046	123,225	182,951
Duration (days)	246	77	4
Contact detection period (secs)	120	20	120
Pairwise contact freq. (per day)	4.6	0.024	7.52
Average contact duration (hours)	0.57	10.45	0.142
Average pairwise inter-contact time (hours)	84.13	47.17	1.883

A. Experiment Setup

The key challenge of conducting the experiments is to establish the knowledge about the initial social relationship among mobile nodes in the network. In our experiments, we exploit the background information about mobile nodes that is included as the demographic data in different traces to emulate the deployment information about the initial social relationship among these nodes. First, the MIT Reality trace is collected from the faculty and students in the MIT Media lab, and hence contains the social relationship among the participants based on their research teams. Second, the Infocom trace consists of attendants to the Infocom conference, whose relationship can be characterized by analyzing their academic profiles. Last, the UCSD trace records the WiFi affiliations of college students during different time periods in their residence halls, and the social relationship among these students can hence be inferred by investigating their dormitories.

Based on such knowledge, we are able to compute the marginal likelihood $\mathbb{P}(Y_t)$ using the method being described in IV, using different time periods of a day (i.e., 24 hours) to emulate different tactical missions. Furthermore, we exploit our previous work, which formulates the transient contact patterns during different short time periods between mobile nodes, to compute the prior contact probability $\mathbb{P}(X_t)$, and exploit both egocentric between centrality to compute the observational probability $\mathbb{P}(Y_t|X_t)$.

We compare our contact prediction framework with the following existing schemes:

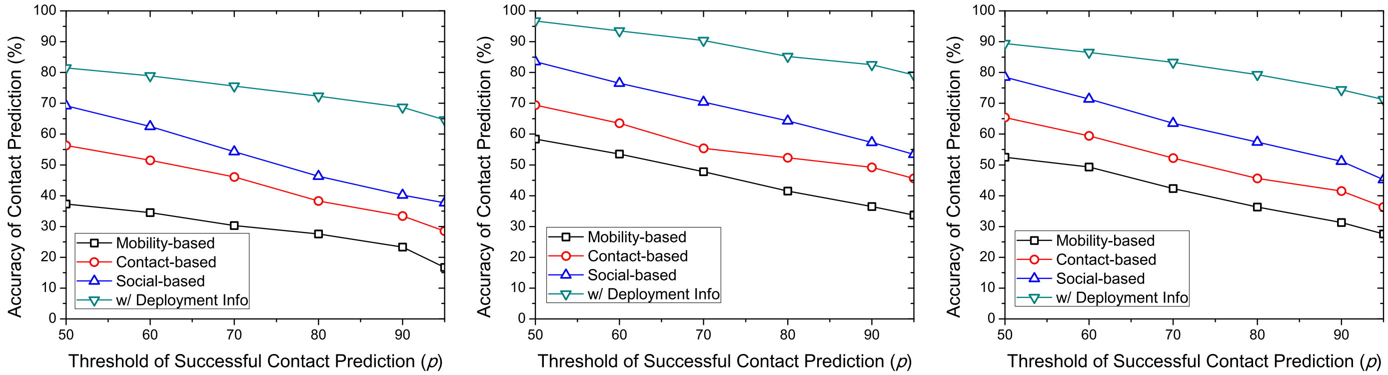
- Mobility-based prediction [12]: Contacts between mobile nodes are predicted by characterizing their mobility patterns. Two nodes are considered to contact each other when they move into the communication range of each other.
- Contact-based prediction [17]: Contact patterns between each pair of mobile nodes are formulated as a homogeneous Poisson process. Future contacts are the predicted by estimating the next inter-contact time between mobile nodes.
- Social-based prediction [8]: Future contacts are predicted according to the betweenness centrality of different mobile nodes.

In our experiments, we use the first half of the trace to estimate the parameters of different contact prediction frameworks, and then use the second half of the trace to evaluate the accuracy of contact prediction. For each contact happened at time t, if the estimated probability of contact occurrence at t is higher than p%, we consider that this contact has been successfully predicted. We evaluate the accuracy of contact prediction with different values of p.

B. Accuracy of Contact Prediction

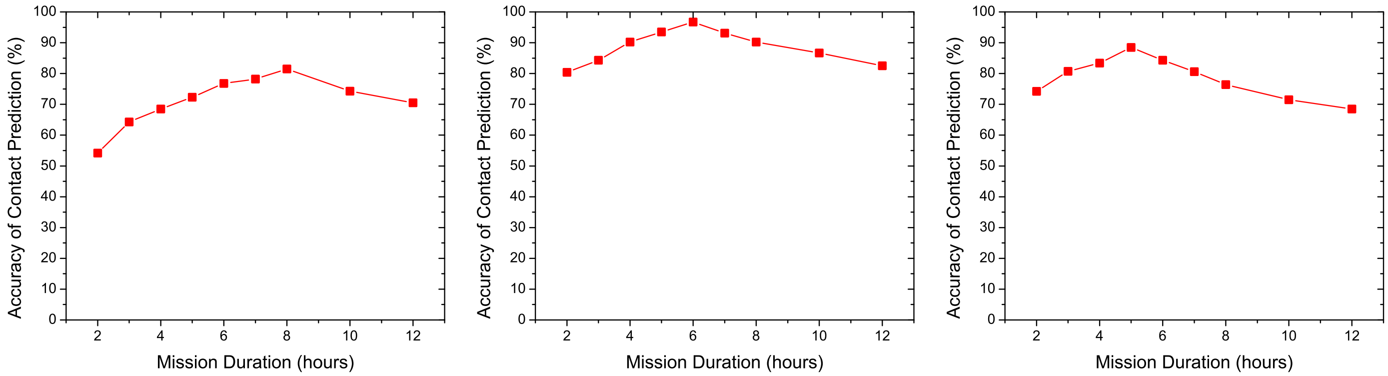
We first evaluate the accuracy of our contact prediction framework, in comparison with other existing contact prediction methods, over different sets of DIL network traces. The evaluation results with different thresholds for determining successful contact prediction (reflected by the value of p) are shown in Figure 2. Generally speaking, the accuracy of contact prediction is trace-dependent, and is mainly determined by the trace size and regularity of nodes' contact patterns in the trace. In smaller traces with more regular contact patterns such as Infocom, it is easier to precisely predict node contacts; while contact prediction will become more difficult if the network size grows and nodes behave more irregularly.

Nevertheless, in all traces, since our proposed contact prediction framework incorporates the deployment information



(a) MIT Reality (b) Infocom (c) UCSD

Fig. 2. Accuracy of contact prediction



(a) MIT Reality (b) Infocom (c) UCSD

Fig. 3. Impact of mission durations on the accuracy of contact prediction

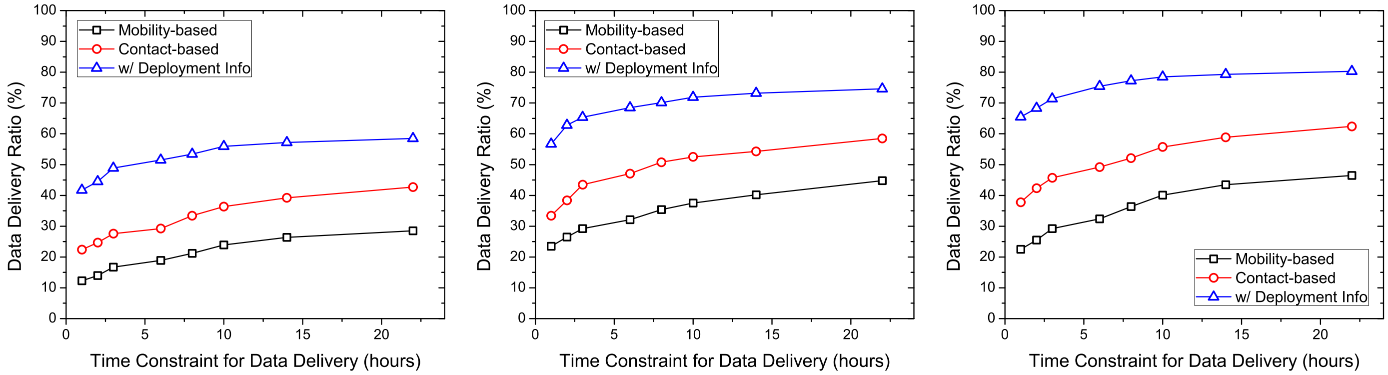
which contains the initial social relationship among mobile nodes in the network, it is able to reach a much higher accuracy of contact prediction compared to other existing schemes. More specifically, it is able to outperform the social-based contact prediction schemes by over 25%, and outperform the mobility-based contact prediction schemes by more than 40%. In particular, when the threshold for successful contact prediction increases and becomes more strict, the advantage of our proposed approach is more significant and could be up to 60%. The major reason for this difference is that higher threshold of contact prediction needs that the predicted time for contact occurrence to be more strictly aligned with the actual contact time, requiring more precise knowledge about social relationship and behavior patterns among mobile nodes.

Furthermore, since we use different time periods of a day to emulate different tactical missions, we also evaluated the impact of the different mission durations on the accuracy of contact prediction. The evaluation results are shown in Figure 3. If the duration of each mission is short, the social relationship among mobile nodes within each mission will relatively change faster, leading to higher extent of behavior dynamics of mobile nodes and lower accuracy of contact prediction. Afterwards, when the mission duration increases, such accuracy of contact prediction improves correspondingly by up to 30%. However, if the mission duration belongs too long, such accuracy drops again because the impact of deployment information has diminished before the mission completes. From Figure 3, we also note that the optimal mission duration that maximizes the accuracy of contact prediction varies over different sets of traces, depending on the specific social relationship and inter-contact times between mobile nodes in the network.

C. Improvement of Data Forwarding Performance

In this section, we further apply our proposed contact prediction framework for data forwarding in DIL network environment, and evaluate the impact of contact prediction accuracy on the performance of data forwarding that is measured by the data delivery ratio. In our experiments, we exploit the results of contact prediction to compute utilities for relay selection following the approach described in [17], and adopt Spray-and-Wait [29] as the data forwarding strategy. We vary the time constraint for data delivery to emulate different application scenarios in practical tactical edge.

The evaluation results are shown in Figure 4. Generally speaking, the data delivery ratio is also trace-dependent and determined by the average inter-contact times between mobile nodes. Shorter inter-contact times result in more contact opportunities in the unit amount of time, leading to a higher data delivery ratio. Since the utilities for relay selection measure the relays' chances of contacting the destinations, they directly correlate the performance of data forwarding to the accuracy of contact prediction. As shown in Figure 4, since our approach is able to significantly improve the accuracy of contact prediction, it is able to correspondingly improve the data delivery ratio by over 30%. In particular, when the time constraint for data delivery is short and requires higher accuracy for contact prediction, the improvement of data delivery ratio could be up to 50%.



(a) MIT Reality (b) Infocom (c) UCSD

Fig. 4. Performance of data forwarding with different methods of contact prediction

VII. Conclusion

In this paper, we present a novel framework for contact prediction in the DIL network environment at the tactical edge. Our basic idea of improving the accuracy of contact prediction is to incorporate the deployment information about warfighters' initial social relationship with each other into account, and to combine these deployment information with the warfighters' in-situ contact patterns for contact prediction. We have developed a Bayesian framework to quantitatively compute the contact probability with analytical modeling on the deployment information. The evaluation results over multiple sets of realistic DIL network traces show that our framework is able to dramatically increase the accuracy of contact prediction, further improving the performance of data forwarding in DIL network environments.

References

[1] DARPA content-based mobile edge networking (CBMEN).

[2] Recent campaigns benefited from improved communications and technology, but barriers to continued progress remain. *United States General Accounting Office (GAO) Report GAO-04-547*, 2004.

[3] 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 MILCOM*, 2005.

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

[5] H. Cai and D. Y. Eun. Crossing over the bounded domain: from exponential to power-law inter-meeting time in manet. *Proceedings of MobiCom*, 2007.

[6] 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.

[7] 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.

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

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

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

[11] L. Freeman. A set of measures of centrality based on betweenness. *Sociometry*, 40(1):35–41, 1977.

[12] W. Gao and G. Cao. Fine-Grained Mobility Characterization: Steady and Transient State Behaviors. In *Proceedings the 11th ACM Interational Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc)*, pages 61–70, 2010.

[13] W. Gao and G. Cao. On Exploiting Transient Contact Patterns for Data Forwarding in Delay Tolerant Networks. In *Proceedings of International Conference on Network Protocols (ICNP)*, pages 193–202, 2010.

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

[15] W. Gao, G. Cao, T. La Porta, and J. Han. On exploiting transient social contact patterns for data forwarding in delay tolerant networks. *IEEE Transactions on Mobile Computing*, 12(1):151–165, 2013.

[16] W. Gao, Q. Li, B. Zhao, and G. Cao. Multicasting in delay tolerant networks: a social network perspective. In *Proceedings of MobiHoc*, 2009.

[17] 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.

[18] W. Hsu and A. Helmy. On Nodal Encounter Patterns in Wireless LAN Traces. *IEEE Transactions on Mobile Computing*, 9(11):1563–1577, 2010.

[19] P. Hui, J. Crowcroft, and E. Yoneki. Bubble rap: social-based forwarding in delay tolerant networks. *Proceedings of MobiHoc*, 2008.

[20] P. Hui, E. Yoneki, S. Chan, and J. Crowcroft. Distributed community detection in delay tolerant networks. In *Proceedings of 2nd International Workshop on Mobility in the Evolving Internet Architecture*, 2007.

[21] T. Karagiannis, J.-Y. Boudec, and M. Vojnovic. Power law and exponential decay of inter contact times between mobile devices. *Proceedings of MobiCom*, 2007.

[22] P. V. Marsden. Egocentric and Sociocentric Measures of Network Centrality. *Social Networks*, 24(4):407–422, 2002.

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

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

[25] 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.

[26] 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.

[27] K. Scott, T. Refaei, N. Trivedi, J. Trinh, and J. P. Macker. Robust communications for disconnected, intermittent, low-bandwidth (DIL) environments. In *Proceedings of MILCOM*, 2011.

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

[29] 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.

[30] S. Taneja and A. Kush. A survey of routing protocols in mobile ad hoc networks. *International Journal of Innovation, Management and Technology*, 1(3):2010–0248, 2010.

[31] Z. Yang, B. Zhang, J. Dai, A. Champion, D. Xuan, and D. Li. E-smalltalker: A distributed mobile system for social networking in physical proximity. In *Proceedings of the 30th IEEE Conference on Distributed Computing Systems (ICDCS)*, pages 468–477, 2010.

[32] Q. Yuan, I. Cardei, and J. Wu. Predict and relay: an efficient routing in disruption-tolerant networks. In *Proceedings of MobiHoc*, 2009.

[33] W. Zhao, M. Ammar, and E. Zegura. A Message Ferrying Approach for Data Delivery in Sparse Mobile Ad Hoc Networks. In *Proceedings of the 5th ACM International Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc)*, pages 187–198, 2004.