CSI: A Paradigm for Behavior-oriented Delivery Services in Mobile Human Networks

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***Abstract*— We propose behavior-oriented services as a new paradigm of communication in mobile human networks. Our study is motivated by the tight user-network coupling in future mobile societies. In such a paradigm, messages are sent to inferred behavioral profiles, instead of explicit IDs. Our paper provides a systematic framework in providing such services. First, user behavioral profiles are constructed based on traces collected from two large wireless networks, and their spatio-temporal stability is analyzed. The implicit relationship discovered between mobile users could be utilized to provide a service for message delivery and discovery in various network environments. As an example application, we provide a detailed design of such a service in challenged opportunistic network architecture, named CSI. We provide a fully distributed solution using *behavioral profile space* gradients and small world structures.**

Our analysis shows that user *behavioral profiles* are surprisingly stable, i.e., the similarity of the behavioral profile of a user to its future behavioral profile is above 0.8 for two days and 0.75 for one week, and remains above 0.6 for five weeks. The *correlation coefficient* of the similarity metrics between a user pair at different time instants is above 0.7 for four days, 0.62 for a week, and remains above 0.5 for two weeks. Leveraging such a stability in user behaviors, the CSI service achieves delivery rate very close to the delay-optimal strategy (above 94%), with minimal overhead (less than 84% of the optimal). We believe that this new paradigm will act as an enabler of multiple new services in mobile societies, and is potentially applicable in server-based, heterogeneous or infrastructure-less wireless environments.

I. Introduction

We envision future networks that consist of numerous ultra portable devices delivering highly personalized, context-aware services to mobile users and societies. Such scenarios elicit strong, tight-coupling between user behavior and the network. Users' mobility and on-line activities significantly impact wireless link characteristics and network performance, and at the same time, the network performance can potentially influence user activities and behavior. Such a tight user-network coupling provides a rich set of opportunities and poses several challenges. On one hand, fundamental understanding of the mobile user behavior becomes crucial to the design and analysis of future mobile networks. On the other hand, novel services can now be introduced and utilize such a coupling to effectively navigate mobile societies, providing efficient information dissemination, search and resource discovery.

In this paper, we propose a novel behavior-driven communication paradigm to enable a new class of services in mobile societies. Current communication paradigms, including unicast and multicast, require explicit identification of destination nodes (through node IDs or group membership protocols), while directory services *map* logical, interest-specific queries into destination IDs where parties are then connected using interest-oblivious protocols. The power and scalability of such conventional paradigms might be quite limited in the context of future, highly dynamic mobile human networks, where it is desirable in many scenarios to support implicit membership based on interest. In such scenarios, membership in interest-groups is not explicitly expressed by users, it is rather implicitly and autonomously inferred by network protocols based on behavioral profiles. This removes the dependence on third parties (e.g. directory lookup), maintenance of group membership (e.g., in multicast) or the need to flood user interests to the whole network, and minimizes delivery overhead to uninterested users.

Applying such a behavior-driven paradigm in mobile networks poses several research challenges. First, how can user behavior be captured and represented adequately? Second, is user behavior stable enough to enable meaningful prediction of future behavior with a short history? How can such services be provided when the interest or behavior cannot be centrally monitored and processed? And finally, can we design privacy-preserving services in this context?

To address these questions we propose a systematic framework with two phases 1) behavioral profile extraction by analyzing large-scale empirical data sets, investigating the stability of users in the behavioral space, and 2) leverage the behavioral profiles for service design – We use the implicit structure in the human networks to guide message and query dissemination given a target profile.

Specifically, we first analyze network activity traces and design a summary of user *behavioral profiles* based on the *mobility preferences*. The similarity of the *behavioral profile* for a given user to its future profile is high, above 0.75 for eight days and remains above 0.6 for five weeks. The surprising observation is that, the similarity metric between a pair of users predicts their future similarity reasonably well. The correlation coefficient between their current and future similarity metrics is above 0.7 for four days, and remains above 0.5 for fifteen days.

This phenomenon demonstrates that the *behavioral profile* we design is an intrinsic property of a given user and a valid representation of the user for a good period of time into the future. We refer to this phenomenon as the *stability* of user *behavioral profiles*, which can be used to map the users into a high dimensional *behavioral space*. The *behavioral space* is defined as a space where each dimension reflects a particular interest. For example, when we consider mobility preferences, each dimension represents the fraction of time spent at a given location. The position of users in the behavioral space reflects how similar they are with respect to the behavioral profile we construct. We propose a new communication paradigm, in which a *target profile* is used to replace network IDs to indicate the intended receiver(s) of a message (i.e., those with *matching* behavioral profile to the target profile chosen by the sender are the intended receivers.). It is a *C*ommunication paradigm in human networks based on the *S*tability of the user behavioral profile to discover the receivers *I*mplicitly, abbreviated as *CSI*. We present two modes of operation under the over-arching paradigm: the *target mode (CSI:T)* and the *dissemination mode (CSI:D)*. The *target mode* is used when the *target profile* is specified in the same context as the *behavioral profile* (i.e., the *target profile* is in terms of *mobility preferences*). The *dissemination mode*, on the other hand, is used when the *target profile* is de-coupled from mobility preferences.

We show that our CSI schemes perform very close to the delay-optimal schemes assuming global knowledge and improve significantly over the baseline dissemination schemes. For the *CSI:T mode*, comparing with the delay-optimal protocol, our protocol is close in terms of success rate (more than 94%) and has less overhead (less than 84% to the optimal), and the delay is about 40% more. For the *CSI:D mode*, our protocol features lower storage overhead than the delay-optimal protocol with more than 98% success rate – *CSI:D* uses a storage overhead less than 60% of the delay-optimal protocol, while the delay of *CSI:D* is about 32% more than the optimal.

Our Contributions

(1) We introduce the notion of multi-dimensional *behavioral space*, and devise a representation of user *behavioral profiles* to map users into the behavioral space. Our study is the first to establish conditions for stability of the relationship between campus users in this space.

(2) We propose *CSI*, a new communication paradigm delivering message based on user profiles. The target profile in CSI can even be independent of the context of behavioral profile we use to construct the *behavioral space*.

(3) We design an efficient dissemination protocol utilizing the stability of behavioral profiles and SmallWorld in mobile societies, then empirically evaluate and validate the efficacy of our proposal using large-scale traces from university campuses.

The outline of the rest of the paper is as follows. We discuss the related work in section II and important background in section III. This is followed by an analysis to understand the user behavioral pattern in section IV. We further discuss the potential usages of this understanding in section V and design our *CSI* schemes in section VI as an example. We use simulations to evaluate the performance of CSI schemes in section VII. Finally, we discuss some finer points in section VIII and conclude in section IX.

II. Related Work

We conduct the first detailed systematic study on the spatio-temporal stability of user behaviors in mobile societies, a new dimension that has not been considered before. We lay the foundation of this work on a solid analysis of empirical user behaviors, enabled by extensive collections of user behavioral traces. Many of them can be found in the archives at [1], [2]. Our effort on the extraction of behavioral profiles and behavior-based user classification is related to the reality mining project [16] and the work by Hsu et al. [4] and Ghosh et al. [20]. We leverage the representation of mobility preference matrix defined by Hsu et al. [4], which reveals more detailed user behavior than the five categories representation used in the reality mining [16] and the presence/absence encoding vector used by Ghosh et al. [20].

In centralized trace analysis, the capability of classifying users based on their mobility preferences [4] or periodicity [19] could potentially lead to applications such as behavior-aware advertisements or better network management. While understanding user behavior for these applications has its own merit, applications in centralized scenario (where user behaviors are collected, processed and mined at an aggregation point) are not our major focus in the paper.

The major application considered in this paper is to design a message dissemination scheme in decentralized environments. While several previous works exist in the delay tolerant network field, most of them (e.g. [3], [5], [17], [6], [10]) consider one-to-one communication pattern based on network identities. The one-to-many communication targeted at a behavioral group presented in this paper is a new paradigm in decentralized environments. Some of the previous work assume existing infrastructure: PeopleNet [18] uses specialized geographic zones for queries to meet. The queries are delivered to randomly chosen nodes in the corresponding zone through the infrastructure. Others (e.g., [17], [10]) rely on persistent control message exchanges (e.g., the delivery probability) for each node to learn the structure of the network, even when there is no on-going traffic. From the design point of view, our approach differs from them by avoiding such persistent control message exchanges to achieve better power efficiency, an important requirement in decentralized networks.

The spirit of our design is more similar to the work by Daly et al. [6], in which each node learns the structure of the network locally and uses the information for message forwarding decisions. They use the SmallWorld network structure [7] which often exists in human networks (as has been investigated in [14], [9]) and push the message toward nodes with high centrality to improve the chance of delivery. However, the learning process still involves message exchanges about past encounters, even in the absence of actual traffic. Our work, on the other hand, relies on the intrinsic behavioral pattern of individual nodes to "position" themselves in the behavioral space in a localized and fully distributed manner, without exchanging encounter history between nodes. The use of user behavioral profiles to understand the structure of the space is similar to the mobility space routing by Leguay et al. [3] and the utility-based routing by Aiklas et al. [8]. The major differences between this work and [3], [8] are two fold: First, we design the CSI:D mode, in which the target profile need not be related to the behavioral profile based on which the message dissemination decisions are made. Second, we also provide a non-revealing option in our protocol, thus no node has to explicitly reveal its behavioral pattern or interests to others, as opposed to [3], [8]. The idea of merging similar users into a group based on their behavior has also been proposed in a

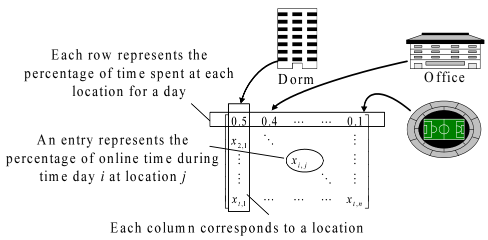


Fig. 1. Illustration of the association matrix to describe a given user's location visiting preference.

TABLE I

FACTS ABOUT STUDIED TRACES

Trace source	USC [12]	Dartmouth [13]
Time/duration of trace	2006 spring semester	2004 spring quarter
Start/End time	01/25/06-04/28/06	04/05/04-06/04/04
Unique locations	137 buildings	545 APs/ 162 buildings
Unique MACs analyzed	5,000	6,582

two-tiered routing structure [10].

Another related paper is the work by Hsu et al. [15] where the authors focus on only sending messages to users with similar behavioral profile to the sender. In this paper we introduce the notion of the *target profile* to decouple the behavioral profile of the sender from the destination profile in the message . This significantly enhances the capability of the message dissemination schemes, by allowing the sender to specify target behavioral profile (in CSI:T mode), or even some target profiles that are orthogonal to the behavior based on which we measure the similarity between users (in CSI:D mode).

III. BACKGROUND

A. Mobility-based User Behavior Representation

We represent mobile user behavior of a given user using the *association matrix* as illustrated in Fig. 1. In the matrix, each row vector describes the percentage of time the user spends at each location on a day, reflecting the importance of the locations to the user[1]. In [4] it has been shown that the *location visiting preferences* can be leveraged to classify users of wireless networks on university campuses. For a given user, the singular value decomposition (SVD) [21] is applied to its *association matrix* M, such that

$$M = U \cdot \Sigma \cdot V^T, \tag{1}$$

where a set of *eigen-behavior* vectors, $v_1, v_2, ..., v_{rank(V)}$ that summarize the important trends in the original matrix M can be obtained from matrix V, with corresponding weights $w_{v_1}, w_{v_2}, ..., w_{v_{rank(V)}}$ calculated from the eigen-values in matrix Σ. This set of vectors are referred to as the *behavioral profile* of the particular user, denoted as $BP(M)$, as they summarize the important trends in user M's behavioral pattern. The *behavioral similarity* metric between two users A and B is defined based on their behavioral profiles, vectors a_i's and b_j's and the corresponding weights, as

$$Sim(BP(A), BP(B)) = \sum_{i=1}^{rank(A)} \sum_{j=1}^{rank(B)} w_{a_i} w_{b_j} |a_i \cdot b_j|, \tag{2}$$

which is essentially the weighted cosine similarity between the two sets of *eigen-behavior* vectors.

[1]While there may be numerous other representations of user behavior, we shall show that this representation possesses desirable characteristics for the purposes of this study. Further investigation of other representations is a subject of future work.

B. Traces

In this paper, we seek a realistic, deep understanding of user behavior patterns by analyzing semester/quarter-long user behavioral logs collected from operational campus networks from public trace archives [1], [2]. We present results based on two data sets from the University of Southern California (USC) and the Dartmouth College (Dartmouth). The details of the data sets are listed in Table I.

We choose to use WLAN traces as they are the largest user behavioral data sets available. The information available from these anonymized traces contains many aspects of the network usage (e.g., time-location information of the users by tracking the association and disassociation events with the access points, amount of traffic sent/received, etc.). The richness in user behavioral data poses a challenge in *representing* the user behavior in a meaningful way, such that the representation not only reveals an intrinsic, stable behavioral profile of a user, but the identified behavioral profile also leads to practical applications. We show in this paper that the *location visiting preferences* (which is only a subset of the user behavioral data) is a stable attribute for both individual users and the relationship between users. This property will prove quite valuable to the design of efficient message dissemination schemes, which we empirically validate using the above traces.

IV. UNDERSTANDING SPATIO-TEMPORAL CHARACTERISTICS OF USER BEHAVIORAL PATTERNS

In this section we introduce our analysis of user behavioral patterns and its significance on the service design. While previous works on user classification based on long-term behavioral trend [4], [20], [19] are useful and in line with our goal, the stability of such classification over time has not been studied systematically. In particular, the short-term behavior of a user may deviate significantly from the *norm*, and the *stability* of user behavioral profiles is a decisive factor for whether it can be leveraged to represent the user's future behavior. In this section we investigate the following questions: (1) How long of behavioral history do we need to classify a user? and (2) How much does the behavior of a given user and its relationship with other users change with respect to time?

We consider the effect of the amount of past history (of user behavior) on its *behavioral profiles*. Each user uses the location visiting preference vectors in the past d days to summarize the behavior in the most recent history – the user retains d location visiting preference vectors for these days, organize

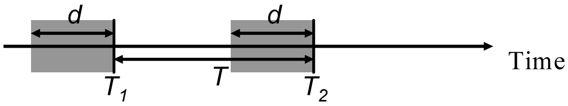


Fig. 2. Illustration: consider the trailing d days of behavioral profile at time points that are T days apart.

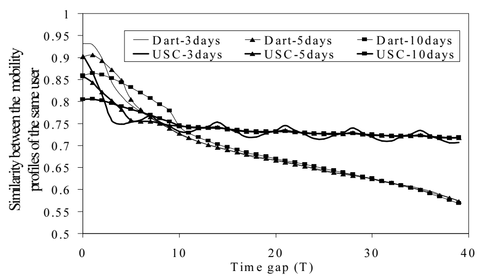


Fig. 3. Similarity metrics for the same user at time gap T apart.

them in a matrix, and use singular value decomposition to obtain the *behavioral profile*, as described in section III-A. We seek to understand how d influences the representation and similarity calculations. More specifically, we look into two important aspects: (1) Whether the representation of a given user is stable across time, and (2) whether the relationships between user pairs remain stable as time evolves.

We first consider the stability of the representation of a given user. Considering two points in time that are T days apart, we obtain the *behavioral profiles* for the same user at both end points, using the logs of the trailing d days ending at those end points, as illustrated in Fig. 2. Then we use the similarity metric defined in Eq. (3) to compare how stable a user's behavioral profile is to one's former self after T days has elapsed. The average results with various values of the time gap, T, and considered behavioral history d are shown in Fig. 3. We notice that, even if we collect a short history of user behavior (say $d = 3$), the representation is similar to the behavior of the user for a long time into the future. When we consider $T = 35$ days apart, the behavioral profiles from the same user still show high similarity, at about 0.6. The amount of history used does not influence the result too much when the considered T is large enough to avoid overlaps in the used behavioral history (i.e., when $T > d$). We conclude that on university campuses, the *behavioral profile* for a given user is stable, i.e., it remains highly similar for the same user across time. One interesting note is that, when the behavioral profile includes only part of a week ($d < 7$), the similarity of the user to its former self shows a weekly pattern (i.e., when T is an integer multiple of seven, the similarity peaks), especially in USC.

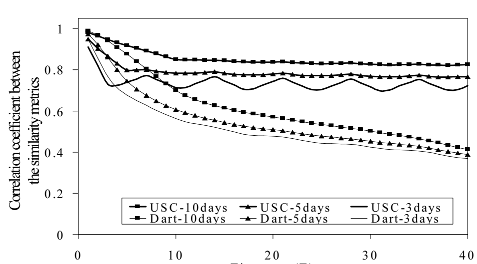


Fig. 4. Correlation coefficient of the similarity metrics between the same user pair at time gap T apart.

Second, we try to quantify how the behavioral similarity between the same pair of users varies with time. For this part, we use Eq. (3) to calculate the similarity between two users, A and B, at two points in time, $Sim_{T_1}(A, B)$ and $Sim_{T_2}(A, B)$, where T_1 and T_2 are T days apart. We perform this calculation to all user pairs, and then calculate the correlation coefficient of the similarity metrics obtained after a T-day interval, as

$$r = \frac{\sum_{\forall A,B}(X - \overline{X})(Y - \overline{Y})}{NS_X S_Y}, \tag{3}$$

where $X = Sim_{T_1}(A, B)$ and $Y = Sim_{T_2}(A, B)$, and the notations $\overline{X}$ and S_X denote the average and standard deviation of X, respectively. N is the total number of user pairs. The correlation coefficient quantifies how stable the relationship between user pairs is. We repeat the calculation for all pairs of users with various d and T values to arrive at Fig. 4. We observe that the similarity metrics between user pairs correlate reasonably well if the considered time periods are not far apart. For T smaller than one week, the correlation coefficient is above 0.62. This indicates, once the similarity between a pair of user is obtained, it remains a reasonable predictor for their mutual relationship for some time period into the future. Although the reliability of the stale similarity data decreases with respect to time, the current similarity of a user pair remains moderately correlated to their future similarity, in the time range up to several weeks. The correlation is above 0.4 for up to five weeks.

The investigation establishes that the user behavioral profile is a stable feature to represent the users – the representation of an individual user and the relationship between users are well correlated with the past history for the near future. Thus we map the behavioral profile to a virtual *behavioral space* [3], in which each user's behavior is quantified as a high dimensional point[2]. The mutual similarity metric between users is a function of their respective positions in this space. In this paper, when we say two users are *similar*, it means they are *close* in the behavioral space (i.e., the *distance* between the two users is small). We also use the term *neighborhood of a node* to refer to the other nodes that are *similar* to this particular node in the behavioral space.

V. The Behavior-driven Communication Paradigm

Profiling users based on stable behaviors is a fundamental step to understand human behavior. Motivated by the stability of user behavioral profiles, we introduce a *behavior-driven communication paradigm* where we use *user behavioral profiles*, instead of network IDs, to represent users. We envision that such a radical approach has several benefits.

[2]The dimension of the behavioral space is the same as the *mobility preference vector* representation, typically in the order of a hundred for these two campuses.

First, it enables behavior-aware message delivery in the network without mapping attributes to network IDs. As each user maintains its behavioral profile, it is now possible to deliver announcements about a sports event on campus towards sports enthusiasts (e.g., people who visit the gym often) or advertise a performance at the school auditorium to the regular attendees of such events.

Second, it facilitates the discovery of nodes with certain behavior patterns. Consider, for example, in the message ferry [11] architecture where nodes with high mobility move messages across the network to facilitate the communication between otherwise disconnected nodes. One can choose a target profile that reflects a mobility profile and thus eliminate the need of knowing the identity of the ferry beforehand or enforcing this mobility pattern on a controlled node – a typical user who happens to have the desired mobility pattern can be discovered and serve as a ferry.

Our *behavior-driven communication paradigm* is applicable to several architectures. In the *centralized server-based architecture*, user profiles could be collected and stored at a data repository, and mined for user classification, abnormality detection, or targeted advertisements. In the *cellular networks*, the low-bandwidth channel between the users and the infrastructure can be leveraged to exchange behavioral profiles and match users. In this paper, however, we consider a *decentralized infrastructure-less networks*, and focus on how stable behavioral profiles are used for better message dissemination. We name this scheme as *CSI*, since it is a *C*ommunication scheme based on the *S*table, *I*mplicit structure in human networks.

VI. Protocol Design

In this section, we first present our premises and design requirements for the CSI schemes. We then discuss the design of the CSI schemes based on in-depth understanding of the relationship between similar behavioral profiles and encounter events.

A. Assumptions and Design Requirements

We assume that each node profiles *its own behavioral pattern* by keeping track of the visiting durations of different locations and summarizing the behavioral profile using the technique discussed in III-A. This is an individual effort by each node involving no inter-node interactions. This can be done by the nodes over-hearing the beacon signals from the fixed access points in the environment to find out its current location. Note that, the use of these beacon signals is only for the node to profile its own behavior – they are not used to help the communication in our protocols (we will re-visit detailed points of this assumption in section VIII). Also, for the ease of understanding, we assume in this section that nodes are willing to send its behavioral profiles to other nodes when needed. A privacy-preserving option that eliminates this operation is also discussed in section VIII.

The goal of our *CSI* scheme is to reach a group of nodes matching with the target profile specified by the sender, under the following performance requirements: (1) The protocol should be scalable, in particular not being dependent on a centralized directory to map target profiles to user identities. (2) It should work in an efficient manner and avoid transmission and storage overhead when possible. Also, it should avoid control message exchanges in the absence of data traffic. (3) The syntax of the target profile should be flexible, allowing the target profile to be not in the same context as the behavioral profiles we use to represent the users. Also the operation of the protocol should be flexible to allow tradeoff between various performance metrics. And finally, (4) the design should be robust and help in protecting user privacy.

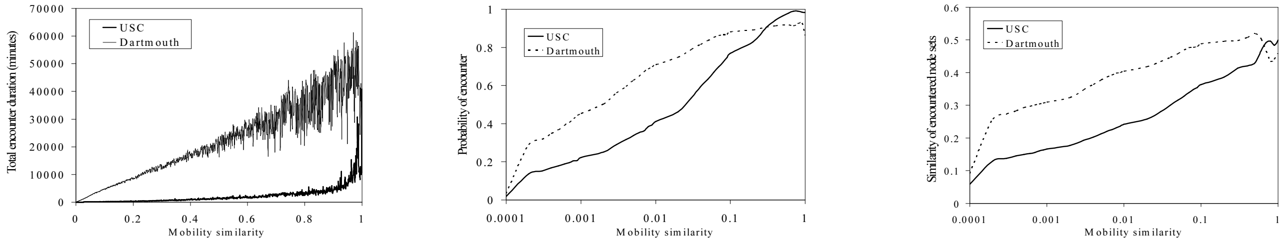
We design two modes of operation for the *CSI* scheme under the above requirements. When the target profile is in the same context as the behavioral profile (in our example, since the behavioral profile is a summary of user mobility, this corresponds to the scenario when the target profile describes users that *move* in a particular way), the *CSI:Target mode (CSI:T)* should be used. When the target profile is irrelevant to the behavioral profile (e.g., when I want to send to everyone interested in movies on campus), the *CSI:D mode* should be used instead. Although it seems that the applicability of *CSI:T* is limited, we note that the behavioral profile (in terms mobility) can sometimes be used to infer other social aspects of the users, such as affiliations or even interests (e.g., people who visit the gym often should like sports in general). Such inferences expand the scenarios in which *CSI:T* can be used. When this is not possible, *CSI:Dissemination mode (CSI:D)* provides a more generic option.

The major challenge involved in the design process is that each node is only aware of the behavioral profile of itself. Furthermore, we require no persistent control message exchanges for the nodes to "learn" the structure of the network proactively when they have no message to send. Nodes only compare their behavioral profiles *when they are involved in message dissemination*. Based on this very limited knowledge about the behavioral space, a node must predict how useful a given encounter opportunity is in terms of achieving the forementioned requirements. Since encounter events may occur sporadically in sparse, opportunistic networks, the nodes must make this decision for each encounter event independent of other encounter events (that may occur long before or after the current one under consideration). Such a heuristic must rely on the understanding of the relationship between nodal behavioral profiles and encounters, which we discuss the next.

B. Relationship between Behavioral Profiles and Encounters

We now analyze the relationship between user behavioral profiles and a key event for user-to-user communication in an infrastructure-less network – *encounters*. *Encounters* in mobile networks refer to events when users are within the radio range of each other and direct communication between the involved devices is possible. In this paper, based on the WLAN traces, we assume that when two users visit the *same location* during overlapped time intervals, they *encounter* with each other.

While it seems intuitive that users visiting similar locations should encounter with each other with higher probability, this is *not obvious* on university campuses. Students and faculty



(a) Total encounter duration. (b) Encounter probability. (c) Similarity of encountered node sets.

Fig. 5. Relationship between the similarity in behavioral pattern and other quantities.

have their own schedules, and they may rarely encounter due to the difference in their schedules although they might be in the same building at different times. Hence we investigate the relationship between behavioral profiles and encounter events, first as a sanity check of our intuition, and more importantly, to understand the relationship between the behavioral patterns and various aspects of the encounter events (e.g., the encounter probabilities, encounter durations, etc.). This helps reveal the *implicit structure* existing in mobile human networks, which is the key to the design of the *CSI* schemes in the following sections.

We classify all node pairs into different bins of behavioral similarity metric (as defined in Eq. (3)), and obtain various characteristics of encounter events as a function of the pair-wise behavioral similarity. In Fig. 5 (a), we show the aggregate encounter time duration between an average pair of nodes given the behavioral similarity. In Fig. 5 (b), we show the probability for a given node pair to encounter with each other, given their similarity. Combining these two graphs, we see that **if two users are similar in behavioral profiles, they are much more likely to encounter, and the total time they encounter with each other is much longer – an indication that nodes with *similar behavioral profiles* indeed are more likely to have better opportunities to communicate.** When two users are similar enough (with behavioral similarity larger than 0.3), they are almost guaranteed to encounter at some point (with probability above 0.9). However, we note that some "random" encounter events happen between dissimilar users. For users with very low (almost zero) similarity, the probability for them to encounter is not zero, although such encounter events are much less reliable (i.e., they occur with much shorter durations, see Fig. 5 (a)).

In Fig. 5 (c) we further compare the behavioral similarity of node A and B versus the sets of nodes A and B encounter. We denote the set of nodes A encounters with as $E(A)$. The similarity of the two sets of nodes is quantified by $|E(A) \cap E(B)|/|E(A) \cup E(B)|$, where $|\cdot|$ is the cardinality of the set. This graph shows, **as two nodes are increasingly similar, there is larger intersection of nodes they encounter. When an unlikely encounter event between *dissimilar nodes* occurs, it helps both nodes to gain access to a very different set of nodes, which they are unlikely to encounter directly.**

The above findings relate to the SmallWorld encounter patterns between mobile users [14]. The key features of SmallWorld networks [7] are high clustering coefficient and low average path length. In the human networks we analyze in this section, people with similar behavior form "cliques". The "random" encounter events between dissimilar nodes build *short-cuts* between these cliques to shorten the distances between any two nodes. We leverage these properties in the protocol design.

C. CSI:Target Mode

In the *CSI:target mode (CSI:T)*, the sender specifies the *target profile (TP)* for the recipients which must have the same format and semantics as that of the user behavioral profile, i.e., in our case the *TP* is a summarized *mobility preference* vector (i.e., the percentage of times the target node(s) visit various locations). For example, we could reach people who like sports by sending messages to those who visit the gym regularly. This criteria could be set up by specifying the *TP* as a vector with only one 1 corresponding to the gym location (hence only time spent at this location is considered). If a given user A has $Sim(BP(A), TP) > th_{sim}$, i.e., its behavioral profile, $BP(A)$, is more similar to TP than a sender specified threshold, we say node A belongs to the group of *intended receivers*. This threshold is set by the sender according to the desired degree of similarity to the TP. The TP and the threshold, th_{sim}, are included in the message header to describe the intended receivers of the message.

We first discuss the intuition behind the design of the *CSI:T mode* using Fig. 6 as an illustration. As per section VI-B, to deliver messages to receivers defined by a given *TP*, one way is to gradually move the message towards nodes with increasing *similarity* to the *TP* via encounters, in the hope that such transmissions will improve the probability of encountering the intended receivers. Finally, when the message reaches a node *close* to the *TP* (in the behavioral space), most nodes encounter frequently with this node are also similar to *TP*. Hence, the message should be spread to other nodes in the *neighborhood* (in the behavioral space) of the node.

Consider the pseudo-code in Algorithm 1. There are two phases in the operation, the *gradient ascend phase* and the *group spread phase*. (1) Starting from the sender, if node A currently holding the message is not an intended receiver (i.e., $Sim(BP(A), TP) < th_{sim}$), it works in the *gradient ascend phase*, otherwise it works in the *group spread phase*. (2) In the *gradient ascend phase*, for each encountered node, the current message holder asks the behavioral profile of the other node, and if the other node is more similar to the TP in the behavioral space, the responsibility of forwarding the message is passed to this node. One can imagine that these similarities

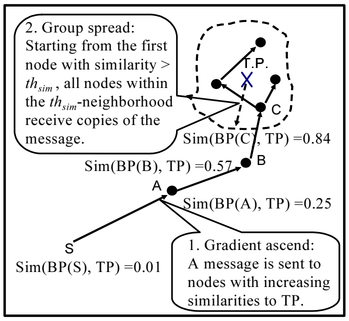


Fig. 6. Illustration of the CSI:T scheme in the *high dimension behavioral space*. One copy of the message follows increasing similarity gradient to reach the neighborhood of the target profile, then triggers group spread.

form an inherent *gradient* for the message to follow and reach the close neighborhood of the *TP* in the behavioral space, hence the name *gradient ascend phase*. Note that, up to this point, there is only one copy of the message in the network – these intermediate nodes who are not similar to the TP only forward the message once. (3) When the message reaches a node with similarity larger than th_{sim} to the *TP*, the *group spread phase* starts. This intended receiver holds on to the message, and requests the behavioral profiles from nodes it encounters. If they are also intended receivers, copies of the messages will be delivered to them. All intended receivers, after getting the message, continue to work in the *group spread phase*. Although multiple copies of the message are generated in the *group spread phase*, it is triggered only when the message is close to the *TP*, thus most of the encounter events and inquiries will occur among the *intended receivers*, reducing unnecessary overhead.

/* $BP(A)$**:** *Behavioral profile* **of node** A ***/**
if *node A has the message* **then**
  if $Sim(BP(A), TP) > th_{sim}$ **then**
    Initiate *Group_spread*();
  else
    Initiate *Gradient_ascend*();

Gradient_ascend(){
while *the message is not sent* **do**
  foreach *node E encountered* **do**
    Get $BP(E)$ from E;
    if $Sim(BP(E), TP) > Sim(BP(A), TP)$ **then**
      Send message to E;

}
Group_spread(){
foreach *node E encountered* **do**
  Get $BP(E)$ from E;
  if $Sim(BP(E), TP) > th_{sim}$ **then**
    Send message to E;

}

Algorithm 1: Algorithm for the CSI:T mode

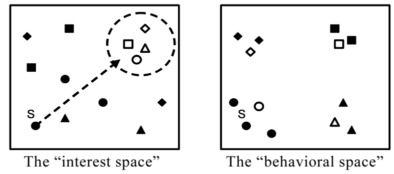


Fig. 7. Illustrations of the *CSI:D* scheme. Left chart: The goal is to send a message to a group of nodes with a similar characteristic in the *interest space* (white nodes in the circle). Right chart: However, they may not be similar to each other in the behavioral space (nodes with the same legend represent similar nodes in the behavioral space).

D. CSI: Dissemination Mode

In the *CSI:Dissemination mode (CSI:D)*, there does not exist a direct relationship between the target profiles of the recipients and their measured behavioral profiles. One particular example is to reach people who like movies on campus. If there is no movie theaters on campus, the measured behavioral profiles (i.e., mobility preference) cannot be used to infer such an interest. This situation is illustrated in Fig. 7. It appears there is little insight provided by the similarities between the nodal behavioral profiles to guide message propagation, as the intended receivers in this case may be scattered in the behavioral space, and the relationship between the target profile and the behavioral profile cannot be quantified. Although it is always possible to reach most users through epidemic routing, this leads to high overhead, and requires all nodes in the network to keep a copy of the message. The objective of *CSI:D mode* is to reduce the numbers of message copies transmitted and stored in the network, yet make it possible for most nodes to get a copy quickly, if they belong to the intended receivers.

We again first discuss the intuition behind the design of the *CSI:D mode* in this paragraph, using Fig. 8 as an illustration. From section VI-B, **since the nodes with high similarity in their behavioral profiles are almost guaranteed to encounter, there is really no need for each of them to keep a copy and disseminate the message. Electing a few** *message holders* **within a single group of similar nodes would suffice.** This intuition leads to the construction of our message dissemination strategy for the *CSI:D*. We aim to have only one *message holder* among the nodes who are similar in their behavioral profiles (or equivalently, pick only one *message holder* within a *neighborhood* in the behavioral space. In Fig. 7, this corresponds to having only one message holder from each group of nodes with the same legend). We add the messages holders carefully to avoid overlaps in the encountered nodes among message holders. As suggested by Fig. 5 (c), we should **select nodes that are very** *dissimilar* **in their behavioral profiles to achieve low overlaps.** Recall that dissimilar node pairs still encounter with non-zero probability, our design philosophy is to leverage these "random" encounter events as *short-cuts* to navigate through the behavioral space efficiently, hopping across the space to reach dissimilar nodes with relatively few message transmissions. Such a design philosophy is also related to the SmallWorld human network structure – a message will be received by an intended receiver shortly once it has reached someone in the receiver's "clique".

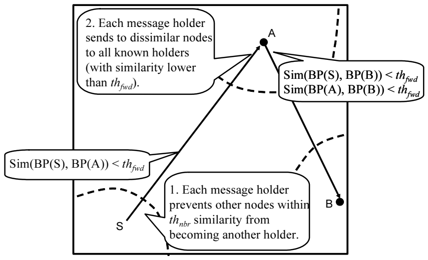


Fig. 8. Illustration of the CSI:D scheme. The idea is to select the message holders in a non-overlapping fashion to cover the entire behavioral space.

Consider the pseudo-code in Algorithm 1. (1) The sender itself starts as the first message holder in the network. (2) Each message holder tries to strategically add additional message holders in the network. When it encounters with other nodes, it asks for the behavioral profile of the other node to be considered as a potential additional message holder. Each message holder keeps a list of the behavioral profiles of all known message holders[3], and the new node has to be dissimilar (with the similarity metric lower than a threshold, th_{fwd}) to all known holders to be added as a new message holder and keep another full copy of the message. (3) If, on the other hand, this node is similar to the message holder (i.e., within similarity threshold th_{nbr}), it uses a single bit to remember that there is a message holder in its neighborhood and propagates this information to similar nodes. This bit is used to prevent excessive message holders in the same neighborhood, even if some nodes have not encountered with the message holders directly. (4) When holders encounter, they update each other with the behavioral profiles of the known holders list, to gain a better view of the situation of message spreading. (5) If two similar holders encounter, one of them should cease to be a holder to reduce duplicated efforts.

Each message holder is responsible for disseminating the actual message to the intended receivers. The message holders sends the *TP* specified by the sender in the message to the encountered nodes. If the encountered node is an intended receiver, the full message will be transferred.

VII. Simulation Results

In this section, we perform extensive simulations with the CSI schemes, based on the derived encounters between users from the two empirical traces. We compare the performances of our proposal to oracle-based forwarding decisions to show that our performance is close to the optimum (in terms of the delivery success rate and the overhead), and does not fall much behind in delay. We also compare CSI to epidemic routing [5] and variants of random walk[4]. In all the simulation cases, we split the traces into two halves, use the first half to obtain the behavioral profiles for all users, and then use the second half of the trace to evaluate the success of our proposed schemes.

[3]Note this list does not necessarily contain all holders in the network. Message holders that are added by a particular message holder are not known to other holders until they meet and sync the lists.

[4]The CSI could not be directly compared with existing routing schemes (e.g., [17], [3], [6], [10]) in DTN as most of them have a different routing objective: reaching a particular network ID.

/* $BP(A)$**:** *Behavioral profile* **of node** A ***/**
/* $H_i(A)$**: The** i**-th known holder of node** A ***/**
/* $holder\_in\_group(A)$**: If** A **knows there is a message holder in its neighborhood */**

if *node* A *is a message holder* **then**
  foreach *node* E *encountered* **do**
    Get $BP(E)$;
    if E *is not a holder* **then**
      if $Sim(BP(E), BP(H_i(A))) < th_{fwd} \forall i$ *and* $holder\_in\_group(E) = false$ **then**
        Elect E as an holder;
        Add $BP(E)$ to holder list;
        Send the message;
        Send $BP(H_i(A)), \forall i$;
      else if $Sim(BP(E), BP(H_i(A))) > th_{nbr}$ *for any* i **then**
        Let E set $holder\_in\_group(E) = true$;
    else
      if $Sim(BP(E), BP(A)) > th_{nbr}$ **then**
        A ceases to be a holder;
      else
        Sync holder lists between node A and E;
else if $holder\_in\_group(A) = true$ **then**
  foreach *node* E *encountered* **do**
    Get $BP(E)$;
    if $Sim(BP(A), BP(E)) > th_{nbr}$ **then**
      Let E set $holder\_in\_group(E) = true$;

Algorithm 2: Algorithm for CSI:D mode.

A. *CSI:Target Mode*

1) Simulation Setup: In the scenario of CSI:T mode, the sender specifies the *TP* and a threshold of similarity th_{sim}. If a node shows a similarity metric higher than th_{sim} to the *TP*, it is an intended receiver. In our evaluation, we use the top-10 dominant behavioral profile[5] (i.e., the behavioral profiles with the most number of people following it, typically in the order of hundreds) in our traces as the *TP*, and for each *TP* we randomly pick 100 users as the senders generating messages targeting at the *TP*. We use the threshold $th_{sim} = 0.8$ as the transition point between the *gradient ascend phase* and the *group spread phase*.

We compare our *CSI:T* scheme with several other protocols discussed below. The *epidemic routing* [5] is a message dissemination scheme with simplistic decision rules: all nodes in the network send copies of messages to all the encountered nodes who have not received the message yet. The *random walk (RW)* protocol generates several copies of the message from the sender, and each copy is transferred among the nodes in a random fashion, until the hop count reaches a pre-set TTL value. *Group spread only* is a simplified version of our protocol. It uses only the *group spread phase*, i.e., the original sender holds on to the message until it encounters

[5]We have also experimented with other target profiles, such as rarely visited locations on campuses or profiles that contain a combination of several locations, and the results are similar to those presented in this section.

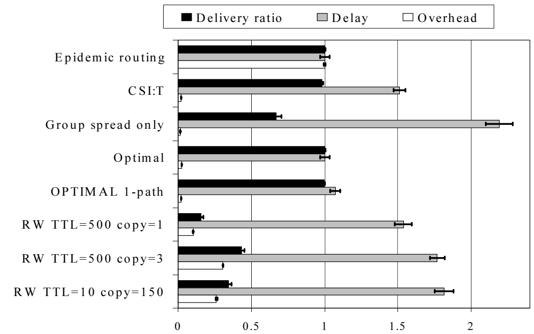
with someone who is more similar than th_{sim} to the *TP* and starts the *group spread phase* directly from there.

We also consider two protocols that require global knowledge of the future. The *optimal* protocol sends copies of the message only to the nodes which lead to the fastest delivery to the targeted receivers, and no one else. This is the oracle-based optimal protocol achievable if one has perfect knowledge of the future, and serves as the upper bound for performance. The *optimal single-forwarding-path* is the oracle-based protocol to find the fastest path to deliver the message to the neighborhood of the *TP* – Using the knowledge of the future, it identifies the path that leads to the earliest message delivery to one of the intended receivers. Once a copy of the message is delivered to the th_{sim}-neighborhood to the *TP*, it follows the same *group spread phase* as in CSI:T. This is the optimal performance (upper bound) for the family of protocols delivering one copy of message to the neighborhood of the target profile, if one chooses a good (shortest delay) path – note that this shortest-delay path may not always follow an increasing gradient of similarities to the *TP*.

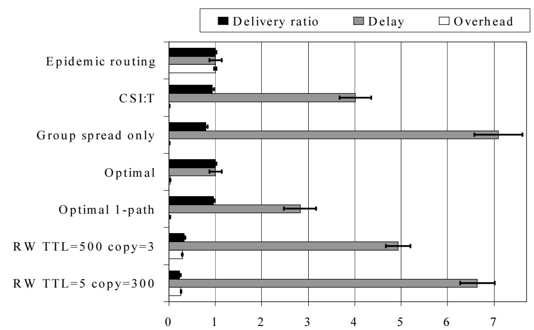
We compare these message dissemination schemes with respect to three important performance metrics: *delivery ratio*, *average delay*, and *transmission overhead*. The *delivery ratio* is defined as the percentage of the intended receivers (those with similarity greater than th_{sim} to the TP) actually received the message. We account for the transmission overhead as *the total number of messages sent* in the process of delivery. See more discussions on the additional overhead of exchanging the behavioral profiles later in section VIII-A.

2) Simulation Results: We show the normalized performance metrics with respect to that of *epidemic routing* (the relative performance for each protocol assuming *epidemic routing* is 1.0) and its 95% confidence intervals in Fig. 9. We observe that *epidemic routing* leads to the highest overhead while its aggressiveness also results in the highest possible delivery ratio and the lowest possible delay. The *random walks* do not work well regardless the number of copies and the value of TTL, as they use no information to guide the propagation of the message towards the right direction. Our *CSI:T* protocol leads to a success rate close to the *epidemic routing* (0.96 for USC, 0.94 for Dartmouth) with very small overhead (0.02 for USC, 0.018 for Dartmouth). For the simplified version, *group spread only*, the delay is longer and the success rate is lower than our protocol. We will further investigate this phenomenon later.

When comparing *CSI:T* with the protocols with future knowledge, we see that there is really not much room for improvement in terms of the success rate and the overhead. Our gradient ascend approach in *CSI:T* is similar to what is achievable even one has the knowledge of the future in these two aspects. Specifically, *CSI:T* has more than 94% of delivery rate and uses *less than* 84% overhead of the *optimal* strategy. The delay, on the other hand, has some room for improvement. Our gradient ascend phase generates only one copy of message from the sender and it moves towards the TP following strictly ascending similarity. Comparing with the best (fastest) path to the TP used in the *optimal single-forwarding-path*, our *CSI:T* has 1.40 and 1.47 times more delay, for USC and Dartmouth,



(a) USC.



(b) Dartmouth.

Fig. 9. Performance comparison of CSI:T to other protocols.

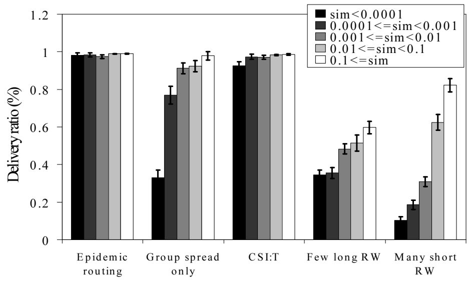
respectively. If we compare with the *optimal* strategy, where multiple copies are generated whenever it helps to improve the delay, the difference is even larger. This calls for a further investigation of selecting good path(s) from the sender to the TP, which we leave out for future work.

We take a closer look at the performance metrics by splitting the simulation cases into categories, depending on the original similarity metric between the sender's behavioral profile and the *TP*, $Sim(BP(S), TP)$. By the split statistics shown in Fig. 10, we see why the *gradient ascend phase* is needed to improve the success rate and reduce the delay. When we use only the *group spread phase*, and the sender is dissimilar from the *TP*, it takes a longer time before any encounter event happens directly between the sender and anyone in the neighborhood of the *TP*, if it happens at all – hence the delay is longer, and the success rate is lower.

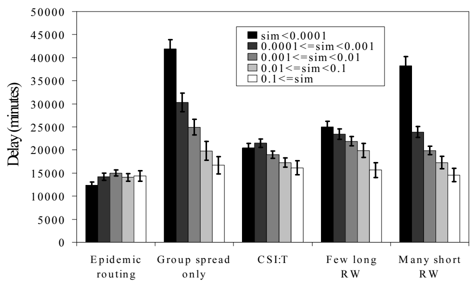
Comparing the differences between two versions of random walks, few long threads and many short threads, reveals an interesting difference. The concept that leads to the difference is illustrated in Fig. 11. Many short threads are better if the sender is close to the *TP*, in terms of both delivery ratio and delay, as the sender generates a lot of threads to "occupy" the neighborhood – since the threads are short, and similar users encounter more frequently, they are likely to stay in the neighborhood. Contrarily, if the sender is far away from the *TP*, long random walk threads provide a legitimate chance of moving close to the *TP*, while short threads provide less hope.

B. CSI:Dissemination Mode

1) Simulation Setup: In the scenario of *CSI:D mode*, the target profile specified by the sender cannot help to determine



(a) Delivery ratio.



(b) Average delay.

Fig. 10. Split performance metrics by the similarity between the sender and the target profile (USC).

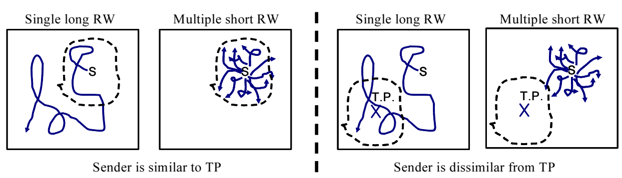


Fig. 11. Illustrations for the comparison between one long random walk and many short random walks.

to where the message should be sent in the behavioral space. Hence, the strategy seeks to keep one copy in every neighborhood in the behavioral space. In our evaluation, we start from 1000 randomly selected users as the senders. Since the target profile of the intended receivers can be orthogonal to the behavioral profile, we create the scenario for evaluation by randomly selecting 500 nodes as the intended receivers for each sender, and consider the average performances. We vary the two thresholds, th_{fwd} and th_{nbr} in our *CSI:D mode* scheme proposed in VI-D, to adjust the aggressiveness of the forwarding scheme. Setting low values for both thresholds leads to less aggressive operations and inferior performances. At the same time is also leads to lower overheads, as the messages are copied to fewer message holders, and the existence of a message holder prevents nodes in a larger neighborhood from becoming another message holder.

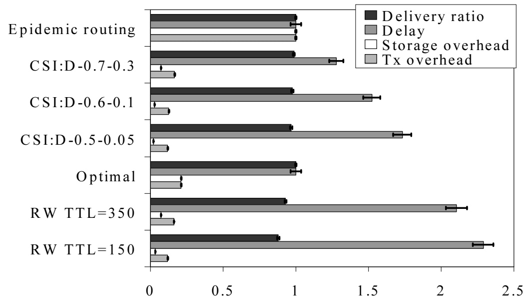
We compare various parameter settings of our *CSI:D* mode with two baseline protocols, the *epidemic routing* and the *random walk*. The epidemic routing works the same way as before, serving as the baseline for comparison. In the random walks, the visited nodes along the walks become message holders and they will later disseminate the messages further when encountering with the intended receivers. The *optimal* protocol again assumes global view of the network and the knowledge of the future. Every node in the network knows who the intended receivers are, and sends the messages to other nodes only if they lead to the fastest delivery to the message to one of the receivers.

The performance metrics we consider are *delivery ratio*, *average delay*, *transmission overhead*, and, in addition, *storage overhead*. Here the *transmission overhead* refers to the total number of transmissions to reach the message holders and the intended receivers. The *storage overhead* is the number of eventual message holders that remains in the network after our scheme is stabilized (recall that some message holders may decide to cease performing the task if another message holder is found with similar behavioral pattern in *CSI:D*). This is the overall amount of storage space invested by the nodes collectively to deliver the message[6]. In the *epidemic routing* and the *optimal* protocol, all nodes that receive the message hold on to the message for future transmissions (there is no distinction between the message holder and a regular node), hence the transmission overhead and the storage overhead are the same.

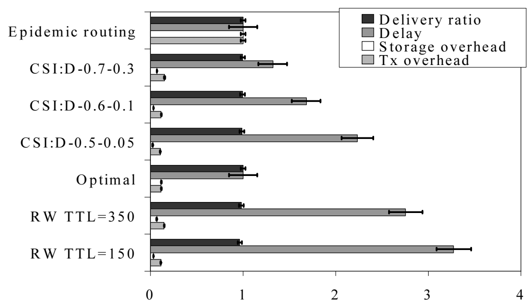
2) Simulation Results: In Fig. 12 we show the average result of the 1000 simulation cases with the 95% confidence interval. We use the legend CSI:D-th$_{\text{fwd}}$-th$_{\text{nbr}}$ for our *CSI:D* scheme. Comparing with the *epidemic routing*, our protocol saves a lot of transmission and storage overhead. It is possible to use only about 7.2% strategically chosen nodes as the message holder and reach the intended receivers with little extra delay (about 32% more), when $th_{fwd} = 0.3$ and $th_{nbr} = 0.7$. Notice that the storage overhead of the *CSI:D* scheme is even lower than the *optimal* protocol (less than 60%) with the objective of minimizing the delay. If one desires further reduction in the overhead, setting lower threshold values provide a way to trade performance for overhead, e.g., setting $th_{fwd} = 0.1$ and $th_{nbr} = 0.6$ cuts the storage overhead to about 3% of the *epidemic routing*. The delay of the *CSI:D* is not much more than the *epidemic routing* or the *optimal*, at around 27% to 32% more when $th_{fwd} = 0.3$ and $th_{nbr} = 0.7$.

For the *random walks*, we have configured the TTL values for them to have similar overhead with the *CSI:D* (i.e., compare RW TTL=350 with CSI:D-0.7-0.3 and RW TTL=150 with CSI:D-0.6-0.1). We notice that although the delivery rate of the *random walk* is also pretty good (1.5% to 10% inferior to the corresponding *CSI:D*), thanks to the non-zero encounter probability between dissimilar nodes, its delay is much longer than the corresponding *CSI:D* (between 50% to 108% more). This is because the *random walk* does not leverage the implicit structure of the human network to select the message holders wisely, as the *CSI:D* does. The *random walk* leaves copies within the same neighborhood of the original sender with higher probability, as similar nodes are more likely to encounter (i.e., the *random walk* will not "leave the neighborhood" in a small number of hops). Hence, there exists significant overlap between the nodes encountered by the selected message holders, and the other nodes that are dissimilar to these holders have to wait for a long time before

[6]Typically, only about a couple dozens of message holders drop the message in the simulation cases. Even if we have accounted for the temporarily invested storage, it adds less than 1% additional storage overhead.



(a) USC.



(b) Dartmouth.

Fig. 12. Performance comparison of CSI:D to other protocols.

some "random" encounter events occur to receive the message, resulting in the longer delay.

VIII. Discussions

A. Additional Overhead

In addition to the message transmission and storage, in our proposed CSI schemes, due to the need for exchanging and maintaining the behavioral profiles, there are some additional overhead. We discuss them in details in this section.

Overhead for exchanging the behavioral profiles We identify some additional components to the actual message transmissions when the encounter events between mobile nodes are leveraged for message dissemination. Some of the components are common to *any* message dissemination schemes, and the others are unique to our CSI schemes.

- The common overhead for all the DTN message dissemination schemes considered include the beacon signals for nodes to discover each other when they encounter, and the exchange of a list of "messages I have seen" to avoid a given node receiving duplicated messages from different nodes. This type of overhead is a function of the encounter patterns itself and is independent of the actual protocol used. We ignore these common factors in our analysis.
- Exchanging the behavioral profiles for the evaluation of mutual similarity is an additional component that exists only in our behavior-aware protocol. These profiles are a handful of vectors associated with its weights. For most of the users, empirically, five to seven eigen-behavior vectors capture more than 90% of the power in their *association matrices* [4]. This is a small constant overhead we pay for each encounter when one of the nodes has some message to send. If the message size is much larger than the overhead, which is usually the case as messages are transferred in a bigger unit (i.e., a "bundle") in DTNs, it is worthwhile to pay this overhead to gain the reduction of transmission counts as we see in section VII. Furthermore, with CSI, if there is no message to send, there is no need to exchange the behavioral profile. Thus, comparing with the protocols that require proactive, persistent exchanges of control messages when nodes encounter (e.g., ProPHET [17] requires the exchange of encounter probability vectors), qualitatively, the CSI schemes have lower overhead, especially when the volume of traffic is low in the network.
- The actual message size has to be augmented with the *TP* as well. This is a constant overhead, and it can be reduced if the target vector is "sparse" (e.g., if the *TP* considers only the visits to the gym exclusively, there is only one 1 in the vector. Instead of adding a vector $(0, ..., 0, 1, 0, ...)$ in the header, the vector can be encoded (i.e., by specifying (gym, 1)) to save space.).
- In the CSI:D mode, the message holders have to exchange the list of behavioral profiles of known holders. This happens only between a small subset (less than 8%) of the nodes, and the exchange is necessary only when there is a difference in the lists. To further alleviate this, the two nodes can compare their known holder lists using a hash value, and exchange only the difference.

Overhead for maintaining the behavioral profiles In order to maintain the behavioral profile, the nodes have to keep track of its visiting time to various locations. Note this does not require a node be aware of all possible locations in the environment – it has to keep track of only the ones it has been to. When two nodes exchange the behavioral profiles, each entry in the behavioral profile contains only a subset of locations with annotations for these locations (e.g., Node A specifies (library, gym) = (0.8, 0.2) while node B specifies (library, computer lab) = (0.4, 0.6)). The nodes will take a union of the location sets when comparing their similarities (e.g., in the previous example, when node A sends the behavioral profile to B, B will convert the profiles to $BP(A)$: (library, gym, *computer lab*) = (0.8, 0.2, 0) and $BP(B)$: (library, *gym*, computer lab) = (0.4, 0, 0.6) before comparing). The required storage on each node is minimal, as we show about three to five days of summarized *mobility preference* is sufficient to establish a stable behavioral profile for the user in section IV.

In addition, if the beacon signals from locations are not available, it is possible to use the mutual encounter vectors as the behavioral descriptors for the nodes – nodes who move similarly should have similar encounter sets. In this sense, we could replace the representation to be totally independent of the infrastructure.

B. Privacy Issues

While the behavior-aware message dissemination schemes achieve good performance with significant overhead reduction, it also raises user privacy concerns. In some cases, individuals may not want to reveal their own behavior. We discuss privacy-preserving options with our CSI scheme below.

First we emphasize that the original design of CSI presented in section VI inherently possesses a privacy-preserving feature: we only use a small subset of user behavior (specifically, the mobility preference) in the behavioral profile, and with the singular value decomposition, we reveal only the summarized trend, not detailed location visiting events for the user. In addition, the behavioral profiles are exchanged only between nodes, not stored in any public directory, and it limits only to when a given node is involved in message dissemination.

We can further reduce the behavioral profile exchanges in the CSI scheme, and hence help to preserve privacy as follows. For the CSI:T mode, when nodes encounter, instead of exchanging their behavioral profile, the node with a message to send would first send to the other node the *TP* of the message and its similarity score to the *TP*. The other node silently calculates its similarity to the *TP* and decides whether to request for the actual message. This completely removes the need for behavioral profile exchanges in CSI:T mode.

For the CSI:D mode, when a message holder looks for potential new holders, instead of asking other nodes to send the behavioral profile, the message holder sends the list of known holder's behavioral profiles to the other node. Since this list contains only the *behavioral profiles* of the known holders, not their *identities*, dissemination of such lists in the network does not pose a threat to the privacy of the message holders. Furthermore, when there are multiple holders in the list, the other node is not able to tell which behavioral profile corresponds to the holder who sends out the list. If the other node decides to become a message holder, its behavioral profile has to be added to the list of known holders. Instead of immediately sending the behavioral profile of the new holder to the old holder, which poses an opportunity for the old holder to link the identity and the behavioral profile of the new holder, the new holder only adds its behavioral profile to its own known holder list, and delays the dissemination for a later holder profile list exchange.

Finally, as a last resort, privacy-minded individuals can always opt-out of the service, and we expect this would not impact the performance severely, as it has been shown that the encounter pattern between nodes in mobile networks is rich enough to sustain up to 40% of nodes opting out before observing a performance degradation [14].

IX. Conclusion and Future Work

In this paper, we propose a paradigm to represent, summarize and manipulate behavioral profiles and use such profiles as targets for the communication. We have presented a novel service of message dissemination in infrastructure-less mobile human networks based on the behavioral profiles of the users. The CSI schemes meet the design goals outlined in section VI-A with respect to efficiency, flexibility and privacy preserving properties. The CSI schemes perform closely to the delay-optimal protocols (with 94% or more success rate, less than 83% of overhead, and the delay is inferior by 40% or less). In addition, we also observe that human behavior as observed in the large scale empirical traces is quite robust and only a few days' worth of data is adequate to summarize and leverage for message dissemination, which is quite surprising.

We are working toward an implementation of the CSI schemes based on mobile devices and consider a real-world evaluation. One key issue is to adapt our algorithm in a more privacy-preserving fashion which is also resistant to spam (e.g., include a reputation system). We are also considering different applications of behavioral profiles, including targeted advertising via our CSI schemes.

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