

# Predictive Data Delivery to Mobile Users through Mobility Learning in Wireless Sensor Networks

HyungJune Lee, *Member, IEEE*, Martin Wicke, Branislav Kusy, *Member, IEEE*,  
Omprakash Gnawali, *Member, IEEE*, Leonidas Guibas, *Fellow, IEEE*

**Abstract**—We consider applications, such as indoor navigation, evacuation, or targeted advertising, where mobile users equipped with a smart-phone class device require access to sensor network data measured in their proximity. Specifically, we focus on efficient communication protocols between static sensors and users with changing location. Our main contribution is to predict a set of possible future paths for each user and store data at sensor nodes that the user is likely to associate with. We use historical data of radio connectivity between users and static sensor nodes to predict the future user-node associations and propose a network optimization process, called *data stashing*, which uses the predictions to minimize network and energy overheads of packet transmissions.

We show that data stashing significantly decreases routing cost for delivering data from stationary sensor nodes to multiple mobile users compared to routing protocols where sensor nodes immediately deliver data to the last known association nodes of mobile users. We also show that the scheme provides better load balancing, avoiding collisions and consuming energy resources evenly throughout the network, leading to longer overall network lifetime. Finally, we demonstrate that even limited knowledge of the future users location can lead to significant improvements in routing performance.

**Index Terms**—Data Delivery to Mobile Users, Trajectory Prediction, Mobility Pattern, Network Optimization, Sensor Networks.

## I. INTRODUCTION

Classic multi-hop wireless routing protocols compute the shortest path in terms of hops or expected number of transmissions (ETX) [68] between sources and destinations in a network. Energy consumption for radio transmissions corresponds to a considerable portion of the total energy consumption at sensor nodes [17]. Since the shortest path minimizes the number of necessary transmissions, this strategy minimizes not only delay but also energy used for data communication.

In the presence of mobility, however, the shortest path computed at one point in time is not necessarily the shortest possible path connecting the source and the sink. A shorter

path might be available, if the nodes move closer to each other in the future. An optimal routing strategy can be devised if the trajectory of the mobile nodes is known.

In this paper, we study the problem of sending information from sensor nodes (as *data sources*) in a sensor network to multiple mobile sinks moving in the same space as the network. Given some information about each sink's trajectory, we aim to minimize the expected routing cost to the sink. We assume that the information sources and sensor network nodes are static (not mobile). Data sinks (humans or vehicles) move inside the area covered by the sensor network and access sensor data through computationally capable devices, such as smart-phones. Finally, we assume that applications tolerate a packet delivery delay in the order of the average network traversal time for mobile nodes, e.g., a few minutes. This is often the case in sensor networks that accumulate measurements until an observer takes a reading [16]. Examples of such data delivery patterns can also be found in applications that sense information in places where people work or live and deliver it to user mobile devices, enabling more intelligent living environments. For instance, location-sensitive data such as store advertisement and customized evacuation notifications [21] can be forwarded to specific mobile users as they come around in the network.

There is a large body of prior work in the field of routing from nodes to mobile sinks. We can classify them into two categories: 1) proactive scheme such as OLSR (Optimized Link State Routing) [13] and DSDV (Destination-Sequenced Distance Vector routing) [47], and 2) reactive scheme such as DSR (Dynamic Source Routing) [24] and AODV (Ad hoc On-demand Distance Vector routing) [46]. The state-of-the-art ad-hoc routing protocols can discover routes without initially knowing the topology of the networks, and this aspect is considered as a big advantage of these protocols over traditional routing protocols like OSPF (Open Shortest Path First) [14] and RIP (Routing Information Protocol) [39]. However, the problem is that their routing performance degrades rapidly with increasing mobility, i. e., resulting in higher route update cost for proactive schemes or higher bandwidth usage of on-demand flooding for reactive schemes as investigated in [53].

To design a robust routing algorithm under sinks' mobility, exploiting some trajectory information of the mobile nodes may be necessary. In some applications, sinks know their future trajectory through the network and can announce it to the network when requesting information. Even if the future trajectory is unknown, since many applications are deployed in environments that constrain motion patterns of sinks to

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HyungJune Lee is the corresponding author and is with the Department of Computer Science and Engineering, Ewha Womans University, Seoul, Republic of Korea (e-mail: hyungjune.lee@ewha.ac.kr).

Martin Wicke is with eddy.systems, San Francisco, USA (e-mail: martin.wicke@gmail.com).

Branislav Kusy is with CSIRO, Brisbane, Australia (e-mail: branislav.kusy@gmail.com).

Omprakash Gnawali is with the Department of Computer Science, University of Houston, Houston, USA (e-mail: gnawali@cs.uh.edu).

Leonidas Guibas is with the Department of Computer Science, Stanford University, Stanford, USA (e-mail: guibas@cs.stanford.edu).

roads, trails, or hallways, not all possible movements within space are actually realized. Moreover, a recent study [56] showed that mobile users move along a limited set of typical spatial trajectories, and the movement shows a certain degree of regularity. This suggests that we can learn the structure in users' movements, called the *mobility pattern* from repeated observations, and exploit the mobility pattern for designing a more reliable and efficient routing scheme that works even under high mobility.

We present a *long-term mobility prediction* algorithm that allows us to predict a sequence of node associations of mobile sinks as shown in Fig. 1. To do this, we present a method for representing trajectories with wireless association, learning typical trajectories from observations, as well as predicting likely association patterns given observed partial association history. We borrowed ideas of sequence similarity, clustering, and alignment from computational biology. Wireless devices carried by mobile sinks run the prediction algorithm to compute and supply information about their future association sequences to the network. We define *trajectory* as a sequence of node associations, and compute similarities between sequences in the association data acquired in a learning phase. Using these similarities, we compute clusters representing typical paths through the network. We then compute a compact probabilistic representation for the clusters that we can use to efficiently find likely future trajectories during prediction.

Based on the long-term mobility prediction algorithm described above, we design a routing scheme that exploits knowledge about the long-term association pattern of mobile sinks within a network of data sources. It aims to minimize energy consumption and network congestion. This enables the routing scheme to scale to multiple mobile sinks and a large number of data sources. For delay-tolerant network applications, which do not require immediate real-time data retrieval, we propose to route data not to the mobile sink directly, but to relay nodes along a predicted path of the mobile node that is close to the data source in terms of communication hops (see Fig. 1). The selected relay node will *stash* the information to be picked up when the mobile node passes within the transmission range of the relay node. We use an integer programming technique to find optimal relay nodes that minimize the number of necessary transmissions while guaranteeing robustness against link and node failures, and achieving better load balancing and more even utilization of network resources.

Our main contributions can be summarized as follows:

- We present *data stashing*, a data delivery scheme that routes data to mobile sinks. In this scheme, each sensor node selects a set of nodes on which its data will be stashed, so that the overall network and energy costs of delivering data to one or more users are minimized.
- We introduce a network-centric representation for trajectories. In this representation, a trajectory is represented as a sequence of associated nodes, giving us all the information we need for data delivery, while abstracting from unnecessary and possibly misleading spatial information. We also develop useful similarity measures for this motion representation which allows us to perform

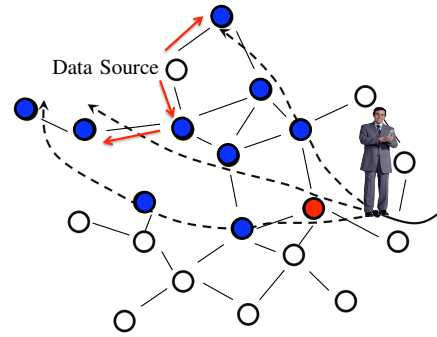


Fig. 1. Overview of our routing algorithm using the anticipated association nodes. The red node is the predicted next association node (through *short-term* prediction [28]), and blue nodes are sequences of the future association nodes (through *long-term* prediction). Packets can be *stashed* for pickup at blue nodes.

clustering.

- We propose a probabilistic representation for sets of similar (but potentially partial) trajectories. This representation can be used to compactly describe a cluster of trajectories, and efficiently find the best-matching cluster given a partial trajectory.

This paper extends our prior work presented in [32] as follows:

- We present a new optimization formulation that allows our algorithm to trade-off routing efficiency for improved data latency.
- We validate our proposed *data stashing* scheme in a real-world testbed where 41 TelosB sensor nodes are deployed, showing a practical applicability.
- We perform qualitative and quantitative analyses on the effects of packet delivery delay and energy saving in terms of network routing performance in a large-scale simulated network.
- We add experimental results to show the geographical load balancing in packet transmission over the network.
- We add experimental results to investigate the geographical location of the selected stashing nodes over the network.
- We add discussions on the applicability of the technique in different types of networks, and the possibility of cross layer integration with the media access control (MAC) layer.

The rest of this paper is organized as follows: After discussing related work in Sec. II, we present our long-term mobility prediction algorithm in Sec. III. In Sec. IV, we propose our predictive data delivery schemes, and Sec. V presents the evaluation results of our proposed approach. After we add discussions in various aspects in Sec. VI, we conclude this paper in Sec. VII.

## II. RELATED WORK

Related work can be classified into two categories: mobility prediction and routing to mobile users.

### A. Long-Term Mobility Prediction

Long-term mobility pattern modeling has been studied using GPS (Global Positioning System) data, or association data

from cellular networks or wireless LANs (Local Area Networks). Because raw GPS data contain many outliers, most of the previous research [5], [27] filter out noisy and unreasonable measurements first. They then identify the possible goal locations from the filtered GPS positions and construct prediction models. Alvarez-Garcia et al. [5] find places where a user spent a significant amount of time, and cluster them into locations. A Hidden Markov model is applied to movement between locations, which is then used to predict future locations. Krumm et al. [27] obtain end-to-end routes from raw GPS data, and use a Bayesian model and a trip similarity clustering algorithm to predict the next location. Further, Lane et al. [29], and Lee et al. [33] not only extract significant places from filtered GPS data, but also try to infer human activity associated with each different place. [29] constructs a user specific activity classification model by embedding inter-person similarity in various aspects of similarity networks. Also, [33] presents a Bayesian network model for activity using context hierarchy based on contextual information from a mobile phone. Their work suggest exploiting high-level context (i.e., users' activities) of a mobile user with higher fidelity.

These previous approaches including [43] infer long-term destinations of mobile users. Recently, [42] proposed a path prediction model based on historical movement trace maps. Our work provides not only the destination prediction, but can also predict all possible future *trajectories* of the user. Furthermore, our techniques rely only on wireless association traces allowing of more generic applicability of mobile users' movement.

Similarly, in cellular networks, some previous work [7], [23] predicts the next cell connection based on various information such as past handoff rate, size of the active set, active set update rate, and signal strength variation. In wireless LAN networks, a theoretical work [3] constructs a Gauss-Markov mobility model for predicting the speed, direction, and randomness degree of mobile users. Further, based on real-world empirical traces, a long-term large-scale measurement study of user-access point (AP) association at Dartmouth [26] has inspired work in mobility prediction. It has been noted that wireless users' locations can be predicted with up to 72% accuracy using an order-2 Markov predictor [58] for users with long trace lengths. Further analysis of the same dataset has suggested the feasibility of predicting the future associations of a mobile user in space and time [57], and a similar study [60] has been conducted for seamless handoffs in wireless LAN. Using a different dataset, Ghosh et al. [18] describe techniques to predict a user's location with respect to social hubs such as buildings and classrooms, rather than individual wireless APs. Although the approaches work with real world mobility data, and use only association data for predicting the future association, they do not explicitly deal with noisy association for classifying mobility pattern clusters. Our work offers an explicit mechanism for classifying user mobility patterns into different representative clusters, even if the wireless association trajectories are noisy.

More recent work has exploited user context information to distribute resources more efficiently across the network and as

a basis for energy-efficient design of network applications [2], [21], [52]. Similarly, our work exploits users' mobility patterns from wireless traces, and our network optimization utilizes the predictive knowledge to improve energy efficiency of routing.

### B. Routing to Mobile Users

There is a large body of research in routing protocols designed to deliver packets to mobile users in wireless networks. Some of these protocols assume little about the network and the mobility pattern of the mobile users and perform network discovery pro-actively or on-demand. Classic protocols such as DSR [24] and AODV [46], which were originally designed for wireless ad hoc networks, and sometimes used in mobile ad-hoc routing, fall into this category. In the wireless sensor network context, protocols such as Directed Diffusion [22], SEAD (Scalable Energy-efficient Asynchronous Dissemination protocol) [25], and TTDD (Two-Tier Data Dissemination) [65] construct energy-efficient routing paths without knowledge of the mobility patterns of the sink.

Especially regarding routing to mobile sinks, mobile trajectories or their sojourn times can be programmed to optimize data forwarding efficiency in [4], [38], [54], [69]. Our work does not assume a programmable trajectory of the mobile sinks. Researchers have formulated computing energy-efficient routes in sensor networks as an optimization problem in [45], [62], [63]. Our work also frames routing as an optimization problem. However, in our optimization formulation a number of stashing nodes or the sinks themselves can be feasible destinations, while also taking into account link reliability and the probabilistic nature of the predicted trajectories of the mobile sinks.

There has been previous work on exploiting predicted mobility to improve the efficiency of routing to mobile users with predictable trajectories. Chatzigiannakis et al. [11] demonstrate an important claim that data collection should be adapted depending on characteristic mobility patterns for reducing energy consumption in routing. Chakrabarti et al. [10] proposed a protocol in which the mesh nodes keep statistics of user visits and transmit information only when the mobile user is within transmission range. Our work does not assume that the trajectory of a mobile node takes it within single-hop transmission range of each mesh node in the network. Most closely related to our work is recent work on the proactive scheme in [61], [67]. Based on the user arrival statistics, a subset of nodes elect themselves as storage nodes and initiate routing tree construction as roots. The mesh network forwards data to these storage nodes so that packets can be relayed to the mobile user. Although our work fits in this general framework, we employ different methods to overcome shortcomings of this approach. Our protocol is based on a clustering algorithm to improve the accuracy of trajectory prediction (as described in Sec. III) and uses the predictive knowledge to help an efficient routing decision which is scalable for many mobile sinks in terms of radio energy consumption and packet delivery reliability.

## III. LONG-TERM MOBILITY PREDICTION

We predict likely long-term association nodes of mobile sinks by using the current association and a past history of

association trajectories. We present a method for learning typical movement patterns from observations, representing trajectories, as well as predicting likely trajectories, given observed partial trajectories. The prediction algorithm is used by the mobile node to compute and supply information about its future trajectory to the network. We characterize the trajectories as sequences of node associations, and find clusters representing typical trajectories. Using multiple sequence alignment techniques to identify similar and dissimilar regions within a cluster, we then compute a compact probabilistic representation for the clusters which we use to efficiently determine likely future trajectories during prediction.

The predicted long-term trajectory of mobile sinks can benefit network applications; this is particularly obvious in efficient data delivery to mobile sinks. For example, when an information source needs to deliver data to multiple mobile sinks, it can select intermediate storage nodes which are close to itself in terms of communication hops, and also lie along the anticipated trajectory of the sinks. *Stashing* the data at the selected nodes, instead of routing the data directly to the sinks at their current positions, allows a mobile sink passing through the network to collect the data at intermediate storage nodes. We can further reduce redundant packet transmissions by sharing data deliveries via intermediate storage relays on nodes contained in several sinks' trajectories. The long-term connectivity prediction thus enables a scalable data delivery scheme for multiple mobile sinks.

#### A. Constructing the Mobility Model

We introduce a *trajectory* in terms of wireless association and present our mobile trajectory clustering method using given trajectories for an off-line learning phase.

In most scenarios, mobile sinks travel along a fairly limited set of trajectories. Oftentimes, this is due to obstacles present in the environment: buildings, bridges, roads, and walkways constrain the possible trajectories. Even without any environmental restrictions, there are usually few interesting start- and endpoints for any given journey, and sinks often follow short(-est) paths from a starting point to a destination, greatly limiting the set of possible trajectories.

It therefore makes sense to find and exploit the structure that is present in the likely trajectories through a network. We will do so by clustering similar trajectories, thus creating a database of historical trajectories, arranged in clusters of similar trajectories in the off-line learning phase. In order to perform practical clustering on trajectories, we require a trajectory representation, a similarity measure, and a compact representation of a cluster of sequences. The following sections describe these concepts in turn.

1) *Trajectory Representation*: In the following, we will represent a single trajectory through the network not in terms of spatial position, but in terms of the associated sensor node at any given time.

Let us consider a mobile sink moving through the network on a given spatial path. Sending periodic beacons and listening for replies, the mobile node can record the nodes in radio range at each beacon time. In each of these sets, we can

determine the association node, for example, by measuring signal strength on the acknowledgment or the beacon packet. This is the node that the mobile node would associate with to send or receive data. We represent trajectories through the network as a sequence of association nodes:

$$T = N_1 N_2 N_3 \dots N_k.$$

We only record changes in the associated node list, i.e.  $N_i \neq N_{i+1}$ . For example, given "s s a a a r r r a n n g h h h h a a e e e e y y o o", the corresponding trajectory is represented as  $T = s a r a n g h a e y o$ .

Note that due to imperfect links and radio signal strength fluctuations in dynamic environments, two node sequences recorded from the same spatial path are not necessarily identical, or even of the same length. To compensate for noisy fluctuations in capturing similar trajectory patterns, we borrow a similarity measure from computational biology where functional, structural, or evolutionary relationships between sequences encoding biological macromolecules have been thoroughly investigated. Also, note that trajectory data can be collected anonymously; the corresponding mobile sink ID is not needed, which helps to mitigate possible privacy concerns.

2) *Similarity Measure*: We use a variant of the *longest common subsequence* metric known from string theory and a variant of the *Smith-Waterman* algorithm [55] to calculate this similarity measure between two sequences.

Informally, to compute the similarity between two sequences  $T_A = A_1 \dots A_{n_A}$  and  $T_B = B_1 \dots B_{n_B}$ , we count how many nodes we have to *insert*, *delete*, or *substitute* in  $T_A$  to obtain  $T_B$ .

We define the partial match function  $F_{AB}(i, j)$ , which computes the similarity between the prefixes of length  $i$  and  $j$  of  $T_A$  and  $T_B$ ,  $A_1 \dots A_i$  and  $B_1 \dots B_j$ .  $F_{AB}$  can be defined recursively:

$$F_{AB}(i, 0) = 0 \quad \text{for } 0 \leq i \leq n_A, \quad (1)$$

$$F_{AB}(0, j) = 0 \quad \text{for } 0 \leq j \leq n_B, \quad (2)$$

$$F_{AB}(i, j) = \max \left[ F_{AB}(i-1, j-1) + s(A_i, B_j), \right. \\ \left. F_{AB}(i-1, j) + d, \right. \\ \left. F_{AB}(i, j-1) + d, \right. \\ \left. 0 \right],$$

where the similarity for insertion or deletion operations,  $d$ , as well as the similarity function on individual nodes are free parameters. In our experiments, we use  $d = 0$ , meaning we see no similarity in deletion or insertion operations. We define a per-node similarity function  $s(A_i, B_j)$  where we set  $s(A, A) = 1$  and  $s(A, B) = 0 \quad \forall A \neq B$ , meaning that we penalize for a different node in substitute operations. With these parameters,  $F_{AB}(n_A, n_B)$  is the length of the *longest common subsequence* in the two sequences.

We often need to compare several partial trajectories  $A$  to a significantly longer complete trajectory  $B$ . As it is defined above,  $F_{AB}(n_A, n_B)$  will be lower the shorter  $A$  is, even if (in the matching part of  $B$ ) there is a perfect match. To

compensate for differences in length of  $A$  or  $B$ , we normalize the similarity measure by dividing by the length of the shorter sequence:

$$sim(A, B) = \frac{F_{AB}(n_A, n_B)}{\min(n_A, n_B)}. \quad (4)$$

Note that the similarity measure we define is not a distance metric.

3) *Cluster Representation*: Based on the pairwise similarities between all pairs of sequences, we apply a hierarchical clustering method. We use the *average linkage* metric which uses the average similarity between objects in two clusters to determine whether clusters are merged. For a more detailed description of the hierarchical clustering method, we refer to [41].

Each cluster consists of a number of similar sequences. During the prediction stage of our algorithm, we will be presented with a partial trajectory  $T$  and asked to find the most likely cluster for this trajectory. While it would be possible to compute average linkage for  $T$  and each cluster, this would entail computing the similarity between  $T$  and each trajectory in the database. To avoid limiting the size of our database, we instead propose a probabilistic representation for each cluster, so that we can efficiently query for the best matching cluster.

We create a representation for our clusters in two steps: for each cluster, we first align all its sequences and then create a probabilistic summary of the aligned sequences.

(a) **Multiple Sequence Alignment**: Given a set of sequences, multiple sequence alignment algorithms compute how the sequences should be lined up in order to maximize overlap. Our algorithm for computing the similarity between two sequences essentially computes a sequence alignment for these two sequences. In the general case, however, multiple sequence alignment is an NP-hard problem [64]. Heuristic alignment methods are widely used for DNA or protein alignments in bioinformatics [35]. We use a modified version of ClustalW, one of the most popular alignment tools [59].

The ClustalW algorithm starts by aligning the most similar sequences, and progressively adds more distant sequences one by one. This iterative procedure yields a good alignment of all sequences. We modify ClustalW to use the set of node IDs instead of an alphabet of amino acids or DNA base pairs. We also use an unweighted substitution matrix, making each substitution equally likely. The computation complexity of ClustalW algorithm is  $O(N^2L^2)$  where  $N$  is the number of sequences and  $L$  is the sequence length [36]. To construct a cluster profile database, the aligned trajectory sequences need to be stored with storage cost  $O(NL)$ .

The output of the algorithm is aligned sequences that have the same length. Gaps in the aligned sequences are marked with a special gap symbol (see Fig. 2). We compute a probabilistic representation from these aligned sequences within a cluster.

(b) **Probabilistic Cluster Representation**: Given the set of aligned sequences of length  $n$ , we construct a probabilistic representation for the cluster, which we call the cluster

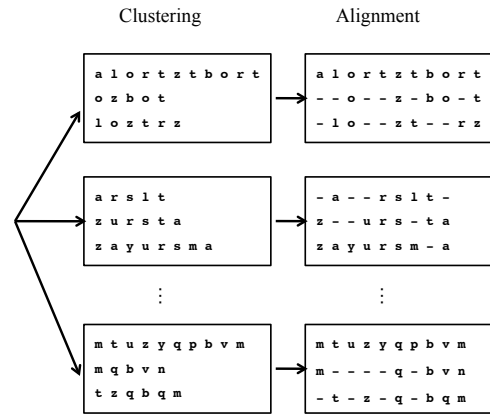
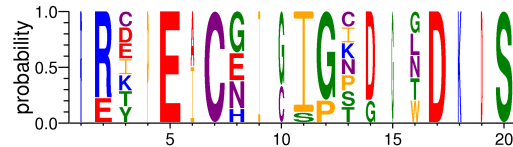


Fig. 2. Clustering and alignment procedures. A number of trajectories are clustered together with respect to sequence patterns, and are aligned by using a multiple sequence alignment algorithm (ClustalW). The aligned sequences form a probabilistic trajectory profile.

<b>RTEACEGIPDS</b>	<b>-RT-EACE-GIP----D--S</b>
<b>RECEIGIPSDS</b>	<b>-R--E-CEIGIPS---D--S</b>
<b>YECI</b>	<b>--Y-E-C---I-----</b>
<b>RECEICGIGNGNS</b>	<b>REC-EICG--IGNG-ND--S</b>
<b>EDECIGPDS</b>	<b>-ED-E-C---IGP---D--S</b>
<b>REHCIGKDS</b>	<b>-R--E-CH-CIGK---D--S</b>
<b>RECIGC</b>	<b>-R--E-C---IGC-----</b>
<b>RIECGSGDLDKS</b>	<b>-RI-E-CG--SG-D-LDK-S</b>
<b>KECGIGTDWDS</b>	<b>--K-E-CG--IGTD-WD--S</b>
<b>RECNIIGDGTDS</b>	<b>-R--E-CN--IG-DGTD--S</b>
<b>REPECNIGIDGDKDS</b>	<b>-REPE-CN--IGID-GDKDS</b>

(a) Sequences in a cluster (b) Sequences after alignment



(c) Profile presentation from the aligned sequences in a cluster

Fig. 3. Sequences belonging to a cluster, the aligned sequences, and their graphical profile generated by WebLogo [15].

*profile*. A profile is a sequence of probability distributions  $P = P_1 \dots P_n$ . At each position  $i$ , the probability distribution  $P_i(A)$  denotes the probability that node  $A$  appears in position  $i$ . This representation can also be considered a 0<sup>th</sup> order Markov model of the set of aligned sequences.

The cluster profiles allow us to efficiently find the most likely cluster, given a partial test sequence. See Fig. 2 for an illustration of clustering and alignment for profile generation, and Fig. 3 for a profile example of sequences after clustering. Sequences classified in a cluster (Fig. 3(a)) are aligned to one another through the ClustalW algorithm as in Fig. 3(b). Given a group of these aligned sequences for each cluster, we calculate the probability distribution over each column index. In this way, we obtain a probabilistic trajectory profile for a cluster and continue this procedure for the other clusters.

For illustration purposes, we generate a graphical represen-



tation of probabilistic trajectory profiles (see Fig. 3(c)) by using WebLogo [15]. The figure graphically represents all possible realizations of sequences within a mobile trajectory cluster. The height of the letters within each stack indicates the relative frequencies for each possibility, while the width of the stacks indicates the relative proportion of valid readings at that position where the more gaps (i.e., spaces to compensate for insertions and deletions) in the sequence at a specific position means a thinner stack.

### B. Connectivity Prediction

In this section, we describe a long-term connectivity prediction algorithm. The prediction algorithm provides a set of possible future trajectory nodes using the mobile trajectory clusters constructed in Sec. III-A.

If the future trajectory of a mobile sink is unknown, our system tries to predict its behavior by comparing it to historical data. We will demonstrate that even limited information about the future relay nodes can significantly improve routing performance in terms of transmission cost and load balancing in Sec. V.

Specifically, we are given a partial trajectory  $T_M = N_1 \dots N_{n_M}$  recorded after the mobile sink enters the network. We would like to compute a set of trajectories through the network that are likely continuations of the recorded partial trajectory. In our experiments, we compute the cluster that  $T_M$  most likely belongs to, and use all elements in that cluster as our set of likely trajectories. For each of the returned sequences, we have to find the most likely position of the last node of our partial trajectory  $T_M$ , so that we can avoid pushing data to nodes that have already been visited by the mobile node. In the next two sections, we describe how we compute the closest cluster (Sec. III-B1), and how we compute the current position of the mobile node within the returned set of sequences (Sec. III-B2).

1) *Cluster Matching*: Computing the similarity between a trajectory and a probabilistic trajectory profile is very similar to computing the similarity between two trajectories. In fact, the recursive definition Eq. (2) can be used unaltered, except that the partial match function  $F_{TP}$  now operates on a trajectory  $T = N_1 \dots N_{n_T}$  and a profile  $P = P_1 \dots P_{n_P}$ . We need to change the definition of the per-node similarity function  $s(N_i, P_j)$  (instead of using  $s(A_i, B_j)$ ) to reflect the likelihood of  $N_i$  given the probability distribution  $P_j$ . We choose

$$s(N_i, P_j) = \begin{cases} eP_j(N_i) & P_j(N_i) > 0, \\ h & \text{otherwise,} \end{cases} \quad (5)$$

and use the parameter values  $d = -1$  in Eq. (2),  $e = 8$ , and  $h = -1$  which have proven effective in our setting. By varying each parameter, we choose a set of parameters that leads to the most accurate cluster prediction for our datasets (see Sec. V). For instance, denser deployments incur higher variability of relay nodes, thus the parameters need to allow for additional mismatches and insertions/deletions.

2) *Alignment*: Once we have found the best-matching cluster, we need to align the partial trajectory with the sequences in the cluster in order to find the part of the trajectories that

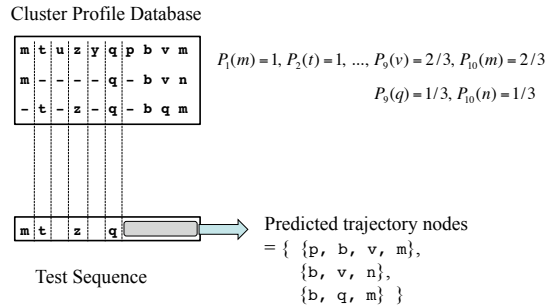


Fig. 4. Sequence alignment of a partial trajectory with a cluster profile.

will be visited by the mobile node. All sequences in the cluster are aligned to each other and the cluster profile using multiple sequence alignment as described in Sec. III-A3. It is therefore sufficient to find an alignment of the partial trajectory  $T$  to the profile  $P$ . In particular, we are interested in the position  $J$  that the last node in the partial trajectory,  $N_{n_T}$ , is matched to in the profile  $P$ .

Note that the Smith-Waterman algorithm implicitly aligns two sequences in order to compute their similarity. We can make this alignment explicit: after we compute  $F_{TP}(i, j)$ , the best-matching position of the last node in  $T$ ,  $N_{n_T}$ , is given by  $J = \operatorname{argmax}_j F_{TP}(n_T, j)$ .

If the matched cluster contains the set of expanded trajectories  $\{T_1 \dots T_k\}$ , all of which have been aligned to be of length  $n$  as described in Sec. III-A3, then the set of trajectories that needs to be considered by the data stashing optimization is  $\{T_1[J, n] \dots T_k[J, n]\}$ . See Fig. 4 for an illustration.

## IV. PREDICTIVE DATA DELIVERY

The main objective of this paper is to develop a routing scheme that delivers data to mobile sinks through a sensor network. We exploit knowledge about the mobility of the sinks to lower the cost and increase the reliability of data transmission.

In particular, we solve the following problem: One (or several) mobile sink moves through a network, collecting local data from the nodes in the network. Traditionally, we would either send all data directly to the current position of the mobile sink (that is, to a node that is close to the mobile sink, which will relay the information to the mobile sink), or not send any data at all, and wait for the mobile sink to collect the data as it passes each of the sensor nodes. The latter option is often infeasible if we cannot control the movement of the mobile sink, or if moving within radio range of each desired node is not an option. We choose a compromise between the two extremes. Using knowledge about the trajectory of the mobile sink, data sources route data to a set of *stashing nodes* that store information along the likely trajectories of the mobile sink.

At the core of our method is an optimization procedure that for each sensor node chooses a set of stashing nodes that guarantee (with high probability) that a mobile sink will receive data from the source (see Fig. 5 for an illustration). The optimization procedure is described in detail in Sec. IV-B.

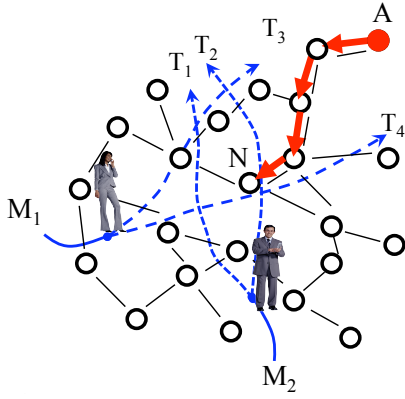


Fig. 5. Our optimization procedure chooses a set of nodes that covers all possible future trajectories (blue dashed line) of mobile sinks, but at the same time is as cheap to route to as possible.

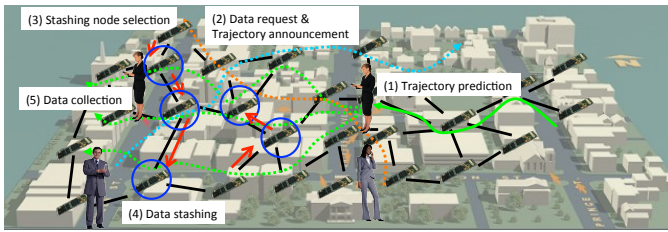


Fig. 6. Overall procedure of our proposed routing protocol of trajectory prediction (by mobile sink), stashing node selection (by data source sensor), and routing.

We assume some knowledge about the possible trajectories that a mobile sink can take. This information is either provided by the mobile sink, or is deduced from motion patterns of sinks in the network, as shown in Sec. III.

Our evaluation in Sec. V shows that exploiting knowledge of sinks' motion can greatly decrease transmission costs and energy use. However, we do require stationary sensor nodes to have some storage capacity for stashing data, and we assume that the data delivered to the mobile sink is delay-tolerant. The sink will collect the data throughout her journey through the network, possibly introducing some delay in data availability to the sink.

#### A. Protocol

In this section, we clarify the overall procedure of trajectory prediction, stashing node selection, and routing. We provide a high-level description of the protocol used to negotiate data stashing for a mobile sink as shown in Fig. 6. The protocol assumes that a mobile sink enters the network and requests data from a set of sensor nodes.

- (1) **Trajectory prediction.** When a mobile sink joins the network, it beacons in regular intervals. Sensor nodes in range reply with their IDs and the sink selects the node whose reply was received with the strongest signal as its *relay node* for proxy. As the sink moves through the network, we can observe a sequence of relay node IDs. We use this sequence to predict a set of likely trajectories that most closely match the recorded prefix

in the database of historical trajectories acquired in an off-line learning phase, as described in Sec. III-B. If the trajectory or set of likely trajectories is known, this step can be skipped.

- (2) **Data request and trajectory announcement.**

The mobile sink announces the set of likely trajectories to the network. The set of trajectories is encoded and broadcast to the whole network. This message can also contain a set of sensor nodes whose data are interesting to the mobile sink.

- (3) **Stashing node selection.** Upon receiving a sink's request for data and a set of likely trajectories, each sensor node (which is a data source) computes a set of stashing nodes that cover the likely trajectories and minimize the routing cost required to send the data to the stashing nodes. The optimization procedure is described in Sec. IV-B.

- (4) **Data stashing.** Sensor nodes forward data to the stashing nodes, for future delivery to mobile sinks.

- (5) **Data collection.** As the mobile sink moves through the network, it regularly beacons to announce its position. If a stashing node receives a beacon, it starts transmitting the data stashed at this node to the mobile sink.

This protocol is easily extensible to multiple mobile sinks. We disambiguate between the sinks based on their unique IDs and discuss scenarios with multiple mobile sinks in Sec. V.

Note that we assume an underlying point-to-point routing protocol such as S4 [40], however, we make no assumptions on the properties of this protocol.

#### B. Network Optimization

Contrary to traditional routing schemes, data delivery by stashing does not route to the current position or in fact, to any single future position of a mobile node. Instead, we route to all possible trajectories of one or several mobile nodes. To this end, we choose a set of nodes that covers all trajectories, but at the same time is as cheap to route to as possible.

We formulate the problem of data delivery from a data source to stashing nodes along a set of trajectories as a linear programming relaxation of a binary integer program. The proposed scheme finds, for each data source, the optimal stashing nodes to which to send the data. Each data source can compute the solution to its particular routing problem independent of the other nodes. In the following, we will assume that a node  $A$  is asked to route data to one or several mobile nodes which travel along a set of possible trajectories  $\{T_1 \dots T_m\}$ . The output of the optimization is a set of stashing nodes  $R = \{R_1 \dots R_k\}$ .

To set up our integer program, let us first define an indicator function  $I(N)$  indicating whether our data source has chosen  $N$  to be part of its set of stashing nodes:

$$I(N) = \begin{cases} 1 & N \in R, \\ 0 & \text{otherwise.} \end{cases} \quad (6)$$

Based on this definition, we can write the objective function to minimize as

$$f = \sum_N I(N)C(A, N), \quad (7)$$

where  $C(\cdot, \cdot)$  denotes the routing cost between two nodes. In our experiments, we use the expected number of transmissions on a link as the routing cost for that hop, and the cost for a path is the sum of the per-hop costs.

In order to make sure that the data can be retrieved by the mobile sinks, there must be at least one stashing node on each of the trajectories. Given the trajectories  $T_i = B_1^i \dots B_{n_i}^i$ , we can write this condition as a single linear constraint per trajectory  $T_i$ :

$$\sum_{0 < j \leq n_i} I(B_j^i) \geq 1 \quad (8)$$

Using these definitions, our problem is to find a set  $R$  that minimizes Eq. (7) subject to the constraints Eq. (8). This problem can be solved by a linear program (LP) if we ignore the integrality constraints. In our case, since the variable  $I(N)$  is either zero or one, we are dealing with the special case of binary integer programming, which we solve using the bintprog optimization toolbox in MATLAB and AMPL/Gurobi.

### C. Optimization to Improve Data Latency

We present an extended optimization problem of selecting stashing nodes, considering how long it will take for a mobile node to pick up the data at the stashing nodes. A certain class of applications may require time-sensitive packet delivery to mobile users. To take into account the factor of how far the selected stashing nodes are located currently from mobile nodes in the predicted trajectory, we apply the *regularization* technique [8] by a factor of  $\alpha$ . We aim to minimize the weighted sum of the objective functions: (1) the total routing cost from data sources to the selected stashing nodes and (2) the average trajectory distance from mobile nodes to the selected stashing nodes.

We set up a weighted version of an integer program as follows:

$$f' = \sum_N I(N) \cdot \left[ C(A, N) + \alpha \frac{\sum_{i=1}^V \text{dist}(M_i, N)}{V} \right] \quad (9)$$

where  $V$  is the number of mobile nodes, and  $\text{dist}(M_i, N)$  is the sequence distance between the mobile node  $M_i$  and the stashing node  $N$  in the predicted trajectory of  $M_i$ .

We find a set of stashing nodes that minimizes the weighted sum of the objective functions Eq. (9), while satisfying the same constraints of guaranteeing data delivery on each predicted trajectory as in Eq. (8).

## V. EVALUATION

We conduct experiments with real-world wireless traces to validate our trajectory clustering algorithm (Sec. V-A). We evaluate our data delivery scheme in a real-world testbed (Sec. V-B) and a larger network simulation (Sec. V-C) by comparing our technique against direct routing which immediately delivers data directly to mobile sinks in terms of routing efficiency and robustness.

We evaluate routing in terms of routing cost, energy saving, packet delivery, and load balance metrics, and compare our

optimization scheme (*Stash*) to two other protocols: a point-to-point proactive distance-vector routing protocol (*Direct*) based on [47] where each static sensor node delivers its data to the currently connected static relay node of each mobile sink, and the idealized stashing scheme that is given the perfect set of future locations for all sinks (*Stash(opt)*). We note that all three protocols that we evaluate use the same underlying point-to-point routing protocols. While more advanced routing protocols (such as [12], [13], [40], [44]) can be integrated with our data stashing algorithm, the evaluation of data stashing benefits for different static protocols is out-of-scope for this paper. The *Direct* protocol compares performance of our optimization scheme to traditional data delivery methods. The *Stash(opt)* scheme serves as an upper bound on what our algorithm could achieve, given perfect prediction. Note that this is not only a theoretical bound; it is achieved if the trajectories of nodes are known in advance — for example because the mobile sink announces them.

When we evaluate the routing cost, we count how many packets were used to deliver data from sensor nodes to destination nodes, after sensors learn the identity of the correct relay or possible relay candidates. In the evaluation of testbed experiments (see Fig. 9) and a larger network simulations (see Fig. 11 and 12), we demonstrate that even without considering the control cost, our *Stash* scheme requires far fewer data packets than the *Direct* scheme. We also compare energy efficiency of *Direct* and *Stash* schemes. It has been observed that energy consumption for one-off computation tasks in sensor networks is typically dominated by the energy consumed for radio transmissions [31], [51]. We thus focus on evaluating energy efficiency in terms of routing cost in our evaluation.

In our experiments, we measure whether packets arrive at the stashing node (or in the direct routing case, at the current relay node), we do not take into account packet loss on the last hop, from the stashing or relay node to the mobile node. Since this affects *Stash* and *Direct* equally, it does not change the comparative analysis, however, it might lower the overall reliability of both methods. Consequently, we only count a packet as delivered if it is stashed at a node that is visited by the mobile node, i.e., if the stashing node is the associated node to the mobile node at any point in time. In reality, even if the stashing node is never selected as the associated node, it might still be within range. While this would slightly increase the reliability of data stashing, we do not believe it would change the qualitative results. We show that benefits of our technique are better load balancing and more even utilization of network resources, such as energy.

Regarding the load balance metric, we measure the number of packets sent by each node and show it in a potential plot and in a cumulative distribution function.

### A. Clustering and Trajectory Prediction

First, we validate our probabilistic trajectory model used for prediction using real-world mobility data traces from UMass DieselNet [6] (shown in Fig. 7). The traces consist of time series of wireless access point (AP) IDs that wireless cards



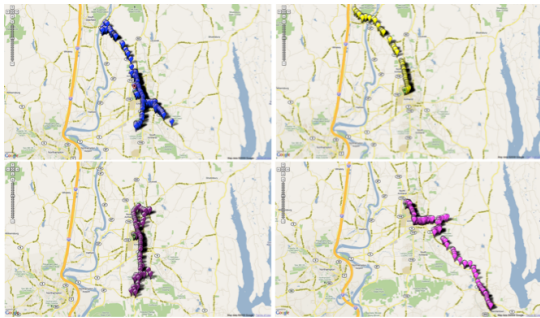


Fig. 7. Typical trajectories of moving buses in UMass from the DieselNet dataset. When a bus is associated with a nearby access point, the access point is shown with a marker.

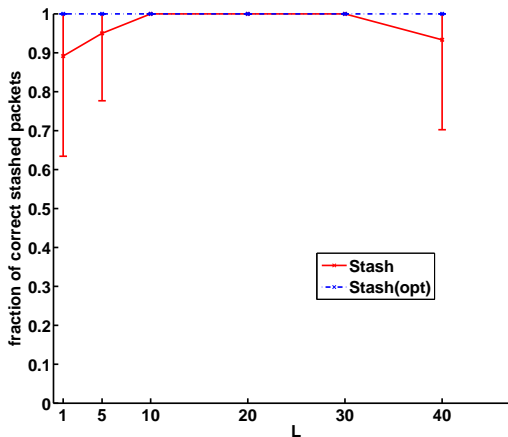


Fig. 8. Fraction of packets stashed on nodes that are actually visited by the mobile node depending on number of nodes  $L$  used for prediction in the DieselNet dataset.

installed in buses connect to. There are 34 buses, 4198 access points, and 789 bus trips in the dataset, covering an area in and around the UMass campus. We evaluate how reliably the selected stashing nodes can connect to mobile sinks. Note that we did not use any bus identification information, but used only wireless association list of each bus trip as the input of our trajectory model.

We tested the hierarchical clustering algorithm described in Sec. III-A. The algorithm ended up with clustering the set of 789 bus trips into 23 clusters. Even though we have no ground truth to compare these clusters against, we visually evaluated the clusters and found them of good quality.

We use the clusters we found in the DieselNet traces to predict likely trajectories for a partial trajectory (which was not part of the training data). Since there is no network data available, we assume that nodes are connected by perfect links, and that routing cost between two nodes is proportional to the Euclidean distance between them. While these idealized assumptions do not allow us to draw conclusions about network-related quality metrics, they help us evaluate the quality of our prediction algorithm in the context of data stashing.

Using the predicted trajectories and the cost metric described above, we select stashing nodes for ten randomly chosen data sources in the network, and measure what percentage of packets the mobile sink is able to retrieve. As



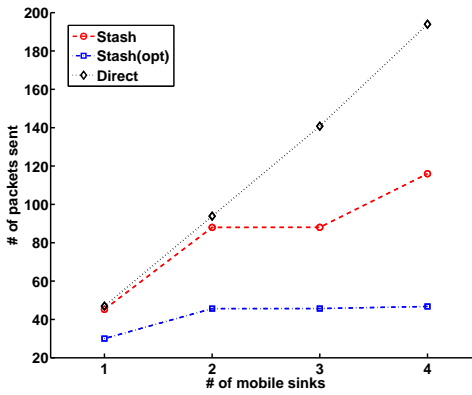
Fig. 9. 41 stationary sensors (marked with red circle) distributed over  $65 \times 100 \text{ m}^2$  and moving paths of mobile sinks in Clark building at Stanford University. 10 different moving paths including the opposite direction are explored while a mobile sink carries a sensor device and communicates with the networks.

Fig. 8 shows, if we base our predictions on a very short historical trajectory, the prediction quality suffers (*underfitting* problem). For accurate prediction, we need longer series of past movement patterns that will allow us to identify future paths. On the other hand, if the historical trajectory is too long, this constrains the possible future user locations to a small set, as few historical trajectories in the training set fit the current data. The error of prediction then increases as a result of *overfitting*. The results show that our prediction method performs well in real-world scenarios for  $L$  between 10 and 30.

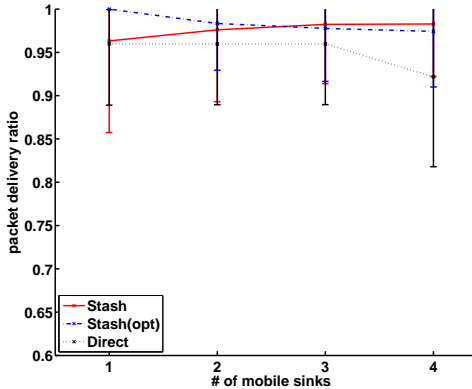
### B. Small-Scale Real-World Network Experiment

We evaluate our algorithms in a real testbed deployed in Clark Center at Stanford University as in Fig. 9. We used TinyOS 2.1 [1] and configured 41 stationary TelosB sensor nodes [49] to form a sensor network in an  $65 \times 100 \text{ m}^2$  area. We set transmission power to 0 dBm that resulted in the radio range of approximately 20 – 30 m. We asked users to carry a TelosB node in the network along 10 different moving paths as shown Fig. 9. The users moved at a speed of approximately 1.4 m/s, and the mobile node exchanged packets with stationary nodes at a rate of 1 Hz. The node that replies back to the mobile node with the highest signal strength is considered as the association node at every beacon time. In these experiments, all of sensor nodes send data to mobile sinks. It should be noted that each unique moving path is highly overlapped with others in part, and also the resulting association nodes are dynamically varying even with the exact same moving path due to the real wireless vagaries. Any mobile node identification or trajectory information other than associated node IDs is not used. Hence, this experiment setup makes the future trajectory prediction neither obvious nor trivial. For evaluation results, the number of nodes for prediction,  $L = 10$  is used.

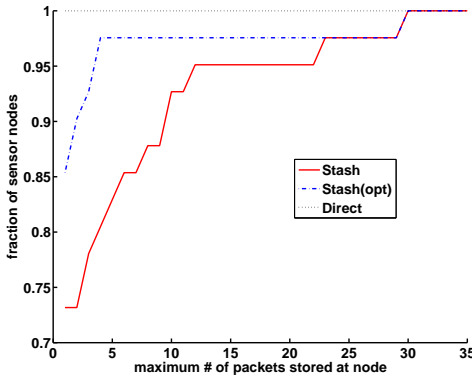
We examine how the number of mobile sinks affects the performance of these algorithms in terms of routing cost, packet delivery reliability, and storage overhead. As the number of mobile sinks increases, routing cost of the *Direct* scheme is proportional to the number of the sinks, whereas stashing algorithms are affected much less, because they exploit overlaps in the different trajectories (Fig. 10(a)). In terms of packet



(a) Routing cost



(b) Reliability. Shown are mean, error bars are standard deviation



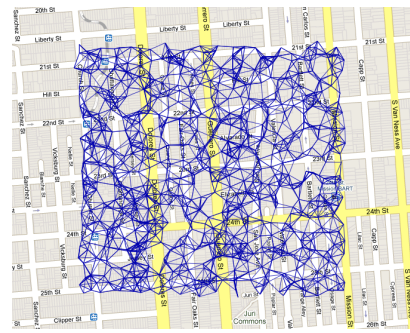
(c) Fraction of nodes storing less than a certain number of packets

Fig. 10. Routing cost, delivery reliability, and storage cost depending on the number of mobile sinks in Clark testbed.

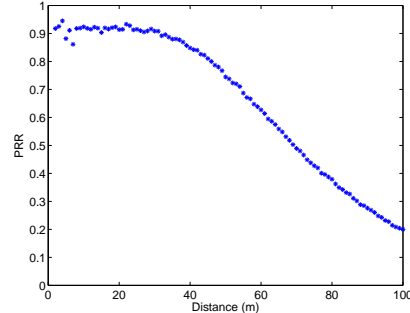
delivery, our stashing algorithm achieves high reliability above 95%, whereas the *Direct* scheme suffers due to independent packet delivery directly to each mobile sink while traveling over a larger number of hops (Fig. 10(b)). Regarding storage overhead, our *Stash* scheme requires only 10 % of sensor nodes to store 10 or more packets (Fig. 10(c)).

### C. Large-Scale Network Simulation Experiment

We also test the algorithms in a larger simulated network of downtown San Francisco. The network consists of 716 sensor nodes in an  $830 \times 790 \text{ m}^2$  area (see Fig. 11). We generated 20



(a) Connectivity graph over 716 sensor nodes where links are shown for PRR > 75%.



(b) Wireless connectivity characteristic in simulation.

Fig. 11. Wireless sensor network in downtown San Francisco for simulation. 716 sensor nodes are distributed over  $830 \times 790 \text{ m}^2$ .

different trajectories, a subset of which we show in Fig. 12. Each vehicle moves at a random speed of  $\mathcal{N}(30, 5^2)$  km/h and broadcasts beacons at 1 Hz. To derive radio signal strengths for transmitted packets, we use a combined path-loss and shadowing model with a path-loss exponent of 3, a reference loss of 46.67 dB, and an additive Gaussian noise of  $\mathcal{N}(0, 5^2)$  dB. These parameters have been derived from measurements in urban environments [20]. We model interference effects using the CPM (Closest-fit Pattern Matching) model [30] in TinyOS 2.1 [1] with `meyer-light` noise traces.

We implemented our routing algorithm in the TinyOS TOSSIM simulator [34] using idealized static shortest-path routing. In our scenario, it is often the case that we route several packets along similar paths. We use multicast to reduce redundant packet transmissions. We ran all of the experiments 10 times, and draw mean values with standard deviation error bars wherever applicable.

Our evaluation shows that *Stash* has lower control overhead than *Direct*. Both *Stash* and *Direct* require flooding that reaches the entire network to announce the presence and paths to the mobile sink. However, there is a key difference: the *Direct* scheme requires continuous flooding to announce each mobile sink's current relays, while in the *Stash* scheme, the mobile sinks need to announce the anticipated trajectory node IDs only once (unless the network needs re-stashing for difficult prediction scenarios). In our 716 node topology, it took 682 packet transmission to disseminate one packet from a mobile sink to the entire network using the Drip dissemination algorithm in TinyOS 2.x. In our simulation setting, the *Direct* method requires one position update every 2 seconds for the sink speed of 30 km/h. This position update needs to



Fig. 12. Moving paths of mobile vehicles where each unique moving path is highly overlapped with others in part. Each vehicle moves at a speed of  $\mathcal{N}(30, 5^2)$  in km/h. We generate 20 different moving paths including the opposite direction as well. All of 20 vehicles are moving over the networks while communicating with sensor nodes as in Fig. 11(a).

be disseminated throughout the network. Hence, the control overhead of *Direct* for this setting is 341 packet transmission per second. On the other hand, in *Stash*, the encoded set of trajectory nodes can be disseminated throughout the network with a total of 7502 packet transmissions per mobile sink.<sup>1</sup> Thus, the control overhead of *Direct* exceeds that of *Stash* after 22 seconds of operation and continuously increases at 341 packet transmissions per second while the overhead for *Stash* remains constant.

Note that the protocols use global knowledge of the network and deliver data to mobile sinks along shortest routes. A specialized protocol like S4 [40] might be a better choice for the dynamic routing environment in sensor networks. To understand the implications of using a scalable routing protocol such as S4 to route packets to the stashing nodes, we ran the S4 protocol in TOSSIM on the same topology with 20 beacon nodes in which we ran *Stash*. We computed the cost of the paths selected by S4 to route packets from the sensor nodes to the stashing nodes. The result shows that the routing cost of *Stash* using S4 is 1.27 times higher than if using an ideal shortest path routing. We do not expect this change in routing algorithm to lead to significantly different results of our comparative evaluation.

We demonstrate that given even limited information about future trajectories of sinks, optimization of routing paths leads to significant improvements in routing performance.

1) *Network Performance*: We evaluated our network optimization scheme against the direct point-to-point and perfect stashing algorithms using the simulated network. In these experiments, all 716 sensor nodes are transmitting data to 1 – 20 mobile sinks. Given the moving paths of mobile vehicles as shown in Fig. 12, we constructed trajectory clusters and their profiles. The average length of a cluster profile is 513.

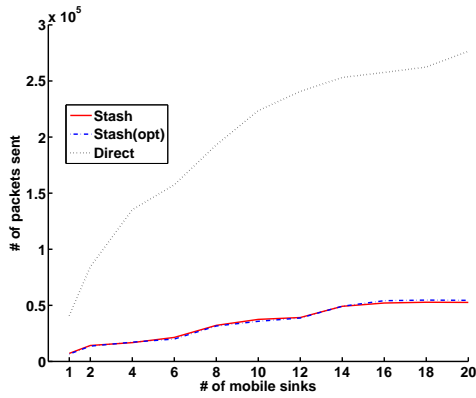
We first analyze how the number of mobile sinks affects the performance of these algorithms. Even though the performance of all algorithms degrades as the number of sinks increases, stashing algorithms are affected less, because they

exploit overlaps in the different trajectories (see Fig. 13(a)). This effectively prevents network congestion. In fact, data stashing requires only 19% of packets to deliver the same data, compared to direct routing, achieving an energy saving of over 80%. Consequently, congestion in the network causes direct routing to drop a significant number of packets while stashing algorithms deliver above 80% of the packets even for 20 sinks (see Fig. 13(c)). The *Stash* routing algorithm uses up to 30 retransmissions just like the state-of-the-art collection protocol CTP [19]. Note that the performance of stashing algorithms also decreases due to increased network congestion, but at a much lower pace.

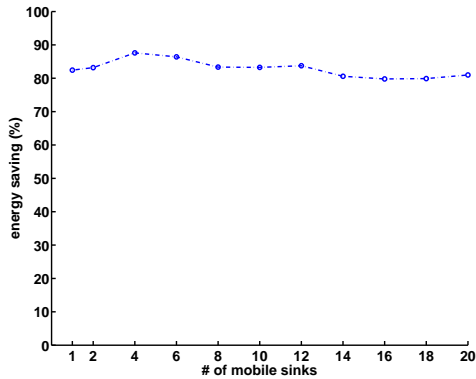
The performance of the predictive stashing scheme is close to the upper bound set by perfect prediction. This means that the combination of probabilistic prediction and data stashing performs well even under a degree of uncertainty (or prediction error). *Direct* scheme, on the other hand, requires a large amount of packet transmissions and suffers from poor packet delivery performance. This demonstrates that *Stash* algorithm can improve routing performance through predictive data dissemination even with a limited knowledge of the future user location.

We also evaluate how the length of predicted trajectories affects performance. If the trajectory prediction is very uncertain far in the future, or if there are some constraints on permissible packet delivery delay, it might be preferable not to use the full predicted trajectories, but only allow stashing at the first  $W$  nodes. The results of these experiments are summarized in Fig. 14. Intuitively, longer trajectories give the network optimization more choice to select future stashing nodes. Consequently, sensors are more likely to find stashing nodes close to their own location, decreasing routing cost and congestion, while significantly increasing energy saving in routing. Note that our optimization scheme can only counterbalance the effects of imperfect trajectory prediction if it is given enough choice. In our experiments, the break-even point is at  $W = 10$ . Achieving high reliability and efficiency of data delivery to the sinks, however, has its cost in increased delay. As  $W$  increases, it is more likely that the stashing nodes are located far in the future along the sink's trajectory.

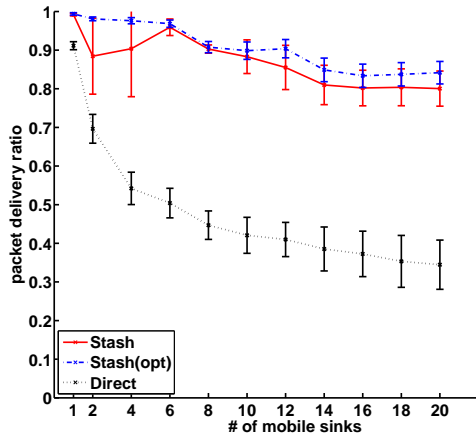
<sup>1</sup>The size of the encoded trajectory requires 11 packets due to 110 byte payload limit in TinyOS packets. Thus, it takes 7502(= 682 × 11) packet transmissions per mobile sink.



(a) Routing cost



(b) Energy saving

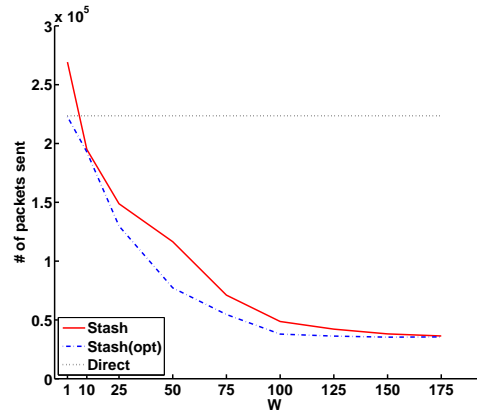


(c) Reliability. Shown are mean, error bars are standard deviation

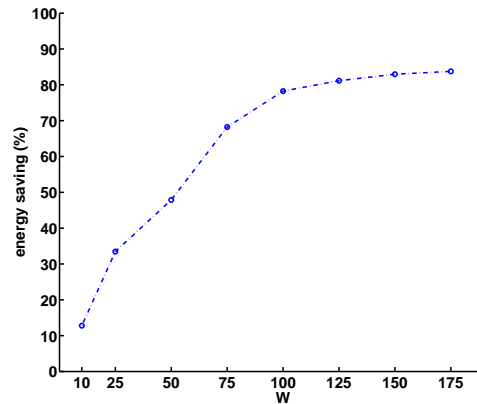
Fig. 13. Routing cost, energy saving, and delivery reliability depending on the number of mobile sinks.

There is another interesting tradeoff between transmission cost and computation cost depending on  $W$ . As  $W$  increases, each sensor node receives a larger number of anticipated trajectory nodes from mobile sinks, and needs to solve a more complex linear program. Also, a larger  $W$  means a longer-term prediction given the same information about trajectory. In practice, especially in large networks where we would expect very long trajectories, one would set a limit of  $W \approx 100$ .

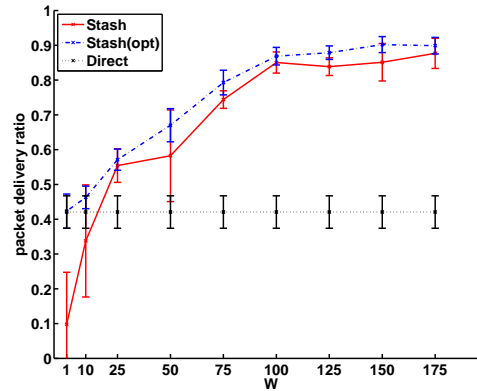
We investigate the impact of prediction performance with data stashing on packet delivery reliability. The prediction



(a) Routing cost



(b) Energy saving



(c) Packet delivery ratio to mobile sinks, representing the mean value and error bars of standard deviation

Fig. 14. Routing cost and delivery reliability depending on the number of predicted trajectory nodes  $W$  for 10 mobile sinks.

algorithm uses the first  $L$  nodes of the sink trajectory to predict the rest. Fig. 15 shows the performance of our prediction algorithm with data stashing (we use packet reception ratio as a proxy) as a function of  $L$ . Too little information about the trajectory leads to worse performance as prediction quality suffers. However, waiting for more information is only useful up to a point: waiting for information also results in fewer choices for stashing, since some of the trajectory has already been visited. In our setting,  $L = 20$  appears optimal.

We evaluate the timing of packet delivery of each scheme



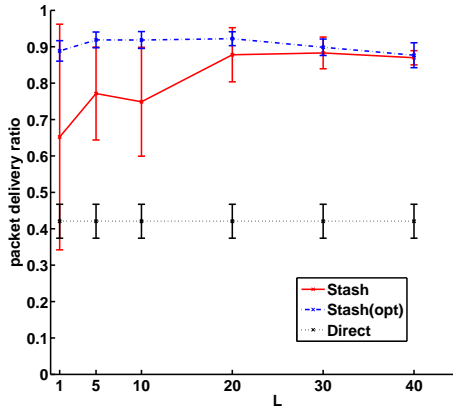
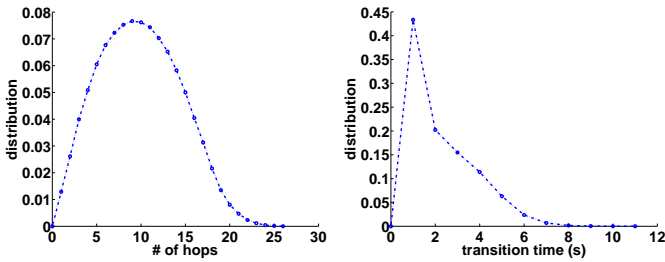
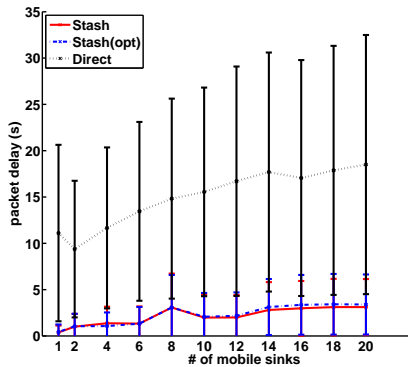


Fig. 15. Packet delivery reliability depending on number of nodes  $L$  used for prediction. Shown is data for 10 mobile sinks, with mean value and error bars showing standard deviation.



(a) Distribution of the number of hops throughout the sensor networks (b) Distribution of sensor node transition time of mobile sinks



(c) Packet delay, representing the mean time and error bars of standard deviation

Fig. 16. Distributions of the number of hops and node transition time of mobile sinks in evaluation data, and packet delay performance. Large packet delay in *Direct* scheme would lead to a critical performance degradation in the dynamic transitions of mobile nodes.

to emphasize why the *Direct* scheme inherently lacks data timeliness. In our simulation setting, the stationary sensor network lead to an average communication hop count of 10, spanning from 1 hop to 26 hops (the distribution of the number of hops is shown in Fig. 16(a)). For a mobile sink speed of 30 km/h, the average transition time of mobile nodes is 2.2 seconds (see the distribution of transition time in Fig. 16(b)). Fig. 16(c) shows that the *Direct* scheme actually needs much longer than that to send a packet to the association node of the mobile node. This means that when the packet arrives at the destination relay node, the mobile node would likely be

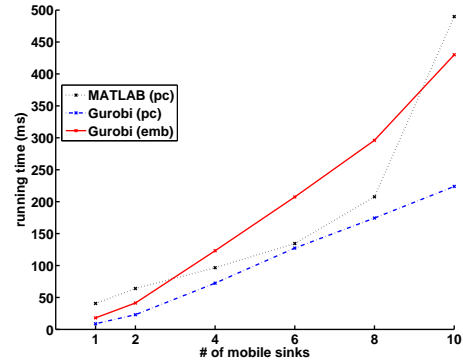
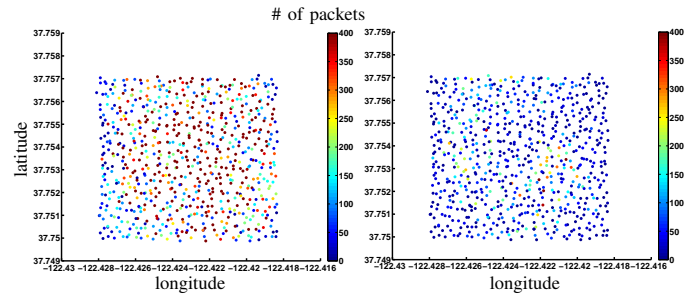
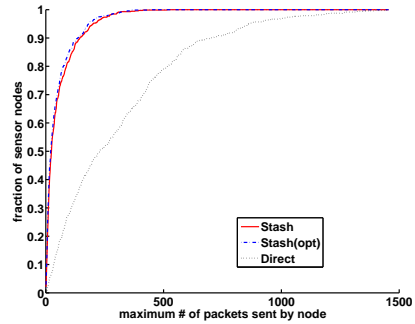


Fig. 17. Running time for a sensor node to solve an optimization problem for stashing in each platform/tool depending on the number of mobile sinks.



(a) Potential plot of the number of packets sent by a node for *Direct* scheme (b) Potential plot of the number of packets sent by a node for *Stash* scheme



(c) Fraction of nodes sending less than a certain number of packets

Fig. 18. Load balancing throughout the networks (for 10 mobile sinks case).

out of range already. In our *Stash* scheme, stashing data at some intermediate storage nodes (somewhere between the data source and the mobile sink) significantly reduces the number of travel hops, and therefore the packet travel time. Because the intermediate storage node will be visited by the sink in the future, travel time is less of an issue.

To evaluate the feasibility of efficiently computing the stashing nodes through optimization on the sensor node platform, we measured the running time for solving the binary integer program described in Sec. IV-B. The results for different platforms are shown in Fig. 17: we tested the performance on a Dell Precision 390 PC with Ubuntu Linux and a 2.4 GHz Core 2 Duo processor, and an embedded platform: a fit-PC2 with Ubuntu Linux and Intel Atom Z530 1.6GHz. We also tested two solvers: the bintprog optimization toolbox in MATLAB and the AMPL/Gurobi solver. The solution time for



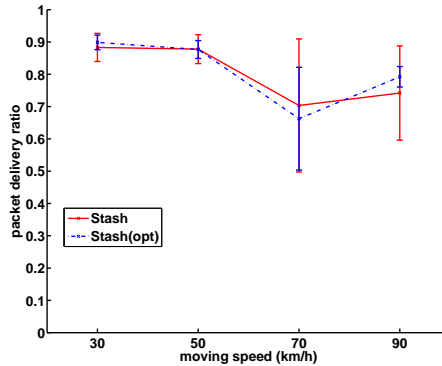
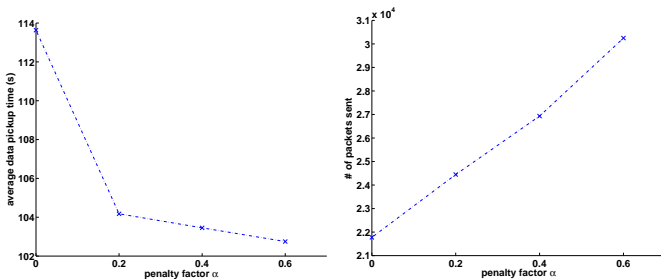


Fig. 19. Packet delivery reliability depending on speed of mobile sinks. Shown is data for 10 mobile sinks, mean value and error bars showing standard deviation.



(a) Average data pickup time by mobile nodes at the stashing nodes with respect to  $\alpha$

(b) Routing cost with respect to  $\alpha$

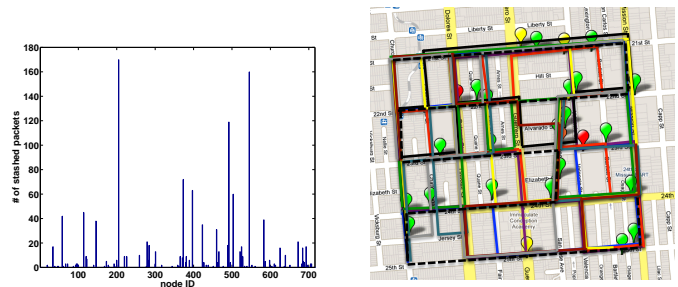
Fig. 20. Impact of the penalty factor  $\alpha$  on the data pickup time and the routing cost in the advanced optimization for 10 mobile sinks.

the optimization problem each node has to solve is less than 500 ms on an embedded platform.

Another strength of data stashing is implicit load-balancing. Fig. 18 shows that data stashing spreads packet transmissions more evenly, as opposed to the tree-like routing patterns seen in direct routing to the current position of the mobile sink. In the *Direct* scheme, there are many hot regions which transmit a large number of packets (see Fig. 18(a)); the *Stash* scheme performs much better (see Fig. 18(b)).

We have also tested the robustness of our data stashing scheme against differences in the speed of mobile sinks. Because the trajectory matching algorithm implicitly compensates for speed differences, changes in the speed of mobile sinks do not have a large impact on reliability. After training with a speed of 30 km/h, varying the speed between 30 and 90 km/h in the testing phase has no significant impact on reliability, which remains above 80% for 30, 50 km/h and above 70% above for 70, 90 km/h in Fig. 19.

We explore how the penalty factor  $\alpha$  in Sec. IV-C affects network performance in Fig. 20. As the optimization procedure gives a larger penalty to a set of stashing nodes that are further away from mobile nodes with a larger  $\alpha$ , the data pickup time can be improved as shown in Fig. 20(a). To achieve this benefit, the routing algorithm needs to sacrifice the routing cost as in Fig. 20(b). As the penalty factor increases from 0 to 0.2, the reduced rate of data pickup time is the most drastic



(a) Storage cost throughout the sensor nodes

(b) Favorite storage node distribution over the networks where  $\bullet$ :  $\geq 150$  packets,  $\circ$ :  $\geq 100$  packets,  $\diamond$ :  $\geq 50$  packets,  $\square$ :  $\geq 10$  packets, presented with mobile sinks' moving paths

Fig. 21. Storage overhead over the sensor nodes for 10 mobile sinks.

given the similar trend in increasing routing cost.

Finally, we evaluate the storage requirements that data stashing algorithms impose on sensor nodes (see Fig. 21). It is likely that data stashing requires more storage than direct routing schemes; the node stashing most data needs to store around 200 packets in our scenario. Such peaks occur at “favorite” stashing locations, which turn out to be the intersections of several trajectories as shown in Fig. 21(b). In our opinion, data storage is generally less problematic than radio transmission in sensor networks, making this a good trade-off.

## VI. DISCUSSIONS

In this section, we try to answer the following questions: (1) how can the data stashing be integrated with duty cycle MAC protocols? (2) what are differences in empirical results between simulated dataset and real-world dataset? (3) what are the scenarios in which the data stashing scheme may not work well?

### A. Integration with Duty Cycle MAC

Although this paper focuses on improving energy efficiency of routing in the network layer, a cross-layer integration with low duty cycle MACs will lead to a more significant energy saving effect. There are two main types of duty cycling MACs in sensor networks: synchronous duty cycle MACs such as S-MAC [66], DMAC [37], Z-MAC [50], and asynchronous duty cycle MACs such as B-MAC [48], X-MAC [9]. Our data stashing scheme allows sensor nodes to receive trajectory announcement from a mobile sink at the same time and perform data stashing simultaneously to multiple stashing nodes. For this reason, synchronous MAC protocols are more suitable to data stashing than asynchronous MACs with respect to control overhead for managing all the wake-up schedules.

To integrate the data stashing scheme with synchronous MACs, the optimization problem of stashing node selection needs to be reformulated considering wake-up schedules of sensor nodes. Data source nodes should choose a set of nodes that are only *awake* at the same time for stashing, while

keeping a low routing cost. By sorting the nodes awake at a specific time among possible trajectory nodes and simply using them as input in the network optimization (Sec. IV-B), it can make our data stashing scheme easily compatible with synchronous duty cycle MAC protocols.

### B. Comparison of Empirical Results between Simulation and Real-world Evaluation

Both empirical results with simulated dataset and real-world dataset (Fig. 10 and Fig. 13) show similar trends in routing cost and packet delivery reliability with respect to the number of mobile sinks in the network. When we take a closer look at routing cost results in Fig. 10(a) and Fig. 13(a), the reduction of routing cost (between *Direct* and *Stash*) is more substantial in simulated dataset compared to real-world dataset as the number of mobile sinks increases. This is related to the variety of stashing node choices from predicted trajectories. Since the Clark testbed forms a relatively small network, the length of wireless traces along the moving paths is smaller compared to wireless traces in simulation dataset. Consequently, finding stashing nodes closer to data sources that are also overlapped with other mobile sinks' future trajectories would be more likely in longer wireless traces. Therefore, our data stashing scheme seems to be more suitable to large scale networks or densely deployed networks in terms of energy efficiency.

If we compare the routing cost between *Stash* and *Stash(opt)* from simulation and real-world evaluation, the gap between *Stash* and *Stash(opt)* is relatively larger in real-world evaluation compared to simulation. This result is related to prediction quality. Because real-world traces embed a higher variability in association sequences due to more dynamics in wireless vagaries, and walking habit and moving speed variations of humans, the predicted trajectory nodes would be represented with more dynamic probabilities. By selecting a larger number of stashing nodes to balance the guaranteed packet delivery, the real-world evaluation causes a higher routing cost.

### C. Limitation in Applicability

One of the most important components in our data stashing scheme is the long-term mobility prediction algorithm that is enabled from intensive pattern learning along moving paths with a certain degree of regularity. If we are given test sequences obtained from new moving paths that do not share most of path segments with paths in the training set, the performance of data stashing would degrade. As an extreme example, our long-term mobility prediction would fail to provide meaningful predictions for test sequences from random motions.

To construct a characteristic database of mobile trajectory clusters, it is important to learn the mobility model from many complete long trips that can be differentiated from one another. If training sequences from only short trips are given in the learning phase, it would harm the quality of our clustering algorithm, making data stashing inefficient.

## VII. CONCLUSION

We have presented algorithms for extracting mobility patterns using association updates over stationary sensor networks, and predicting long-term trajectories of mobile sinks. We focused on the common case that the data is delay-tolerant. We have designed a routing scheme which routes data not to the mobile sink directly, but instead to relay nodes along a predicted path of the mobile sink that are also close to the data source in terms of communication hops. These techniques significantly reduce radio energy consumption for packet routing while ensuring high packet delivery ratios.

Our experiments indicate that our scheme provides much better load-balancing, avoiding collisions and consuming energy resources evenly throughout the network, leading to longer overall network lifetime. More importantly, we demonstrate that given limited information about future trajectories of sinks, optimization of routing paths leads to significant improvements in routing performance. The proposed method provides not only a mobile routing protocol, but a way to improve any existing protocol by learning and exploiting mobility patterns.

Currently, we only select stashing nodes once, and do not monitor the progress of the mobile sinks as they move through the network. In scenarios where prediction is more difficult, recomputing the set of stashing nodes and correcting prediction errors by re-stashing at newly predicted nodes could significantly increase robustness.

The trajectory clustering algorithm is currently executed in an off-line learning phase. However, our proposed scheme does not necessarily require a separate off-line phase. As each mobile device keeps updating its own trajectory model, each mobile node can predict its own anticipated trajectory using a local model. If the network size is very large, it may not be feasible to maintain huge databases of mobility trajectories in a mobile device. In the future, we anticipate working on distributed or hierarchical computation and storage of the mobility models.

Interesting directions for algorithmic improvements include a more sophisticated clustering method that explicitly represents partial trajectories and is able to partition long trajectories into short pieces that can be clustered more efficiently. A multi-tier or hierarchical approach to deal with extremely large networks is another avenue for future work.

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**HyungJune Lee** is an Assistant Professor in the Department of Computer Science and Engineering at Ewha Womans University, Seoul, Republic of Korea. He received his B.S. degree in Electrical Engineering from Seoul National University, Republic of Korea in 2001. He obtained his M.S. and Ph.D. degrees in Electrical Engineering from Stanford University in 2006 and 2010, respectively. He joined Broadcom as Sr. Staff Scientist for working on research and development of 60GHz 802.11ad SoC MAC. Also, he worked for AT&T Labs as Principal Member

of Technical Staff with the involvement of LTE overload estimation, LTE-WiFi interworking, and heterogeneous networks. His current research interests include future wireless networks over IoT, 60GHz, 5G cellular, and heterogeneous networks.



**Martin Wicke** is currently working on AI and programming languages at eddy.systems. He got his PhD from ETH Zurich working on computer animation and physical simulations, and worked on sensor networks while at Stanford University.



**Branislav Kusy** is a principal research scientist at Autonomous Systems, CSIRO, Australia. Prior joining CSIRO, he received his PhD from Vanderbilt University and spent 2 years at Stanford University as a postdoctoral fellow. He has more than 10 years of experience with developing system services for networked embedded systems, algorithms for spatio-temporal coordination of nodes, and real-world deployments of sensor network technology. He is currently focusing on innovative signal processing and adaptive sampling in distributed embedded networks

operating under various constraints, such as uncontrolled mobility, limited energy resources, or the lack of physical access to the device. Specifically, he is working with wearable technology for tracking location, activity, and environmental factors for various applications, including disease spread in animal/human populations, biosecurity, and future manufacturing.



**Omprakash Gnawali** is an Assistant Professor at the University of Houston, USA. He was a Postdoctoral Scholar at Stanford University, got his Ph.D. from the University of Southern California, and received his Masters and Bachelors degrees from the Massachusetts Institute of Technology. His research lies at the intersection of low power wireless networks and embedded sensing systems. His contribution to wireless sensor network routing, Collection Tree Protocol, has been widely adopted in research and academia and has informed the IPv6 low-power

wireless networking standard.



**Leonidas Guibas** obtained his Ph.D. from Stanford under the supervision of Donald Knuth. His main subsequent employers were Xerox PARC, DEC/SRC, MIT, and Stanford. He is currently the Paul Piggott Professor of Computer Science (and by courtesy, Electrical Engineering) at Stanford University. He heads the Geometric Computation group and is part of the Graphics Laboratory, the AI Laboratory, the Bio-X Program, and the Institute for Computational and Mathematical Engineering. Professor Guibas interests span geometric data analysis,

computational geometry, geometric modeling, computer graphics, computer vision, robotics, ad hoc communication and sensor networks, and discrete algorithms. Some well-known past accomplishments include the analysis of double hashing, red-black trees, the quad-edge data structure, Voronoi-Delaunay algorithms, the Earth Movers distance, Kinetic Data Structures (KDS), Metropolis light transport, and the Heat-Kernel Signature. Professor Guibas is an ACM Fellow, an IEEE Fellow and winner of the ACM Allen Newell award.