MobiCom 2011 Poster: Investigating Mobility Heterogeneity for Relay Node Selection in Opportunistic Networks

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Opportunistic networking is a mobile communication paradigm utilizing spontaneously arising networking options for data forwarding. Although node movement affects the forwarding capabilities of these nodes, the utilization of this knowledge for local forwarding decisions is still not sufficiently exploited and a major aim of our approach. We describe node heterogeneity along movement features capturing urban user movement and how to derive movement activities from these features. Hereby, we summarize main results of an experimental study based on real-world GPS data of 252 daily trips. In a second step, we explain how movement characteristics of mobile nodes may influence data dissemination and present first simulation results indicating that the heterogeneity in movement activities indeed influences the performance of opportunistic data dissemination.

I. Motivation and Related Work

Opportunistic networks are challenged by intermittent connectivity impairing routing and forwarding protocols. To cope with this challenge several disruption-tolerant forwarding protocols have been proposed in the past, where forwarding decisions are made locally depending on current and predicted connection opportunities of each node. Although node contact opportunities are both constrained and facilitated by the mobility of nodes, mobility patterns are often left unexploited by routing and forwarding solutions. Our approach focuses on capturing and utilizing movement features of urban user mobility to, finally, estimate the node's likely contact and forwarding opportunities.

Among the few approaches utilizing mobility information for relay node selection, MobySpace routing favors nodes as relays which show location visiting frequency patterns similar to the destination node's patterns [6]. Most-Mobile-First Spraying uses utility-based replication where nodes of higher mobility are expected to show better contact characteristics [8]. Similarly, nodes showing high mobility in terms of travel distance are used for relaying in the Scale Free approach [7]. In our approach, we investigate the potential impact of a wider set of movement characteristics and activities on data forwarding to identify best forwarding nodes.

Introducing mobility-awareness to routing protocols requires the understanding of mobility behavior and its impact. Analyzing patterns that are found in real-world mobility traces, e.g., based on WiFi hotspot attachments or GPS data is one way of approaching this challenge [2, 5]. A different approach is taken by survey-based modeling of mobility where knowledge from time use or traffic studies is used to describe typical mobility behavior for scenarios, such as commuting to the office, going out for lunch, etc. [1, 4].

Our approach, i.e., mobility-aware routing and forwarding, requires in-depth understanding of a node's relay capabilities related to its mobility behavior. In previous work [3], we investigated how movement activities differ in terms of movement characteristics by relating trip purpose to movement features and evaluating the approach by GPS trace data of daily trips in an urban area as summarized in Section II.

Here, we extend this work by focusing on the expected impact of movement features on data dissemination performance which, finally, should allow us to develop appropriate selection schemes for best forwarding nodes. In Section III, we describe main forwarding metrics and potential impacts which are investigated by means of simulation; first findings of the corresponding experiments are outlined in Section IV.

II. Studying Movement Patterns

To analyze the pattern variations shown by different movement activities, we define a set of movement features and provide a classification approach to automatically derive activity labels for trips.

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II.A. Characterizing Mobility

Based on a comprehensive literature survey, eight features describing movement are introduced based on temporal and spatial information. First, the *velocity* is used. The intensity of a *directional change* is calculated between the current direction and the direction measured at a configurable distance in the history path (in our study, 20m). A time period is considered as *pause time* if the velocity is below a certain threshold (here, 0.5m/s for at least 5s). The *start time* is defined as the hour of day a trip starts. The *flight length* is the length of a path traveled between two consecutive pause times. The *mobility range* is defined as the distance of each position within a trip to the center of the area covering the trip (here, a rectangle). Positions are counted as a revisited position, if a node moved away a certain distance (here, 50m) and moves in proximity again (here, 20m); the derived features are *number of revisits* and *time between revisits*.

II.B. Estimating Movement Activities

The relation between movement features and movement activities is investigated by classifying trips along their movement features using a *Naïve Bayes* classifier (which was evaluated against other classifier and showed good results). The classifier is used to calculate the probability for all different activities under a given multi-variate vector describing the eight movement features observed for one trip. Then, the movement activity with highest probability can be assigned to the trip.

III. Mobility-aware Forwarding

It is expected that a node's utility for forwarding can be estimated once knowing its movement features. If only the movement activity is known, the expected movement features can be derived based on feature distributions observed for this activity. However, to understand the potential and limits of mobility-aware forwarding, the effects of movement features on forwarding metrics have to be further studied. Among the most important metrics we investigated are:

- *Contact time.* The contact time is measured as the time two nodes stay in communication range. It is expected that this metric shows correlations, e.g., to pause times and velocities.
- *Forwarding distance.* The forwarding distance of a mobile node is defined as the distance it can reach; here, it is given by the number of different sub-areas visited by the mobile node. This metric is expected to be affected, e.g., by flight length and mobility range.
- *Coverage.* Here, the spatial distribution of information is investigated. We divide the observation area into sub-areas and determine the fraction of sub-areas which have received a message. Flight length and mobility range are expected to be affecting characteristics.

IV. Experiments and Results

Two experimental steps are described: *(i)* estimating movement activities based on the movement feature set and *(ii)* investigating the impacts of different movement activities on data dissemination.

IV.A. Movement Traces Analyzed

To record movement trajectories of every-day trips we conducted a data gathering study with 13 volunteers in Vienna over one month. The study participants were equipped with small GPS receivers and a 'track book' to report semantically important information about the trips, such as activity category and modes of transport. The activity categories represented most frequently in the data set are: *Way to work*, *Evening*, *Tourist*, and *Shopping activity*. In total, 252 trips are used which are labeled by these four categories.

IV.B. Movement Activity Estimation

After selecting half of the data set for training and half for testing, the Naïve Bayes classifier achieved a true positive rate of 80.65% (the classification results are detailed in [3]). By studying the empirical density functions of each feature, differences along all features can be observed. *Number of revisits* and *start time* are among the most important features for distinguishing activities in the data set. Figures 1(a) and 1(b) show excerpts of the features' ECDFs.

Along the *number of revisits*, differences can be observed between all ECDFs. For example, small numbers of revisits occur often in *Way to work* trips where position revisits may occur only in few situations such as walking back on a street section after getting off a bus. In contrast, *Evening* trips show high occurrences of a large number of revisits relating to taking similar routes when approaching and leaving popular places. The ECDFs of the *start time* depict the expected differences between activities in an urban setting during daytime and evening time (a comprehensive description of all features is given in [3]).

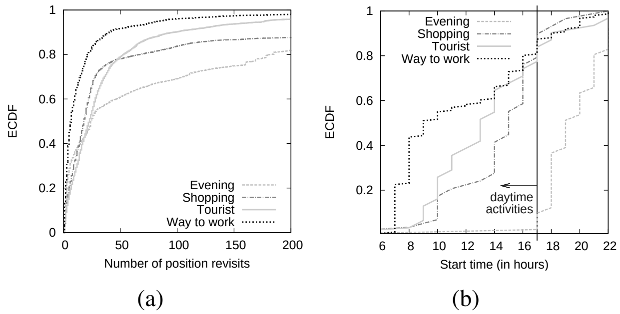

Figure 1: Excerpts of the ECDFs for (a) number of position revisits and (b) trip start time (day/night).

IV.C. Impact on Data Dissemination

An opportunistic networking scenario is investigated along the dissemination metrics introduced in Section III. The movement of 200 nodes is simulated according to the ECDFs of the movement features determined by the movement activities on a 6km $\times$6km area using the simulation tool AnyLogic[1]. Sub-areas are defined by a grid of stationary nodes acting as sinks with inter-spacing of 500m (to calculate, e.g., the coverage). The transmission range of nodes is set to 100m. For each activity, five simulation runs are performed (one activity active per run). First results are summarized here based on the observed distribution functions:

- The *contact time* is affected by pause time. Longer contact times relate to longer pause times; e.g., Way to work trips show a large number of short contact times (i.e., ≤ 150s).
- The highest fraction of nodes that achieve a small *forwarding distance* (less than 4 sub-areas visited) is exhibited by Tourist trips related to their short flight lengths, while the largest distance can be found in the Way to work activity (large flight lengths).
- The mean maximum *coverage* value is at the lowest for Evening activities (70.30%, σ=1.41%) as a high proportion of longer pause times and shorter flight lengths can be found here. The highest coverage (96.57%, σ=2.19%) is achieved in the Way to work activity. For visualization purpose, Figure 2 shows the areas of the stationary node grid covered after half and total simulation time t ($t = 61200s$) for one simulation run per activity. Differences are visible in achieving an overall coverage of the area, but also w.r.t. how fast the coverage is achieved and whether there are areas which are never reached.

[1] http://www.xjtek.com/anylogic/

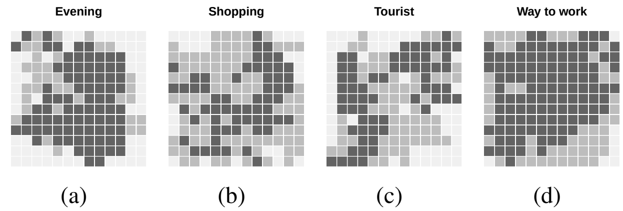

Figure 2: Spatial distribution of available information at time $t/2$ (dark gray) and t (dark and light gray).

V. Conclusion

To apply mobility-aware opportunistic networking, we detailed the characterization of mobility behavior along eight movement features. We described the differences observed for every-day activities in an experimental study of 252 labeled daily trips. Additionally, we presented simulation-based forwarding performance results of mobile nodes behaving according to the observed movement activities. First observations show that the different activities indeed lead to different forwarding performance results in terms of the metrics contact time, forwarding distance, and coverage. In future work, we plan to conduct an extended analysis and to develop forwarding schemes utilizing mobility knowledge.

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