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Study of Wireless Epidemic Spread in Dynamic Human Connectivity Traces

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Introduction

Increasing numbers of mobile computing devices form dynamic networks in daily life. In such environments, nodes (i.e. laptops, PDAs, smart phones) are sparsely distributed, forming a network which is often partitioned due to geographical separation or node movement. We envision a new communication paradigm using dynamic interconnectedness between people leading towards a world where digital traffic flows as people encounter each other [7]. Delay Tolerant Networks (DTNs) [3] aim at supporting such network environments. Efficient forwarding algorithms for such networks are emerging, mainly based on epidemic protocols where messages are simply flooded when nodes encounter each other. Epidemic information diffusion is highly robust against disconnection, mobility and node failures, and it is simple, decentralized and fast. However, careful tuning to achieve reliability and minimize network load is essential. Thus, it is important to understand not only the physical topology but also the underlying logical network structure.

The quantitative modeling of human dynamics is difficult and has not been explored in depth. The emergence of capturing traces of human interactions in online and pervasive environments allows us to understand details of human activities. For example, the Reality Mining project [4] collected proximity location and activity information, with nearby nodes being discovered through periodic Bluetooth scans and location information from cell tower IDs. Other groups have performed similar studies. Most of these studies [3] use Bluetooth to measure device connectivity, while others rely on WiFi. The duration of experiments varies from two days to over one year, and the numbers of participants differs.

We have analyzed various traces and shown a hidden stable logical topology, which consists of a group of people forming socially meaningful relationships [6][9]. Our focus is on human-to-human communication, where it is assumed that social networks play a major role in epidemic spread. We present our study of information flow during epidemic spread in such dynamic human networks by short range wireless communication, a topic which shares many issues with network-based epidemiology. Most social networks are neither random nor regular but complex [1]. The properties of nodes include fixed states, variable states, neighbor nodes, and network positions (i.e. centralities). A complex system requires not only an understanding of the elements in the system but also of the interactions and patterns between the elements. Thus, observing communication over the network is expected to provide guidance for inferring the network structure and, vice versa, the network structure affects the communication. We explore hub nodes extracted from human connectivity traces and show their influence on the epidemic to demonstrate the characteristics of information propagation.

To understand the network structure requires three key metrics: 1) the average path length to show the distance of a pair of nodes, 2) the cluster coefficient to indicate how well nodes are clustered, and 3) the degree distribution. In DTNs the topology changes every time-unit where data paths may not exist at any one point in time but potentially do exist over time. Thus, existing metrics for static networks are problematic to apply. We consider a model for time paths based on graph evolution, **Time-Dependent Networks**, where links between nodes are time-windows dependent.

Discussion

- **Human Dynamics:** Figure 1(a) depicts the epidemic spread changing the value of time to live (TTL) of the message from six hours to one day. A day cycle of human dynamics leads to high spread [10].
- **Weighted Graph:** The connectivity traces can be represented in the form of weighted graphs called contact graphs, with the weight of an edge representing the contact duration and frequency for the two end vertices. We use weighted network analysis [8] for understanding human interaction (i.e. community detection and weighted node centrality). See [6][2] for details.
- **Hub Nodes:** Understanding the nodes' participation in the network is important. Centrality measurements give insight into the roles of nodes in a network. We have defined the following hubs for the time-dependent network based on the concept of centralities defined by Freeman [5].

  DEGREE Hub*:* is the total degree of each node that indicates the popularity of the node (i.e. *Degree Centrality*).
  RANK Hub: indicates *Betweenness Centrality* in time-dependent networks. We simulate flooding over the temporal graph extracted from the trace and count how often each node is used to relay data to other nodes.
  CROSS Hub: defines how often a node appears at different locations that indicates *Mobility Centrality*.

- **Impact of Hub Nodes:** Figure 1(b) shows the impact of hub nodes during the epidemic spread, where the top 100 of each type of hub node are inactivated. The disappearance of DEGREE Hub or RANK Hub completely killed the epidemic spread. On the other hand, CROSS Hub does not show as dramatic an impact as do the other two types of hub nodes.

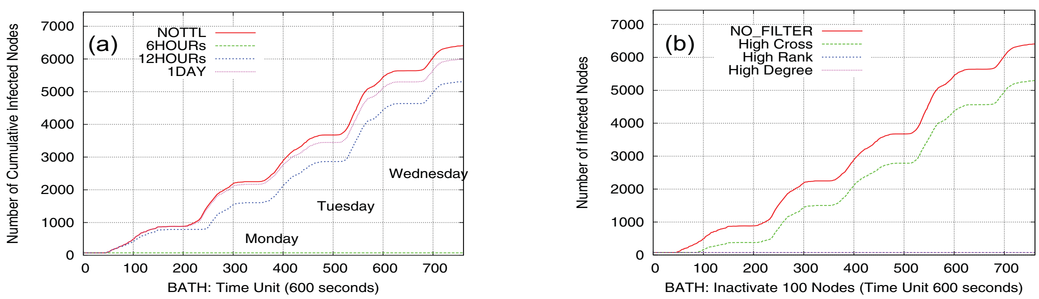

Fig.1. Wireless Epidemic Spread in Human Connectivity Trace

Hubs can de-fragment the network and contain distinct characteristics to influence data flow within the network [11]. Networks represent flows of information and make it possible to characterize the complex systems. A network is a map of interactions because communication is fundamental in our society. We present results from our study analyzing the human connectivity traces ranging from community detection, hub detection and correlation, and propagation stages of epidemic spread. Finally, we emphasize the use of real world data and believe that our study will provide interesting insight into the nature of human interactions. Online based social networks have been studied, but understanding of network structures and models hidden in pervasive dynamic human networks is a still untouched research area with much potential. Our ultimate goal is a complete understanding of human-to-human network models in the urban space.

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