Poster Abstract: Recovering Network Topology with Binary Sensors

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Abstract

We present a method to extract topology information from detection events of mobile entities moving through a network of binary sensors. We extract the topological structure of possible paths in the network by analyzing the time correlation of events at different sensors. The histograms of time delays between any two sensors contain the necessary information to reconstruct the network topology. This data is heavily corrupted by noise due to multiple agents in the network. We therefore use a mixture model of multiple Gaussian and a uniform distribution to explicitly isolate the noise. Our algorithm yields a graph representing the topology of our sensor network along with average travel time between nodes.

Categories and Subject Descriptors

H.4.m [**Information Systems Applications**]: Miscellaneous

General Terms

Algorithms, Experimentation

Keywords

Sensor Networks, Topology Recovery, Unlabeled Data

1 Introduction

Recovering the topology of an embedding space is an interesting problem that provides information to a wide variety of applications. For example, motion patterns of customers in a store are interesting to the store owner in finding the optimal location of its products to maximize exposure. Understanding the movement and learning the routes of wildlife species in a region where development is underway can provide essential information to environmentalists.

While reconstructing the topology of a region with labeled data is relatively straightforward, building the topology with unlabeled events using passive sensors is less trivial. Previous research [4, 3, 5] has focused on using vision based sensors to detect the connectivity between sensor nodes. Lobaton *et al*. [2] use higher dimension observations unique to camera sensors to provide more detailed information of mobile entities in the network. Tovar *et al*., [6] use binary detection beams to understand possible paths of mobile agents. These approaches make assumptions on the environment, or require complex sensors. We aim to extract topology information using only minimal sensing capability.

We use Pyroelectric InfraRed (PIR) sensor nodes to detect motion of objects in the environment. We create a histogram of time differences of event detections between any two nodes and proceed to determine if there is a path between these two nodes. The histograms are noisy due to the effect of several agents traveling in the network. We use a mixing model that combines a number of Gaussians as well as a uniform distribution to isolate the relevant data. If we find statistically significant evidence for a link between two nodes in the network, our algorithm proceeds to determine if there is a direct path in the network, or an indirect path that passes through another node. We present some results obtained in simulation and a hardware platform that is being deployed in our lab for experimental evaluation.

In Sec. 2, we discuss how to extract link information, which we extend to topological extraction in Sec. 3. In Sec. 4, we describe the setting of our experiment using PIR sensors.

2 Extracting Correspondence

To detect connectivity, we collect a large set of motion detection events and construct a histogram of the time differences between events on two nodes A and B. If there is a path between A and B, a large number of events will have a time difference that is close to the average transition time between A and B.

We fit a mixture of functions to this histogram to extract correlations. As Ellis *et al*. [1] have shown, fitting a naive Gaussian mixture model does not work due to the noise caused by other agents moving around in the network. These events do not correspond to the movement of a single agent between the two nodes and generate a uniform distribution of time differences. To capture both noise and signal in our histogram we use a mixture model consisting of K Gaussian distributions and one uniform distribution. Eq. (1) shows a description of our overall function and the mixing parameters π_k that we wish to find. We use an expectation maximization (EM) algorithm to maximize the log-likelihood of our objective function $p(x)$, and update the parameters π_k at each step.

$$p(x) = \sum_{k=1}^{K} \pi_k N(x \mid \mu_k, \sigma_k^2) + \pi_{K+1} U(x) \qquad \sum_{k=1}^{K+1} \pi_k = 1 \quad (1)$$

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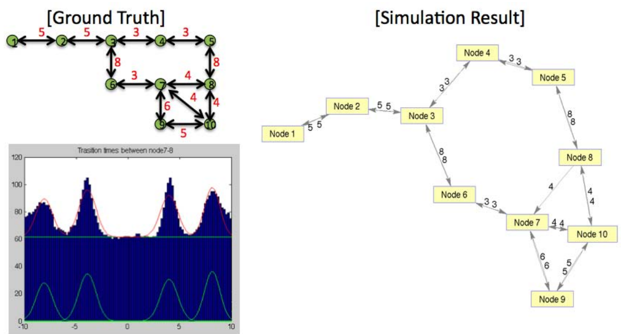

Figure 1. Simulation results: Histogram of the time difference of events between nodes 7 and 8 and the Gaussian signal and noise component captured from mixture model (bottom left). Recovered topology with aid of volume analysis (right), ground truth (upper left).

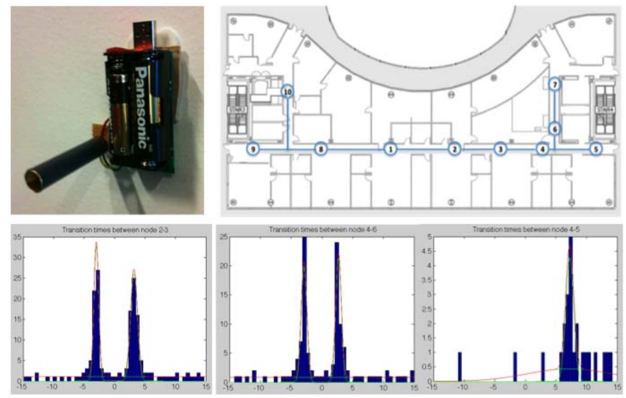

Figure 2. A TelosB mote with a Panasonic PIR sensor is deployed inside an office building. Correlation detections of some of the links are shown.

Figure 1 shows an example of our mixture model capturing underlying signals from a histogram. The green curves correspond to the Gaussian distributions and a uniform distribution corresponding to the noise level.

3 Topology Estimation

A connection between two nodes can be due to a direct path, or an indirect path that passes through another node.

We first assume that shorter path lengths do not combine to equal longer path lengths. The topology of the network can be then simply determined by sequentially checking if each detected path's length is a combination of previously confirmed shorter path lengths. If this is the case, we can conclude that the detected path is actually an indirect path, and there is no direct connection between the two nodes.

We can remove this assumption by analyzing the volume of events between the two nodes. For example, we could have confirmed a direct path between nodes A-B and B-C with transition times 3 and 4 respectively. If we detect a path between A-C with transition time 7, we cannot determine if this is the result of a direct link A-C, or the indirect link A-B-C. However, by comparing the volume of events in each path we can distinguish between the two.

To properly determine the volume of events between two nodes, we consider a pair of events an *inlier* if the pair is associated with a specific trajectory, and an *outlier* if there is no actual correspondence between the two events. With these definitions, we can estimate the probability that each event pair is associated with an actual agent crossing the nodes. Furthermore, we can estimate the probability that a sequence of time stamps was created by an agent moving through the network. We use Monte Carlo sampling to estimate which proportion of a histogram is due to a specific path. We can thus distinguish whether a correlation detected in a histogram relates to a direct path or an indirect one. Figure 1 shows a simulation result that recovers the topology of the underlying network by following this process.

4 Experiment Setting

To gather experimental data we have deployed 10 TelosB motes indoors. Each node is equipped with a low power PIR sensor. A moving object will typically trigger multiple times as it moves across the field of view, and we therefore use a simple window filter to infer it as a single event. We restrict the field of view such that the sensor can distinguish between multiple people provided they are separated by around 1 m.

Figure 2 shows the result of the correlation captured from our experimental deployment. Most edges between motes are bidirectional. However, we have edges like 4-5, where the path is one way, due to the fact there is an exit door at the end of mote 5, which people cannot enter from.

5 Conclusions

We have presented an algorithm that recovers the topology of a sensor network with binary sensing. We use a statistical model to extract the topology from simple observations.

The volume analysis part of our algorithm requires heavy computation, and therefore a simplified approximation of this method will make the algorithm more efficient for discovering the topology in complex networks. Finally, the PIR sensors provide probabilistic information about the speed of moving objects, as well as the size of a group of objects moving together. Incorporating this information in our models can provide more accurate topology recovery.

6 References

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