Topology recognition in Wireless Sensor Networks

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ABSTRACT

Using self-organizing wireless sensor networks for object tracking requires ordering events with regard to time and location. In labyrinth-shaped topologies, one-dimensional ordering suffices within the different parts of the network. We present an algorithm to derive this ordering without the use of location information. Local order knowledge in the nodes can then be additionally used to detect junctions.

INTRODUCTION

An important aspect of wireless sensor networks is the logical partitioning into sub-networks. This aspect is fundamental for a lot of location-aware applications. Furthermore, applications often require an ordering of the nodes with respect to their environment, e.g. for object tracking. Computation of such location information can either be done at a central point or by the nodes themselves. The latter is beneficial in order to reduce the amount of transmitted data. Since the energy consumption decreases with decreasing amount of data transmissions, a localized algorithm helps to increase the overall lifetime of the network [1, 5].

We assume that the wireless sensor network consists of a topological structure resembling road networks or corridors in buildings and that the devices are equipped with motion detectors. In [4] a method for topology recognition is described, particularly with regard to border and junction detection, but while this paper deals with extreme high densities, we assume rather sparse networks.

The problem requires detecting the one-dimensional spatial ordering of neighbors within the communication range. Since passing objects cause ordered chains of motion detection events, movement directions can be inferred by mapping object detection events to this spatial order of the nodes.

OUR APPROACH

This section describes our localized algorithm to detect the one-dimensional ordering of a node and its neighbors. Let N be the node computing its *local topology*, i.e. the ordering of its neighbors. Our algorithm comprises 3 steps:

1. Detection of *border nodes*, i.e. far away nodes near the maximum communication distance
2. Computation of *chains* from border nodes to N
3. Mapping the remaining nodes onto the path nodes

Note that N only needs information of its direct neighbors, which minimizes the communication costs. Figure 1 shows exemplarily the three steps of the algorithm.

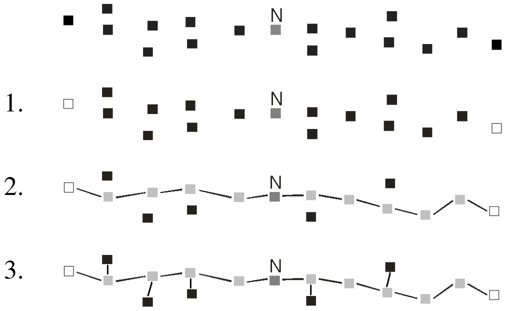

Figure 1: Algorithm steps

First, N has to detect its border nodes. We base this detection of border nodes on the number of common neighbors. Border nodes have fewer neighbors in common with N than nodes closer to N. With an exchange of the neighbourhood lists a counting of the common neighbors becomes possible. So N counts these numbers and selects border nodes using a threshold, e.g. all nodes which can communicate to less than the half of its neighbors.

Second, N orders these selected border nodes into groups by estimating the distances between them. The distance estimates are also based on the number of common neighbors. Border nodes are sorted into the same group if they are close to each other, i.e. if they have many neighbors in common. For each group N determines one *representative node,* preferably the most distant one. Then, N computes chains from the representative nodes to itself by searching a path from the representatives to it.

Third, nodes which are not within one of the computed chains will be *mapped* onto the nearest *chain node*, i.e. if a remaining node detects a motion event it is considered as if the corresponding chain node had detected it.

The topology recognition depends on the quality of distance estimation. Here it is not important to get correct absolute values but correct distance relations, i.e. the estimated distance to a closer neighbour must be smaller than the estimated distance to a far away neighbour. Otherwise nodes are mapped in a wrong way. For this reason, we use an estimation method that does not rely on unreliable measurements of physical wireless communication properties. Radio interferometry features promisingly low errors but brings in specific requirements to the RF chip [2].

A disadvantage of using the number of common neighbors is that it assumes a uniform node distribution. Local differences in the node density result in failing detection of representatives as depicted in figure 2. Hence node density fluctuations must be detected and compensated.

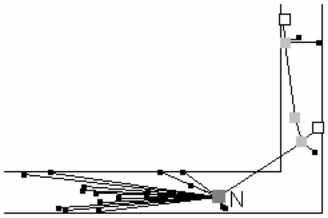

Figure 2: Failing detection of border nodes

We chose SHAWN [3] for a simulative analysis and conducted studies both, grid-based and uniform distributed arrangements. For each distribution we evaluated our algorithm with exact, random error afflicted and estimated distances. Figure 3 shows the evaluation results. The values signify the correctness of the computed chains, i.e. the percentage of correctly ordered nodes.

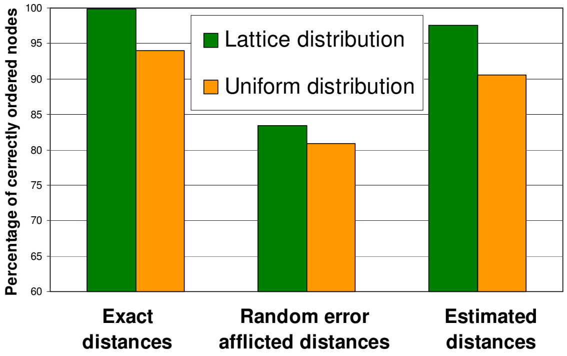

Figure 3: 82 nodes with 12 neighbors per node on the average

The results using the estimated distances (right) are nearly as good as with the exact distances (left) although prone to estimation errors of 12% to 20% of the original distance. This dates back to the preserved distance relations in contrast to estimates afflicted with the random error of 20% (center). Here the nodes compute not only wrong paths but also wrong mappings. Furthermore, the results of the simulations based on the uniform distributions are nearly as good as the grid-based ones.

In addition, we executed simulations with different node densities. While low node density causes short chains and hence more fragile object detection and tracking, high density causes an increased fraction of nodes mapped to chain nodes as illustrated in figure 4. This leads to less significant chains because of mapping errors.

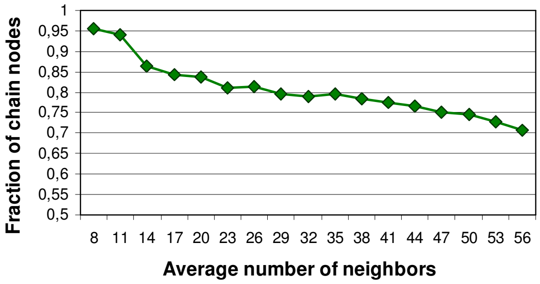

Figure 4: Average fraction of chain nodes depending on the node density

CONCLUSION

This paper proposes a localized algorithm to detect the one-dimensional spatial ordering of nodes within the communication range. We have shown that it provides rather good results in spite of error afflicted distance estimates. For the algorithm it is less important to work with exact distance values. It only matters that the distance relations are preserved.

Furthermore we have seen that high densities cause relatively more mappings, so it is not reasonable to increase the node density more than an appropriate quantity.

Our research shows promising results for detecting network topologies in simulated environments. Future work will focus on the one hand on grouping the nodes according to the network part they belong to. On the other hand we want to evaluate the algorithm within a real world study.

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