A New Approach for Boundary Recognition in Geometric Sensor Networks

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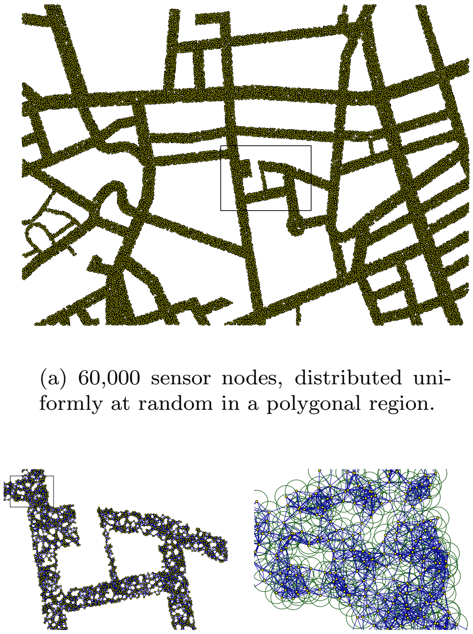
Abstract

We describe a new approach for dealing with the following central problem in the self-organization of a geometric sensor network: Given a polygonal region R, and a large, dense set of sensor nodes that are scattered uniformly at random in R. There is no central control unit, and nodes can only communicate locally by wireless radio to all other nodes that are within communication radius r, without knowing their coordinates or distances to other nodes. The objective is to develop a simple distributed protocol that allows nodes to identify themselves as being located near the boundary of R and form connected pieces of the boundary. We give a comparison of several centrality measures commonly used in the analysis of social networks and show that *restricted stress centrality* is particularly suited for geometric networks; we provide mathematical as well as experimental evidence for the quality of this measure.



(a) 60,000 sensor nodes, distributed uniformly at random in a polygonal region.

(b) A zoom into (a) shows the communication graph.

(c) A further zoom into (b) shows the communication ranges.

Figure 1: Scenario of a geometric sensor network, obtained by scattering sensor nodes in the street network surrounding Braunschweig University of Technology.

1 Introduction

In recent time, the study of wireless sensor networks (WSN) has become a rapidly developing research area that offers fascinating perspectives for combining technical progress with new applications of distributed computing. Typical scenarios involve a large swarm of small and inexpensive processor nodes, each with limited computing and communication resources, that are distributed in some geometric region; communication is performed by wireless radio with limited range. As energy consumption is a limiting factor for the lifetime of a node, communication has to be minimized. Upon start-up, the swarm forms a decentralized and self-organizing network that surveys the region.

From an algorithmic point of view, the characteristics of a sensor network require working under a paradigm that is different from classical models of computation: Absence of a central control unit, limited capabilities of nodes, and limited communication between nodes require developing new algorithmic ideas that combine methods of distributed computing and network protocols with traditional centralized network algorithms. In other words: How can we use a limited amount of strictly local information in order to achieve distributed knowledge of global network properties?

This task is much simpler if the exact location of each node is known. Computing node coordinates has received a considerable amount of attention. Unfortunately, computing exact coordinates requires the use of special location hardware like GPS, or alternatively, scanning devices, imposing physical demands on size and structure of sensor nodes. As we demonstrated in our paper [4], current methods for computing coordinates based on anchor points and distance estimates encounter serious difficulties in the presence of even small inaccuracies, which are unavoidable in practice.

As shown in [3], there is a way to sidestep many of the

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above difficulties, as some structural location aspects do *not* depend on coordinates. This is particularly relevant for sensor networks that are deployed in an environment with interesting geometric features. (See [3] for a more detailed discussion.) Obviously, scenarios as the one shown in Figure 1 pose a number of interesting geometric questions. Conversely, exploiting the basic fact that the communication graph of a sensor network has a number of geometric properties provides an elegant way to extract structural information.

One key aspect of location awareness is *boundary recognition*, making sensors close to the boundary of the surveyed region aware of their position and letting them form connected *boundary strips* along each verge. This is of major importance for keeping track of events entering or leaving the region, as well as for communication with the outside. Neglecting the existence of holes in the region may also cause problems in communication, as routing along shortest paths tends to put an increased load on nodes along boundaries, exhausting their energy supply prematurely; thus, a moderately-sized hole (caused by obstacles, by an event, or by a cluster of failed nodes) may tend to grow larger and larger.

We show that using a combination of geometry, stochastics, and tools from social networks, a considerable amount of location awareness can indeed be achieved in a large swarm of sensor nodes without any use of location hardware. The result is a relatively simple distributed algorithm for boundary recognition in large geometric sensor networks that shows excellent performance for test networks with 80,000 nodes.

2 Centrality Measures for Social Networks

A different area studying large and complex graphs is the field of *Social Networks*, where nodes represent individuals in a large collective, and edges indicate some interaction between them. (See the recent book [1] for an overview and an extensive list of references.) Identifying asymmetries within a network is a natural approach; one particular way of doing this is based on so-called centrality indices, i.e., real-valued functions that assign high values to more "central" nodes, while "boundary" nodes get low values.

In the last five decades, many different centrality indices have been proposed. There are two major classes: One is based on local properties of the graph, so it is particularly suited for typical scenarios of sensor networks and will be discussed in some detail. The other class is based on more global properties, e.g., the computation of eigenvalues of the adjacency matrix, so it is less useful for our purposes.

Centrality indices of the first class can be subdivided into three subclasses: The first considers the distances to other vertices, the second determines the number of vertices at a given distance, while the third makes use of shortest paths containing a given vertex.

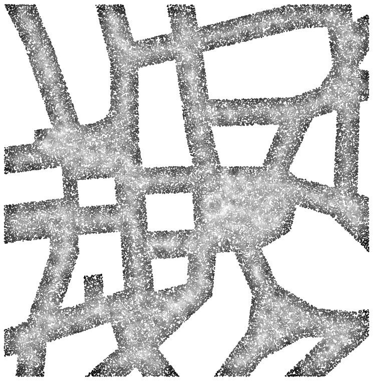


Figure 2: k-hop neighborhood for k=4.

Considering the maximum distance to another vertex in the graph (based on hop-count) does not reflect local topological structures in a sensor network; in particular, it fails to indicate closeness to interior boundaries. The size of the k-hop neighborhood is better suited, and (for the simple choice $k = 1$) was indeed the basis for our approach described in [3], as it is an indicator for the size of the intersection of the communication range of a node with R. It is tempting to try to improve the results by increasing k, but this is not without drawbacks with respect to topological properties, as a boundary node close to a "thick" part of R may get a better value than an interior node that is located in a "thin" part of the region. See Figure 2 for a scenario with 80,000 nodes; index values are represented on a color scale from dark (low) to light (high).

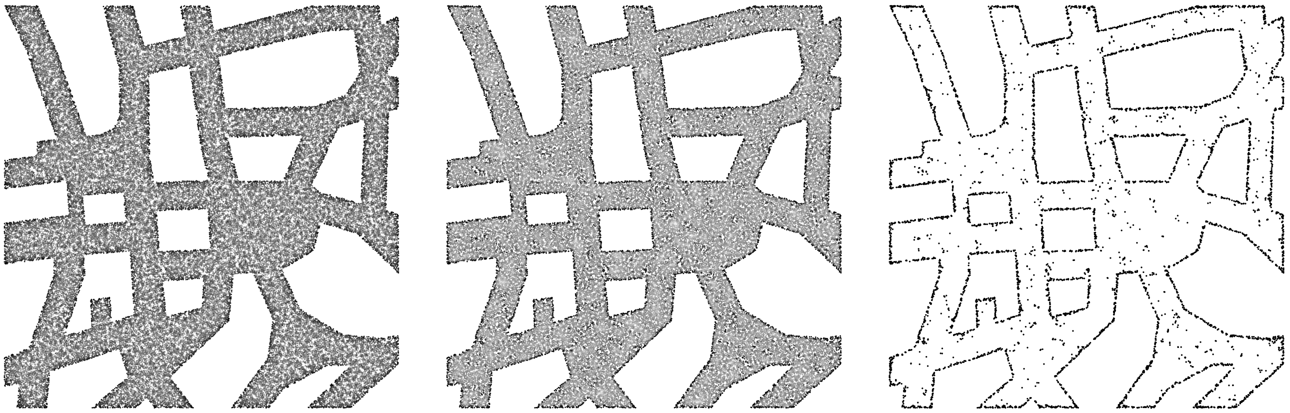
This leaves the structure of shortest paths. In particular, the *stress centrality* $stress(v)$ is defined as the number of shortest paths containing v:

$$stress(v) := \sum_{s \in V} \sum_{t \neq s \in V} \sigma_{st}(v), \qquad (1)$$

where $\sigma_{st}(v)$ denotes the number of shortest paths containing v. Only considering vertices within a given distance δ yields the *restricted stress centrality*:

$$stress(v, \delta) := \sum_{s \in V_\delta(v)} \sum_{t \neq s \in V_\delta(v)} \sigma_{st}(v). \qquad (2)$$

In the context of a communication network, this measure can be motivated as follows: If each vertex sends a message to every other vertex along all shortest paths, the stress centrality counts how many times vertex v is busy with passing on a message. As there may be quite many shortest paths, it is reasonable to assume that a vertex sends a message to some other vertex and uses any of their shortest paths with the same probability, i.e., $1/\sigma_{st}$, where σ_{st} denotes the number of shortest



(a) Betweenness centrality.

(b) Stress centrality.

(c) Restricted stress centrality with threshold filter.

Figure 3: Performance of different centrality measures, shown for a scenario of 80,000 nodes distributed uniformly at random.

paths between s and t. The probability of any vertex v that it has to transport the message is thus given by $\rho_{st}(v) := \frac{\sigma_{st}(v)}{\sigma_{st}}$. The *betweenness centrality* $betw(v)$ is defined as the sum over all $\rho_{st}(v)$:

$$betw(v) := \sum_{s \in V} \sum_{t \in V} \rho_{st}(v). \tag{3}$$

See Figure 3(a) for the evaluation of betweenness centrality for our example, while Figure 3(b) shows the stress centrality. (Again, low values are indicated by dark dots, while high values are represented by light color.) A detailed analysis for restricted stress centrality is given in the following section.

3 Using Restricted Stress Centrality

In the context of a sensor network, it takes a number of algorithmic steps to evaluate a measure and use the results for extracting global features like boundaries. Some of those details are described in our paper [3], and can be used analogously for other measures: Using an auxiliary tree structure (which is easy to obtain), we can aggregate local results globally in order to determine appropriate threshold values. Once a threshold has been set, it can be distributed to all nodes in the network; after that, each node simply checks whether its centrality index is above or below the threshold, resulting in a classification as "interior" or "boundary". A good index must have the following properties:

- It should require only simple local computations for each node.
- Setting a good threshold value should be relatively easy. In other words: The distributions for interior nodes and for boundary nodes should be well-separated.

Theorem 1 *Using the restricted stress centrality* $stress(v, 1)$*, nodes are classified correctly with high probability for sufficiently large node density.*

See Figure 3(c) for the result for restricted stress centrality for relatively moderate density: It can be seen that all boundary nodes are correctly classified. The interior contains a number of false positives, which can be eliminated by additional filters.

Discussion of Theorem 1. Let v be a node in the network, and let $\delta(v)$ be the number of neighbors of v. Furthermore, $stress(v, 1)$ is the number of nonadjacent neighbors of v. Then the normalized coefficient $st(v) := \frac{2stress(v,1))}{\delta(v)(\delta(v)-1)}$ describes the fraction of pairs of neighbors that are nonadjacent, i.e., that have a shortest-path connection via v, so $\mathbb{E}[stress(v, 1)] = \mathbb{E}[st(v)] \left(\begin{array}{c} \mathbb{E}[\delta(v)] \\ 2 \end{array} \right)$. Now consider any neighbor w of v. Let $C(v) := \{p \in R \mid d(p, v) \leq r\}$ be the portion of R that is within communication range of v. See Figure 4; let $N_w := C(v) \cap C(w)$, and $M_w := C(v) \setminus C(w)$. For a uniform random distribution, the expected fraction of neighbors of v that are not adjacent to w corresponds to the ratio of areas $\frac{Ar(M_w)}{Ar(C(v))}$. Integrating over all possible positions of w, we get an overall expected value $st(v) = \frac{1}{Ar(C(v))} \int_{w \in C(v)} \left(\frac{Ar(M_w)}{Ar(C(v))} \right) dw$.

As the size of the areas also depends on the distance s of v from the boundary, solving this integral in closed form for all s would require finding a primitive that contains d as an explicit parameter; this appears to be hopeless, even using ideas as described in [5]. However, for specific values of s, an explicit numerical calculation is possible: For $s \geq r = 1$ and $d(w, v) = x$ the area of M_w turns out to be $\frac{8\left(\arccos\left(\frac{x}{2}\right) - \frac{1}{2}\sin\left(2\arccos\left(\frac{x}{2}\right)\right)\right)}{3}$. The resulting in-

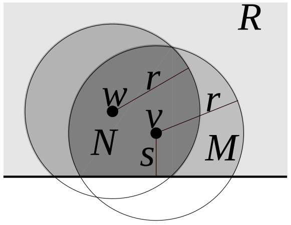


Figure 4: For any given neighbor w of v, the expected fraction of neighbors of v that are not neighbors of w is given by $\frac{|M|}{|N \cup M|}$.

tegral $\sigma = \int_0^1 x \left(1 - \frac{2\left(\arccos\left(\frac{x}{2}\right) - \frac{1}{2}\sin\left(2\arccos\left(\frac{x}{2}\right)\right)\right)}{\pi}\right) dx$ can be solved numerically, resulting in a value of $\sigma = 0.4134966716$.

For determining threshold values for separating interior and boundary values of st, we also need the random distribution of st for different values of s. These distributions can be determined with additional numerical computations; using a Monte-Carlo simulation, we obtained distributions like the ones in Figure 5: Shown are the distributions for 20 expected neighbors (5(a)) and for 200 expected neighbors (5(b)); the left (red) curve shows the distribution of st for a node v on the boundary, while the right (green/blue) curve shows the distribution completely in the interior of R. The probability of error for a specific threshold is given by the normalized area to the right of the threshold below the left curve (false negatives) or by the normalized area to the left of the threshold below the right curve (false positive). Clearly, the error becomes arbitrarily small for large neighborhood size. □

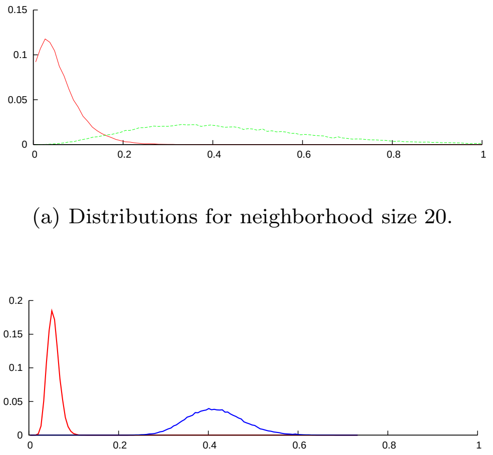
For intermediate sizes as the one in our example, choosing a relatively large threshold value avoids too many false negatives, at the expense of a limited ratio of false positives.

4 Algorithm

In [3], we showed how to estimate $\mathbb{E}[\delta(v)]$ for a node v of boundary distance $s \geq r$, i.e., a node on the inside of the network. The algorithm constructs a tree, collects a node degree histogram and floods the result to all nodes. Both the total runtime of the algorithm and the total size of messages is $\mathcal{O}(|V| \log^2 |V|)$. Each node stores a constant threshold value $0 < \theta < \sigma$ that has been chosen in advance. If

$$st(v) \leq \theta \left(\begin{array}{c} \mathbb{E}[\delta(v)] \\ 2 \end{array} \right) ,$$

the node declares itself to be a boundary node. In experiments, we found $\theta = 1/3$ to be a particularly good choice.



(a) Distributions for neighborhood size 20.

(b) Distributions for neighborhood size 200.

Figure 5: Random distribution of restricted stress centrality for a node on the boundary and in the interior, for different neighborhood sizes.

5 Conclusion

We showed that restricted stress centrality is a useful index for extracting topological boundary information from a geometric sensor network, provided that the distribution of nodes follows a suitable random distribution. As this is a rather strong assumption, it appears desirable to come up with more general methods. Moreover, an approach based on random distributions may still fail in some rare cases (even though the probability of failure is extremely low), so it is particularly interesting to develop deterministic methods for boundary recognition. Such an approach is described in our forthcoming paper [2].

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