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Research Article

Connectivity-based Boundary Extraction for distributed wireless Nodes

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Abstract

A novel Connectivity- based Boundary Extraction scheme for large-scale sensor networks. Connectivity-based Boundary Extraction for the topology has shown great impact on the performance of such services as location, routing, and path planning in wireless sensor networks. Connectivity-based Skeleton Extraction (CASE) algorithm, to compute skeleton graph that is robust to noise, and accurate in preservation of the original topology. Boundary detection algorithms, which are used to extract accurate Boundary nodes. Segmentation algorithm does not require sensor locations and only uses network connectivity information. Each node is given a 'flow direction' that directs away from the network boundary. A node with no flow direction becomes a sink, and attracts other nodes in the same segment. We evaluate the performance improvements by integrating shape segmentation with applications such as distributed indices and random sampling. To find the boundary nodes by using only connectivity information propose a simple, distributed algorithm that correctly detects nodes on the boundaries and connects them into meaningful boundary cycles.

Keywords: *Connectivity-based, Boundary Extraction, Randomly distributed, Boundary detection*

1. Introduction

Sensor network is used for the geographical environment. Main feature is geographical boundary. Boundary extraction method is used for sensor network. A CABET, a novel Connectivity- Based Boundary Extraction scheme for large-scale sensor networks. Connectivity- based Skeleton Extraction (CASE) algorithm to compute skeleton graph that is robust to noise, and accurate in preservation of the original topology. In addition, CASE is distributed as no centralized operation is required, and is scalable as both its time complexity and its message complexity are linearly proportional to the network size. The skeleton graph is extracted by partitioning the boundary of the sensor network to identify the skeleton points, then generating the skeleton arcs, connecting these arcs, and finally refining the coarse skeleton graph. A highlight of CABET is its non-uniform critical node sampling, called r0-sampling, that selects landmarks to form boundary surfaces with bias toward nodes embodying salient topological features. Simulations show that CABET is able to extract a well-connected boundary in the presence of holes and shape variation, with performance superior to that of some state-of-the-art alternatives. In addition, we show how CABET benefits a range of sensor network applications including skeleton extraction, segmentation, and localization. Topology discovery in particular identifying boundaries in a sensor network. Suppose a large number of sensor nodes are scattered in a geometric region, with nearby nodes communicating with each other directly. To find the boundary nodes by using only connectivity information. A simple distributed algorithm that correctly detects nodes on the boundaries and connects them into meaningful boundary cycles. The medial axis of the sensor field, which has applications in creating virtual, coordinates for routing. The algorithm gives good results even for networks with low density also prove rigorously the correctness of the algorithm for continuous geometric domains. Routing is elementary in all communication networks.

The design of routing algorithms is tightly coupled with the design of auxiliary infrastructure that abstracts the network connectivity. For networks with stable links and powerful nodes, such as the Internet, infrastructures such as routing tables are constructed and maintained so that routing can be performed efficiently at each router by a routing table look-up, and routing paths are close to optimum. For networks with fragile links, constantly changing topologies, and nodes with less resourceful hardware, such as *ad hoc* mobile wireless networks, routing tends to be on-demand with no pre-computed infrastructures.

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However, without any auxiliary infrastructure, discovery of routes may have to rely on flooding the network. Location-free boundary recognition is crucial and critical for many fundamental network functionalities in wireless ad hoc and sensor networks. Previous designs, often coarse-grained, fail to accurately locate boundaries, especially when small holes exist. To address this issue, a fine-grained boundary recognition approach using connectivity information only. This algorithm accurately

2. Related Work

A novel boundary extraction method, named CABET that recovers the network shape well, using connectivity information only. CABET is fully distributed and is scalable, with overall message complexity linear with the network size. Boundary extraction method is used 3D sensor network. Critical Node Identification it identifies a shapes. There are three types of such nodes: namely convex critical nodes, concave critical, nodes, and saddle critical nodes. These nodes are especially important for capturing the distinct features of the geometric environment [Hongbo Jiang, April 2014].These two categories of methods have been explored in recent years. The first category, boundary detection, focuses on detecting nodes on the inner or outer boundaries. Geometric methods for boundary detection use geographical location information

3. Methodology used

Introduces the methodologies. It gives the explanation of different boundary Extraction methods (algorithms) and also the comparative study of them based on the performance evaluation parameters.

3.1 Connectivity-basd Boundary Extraction

A connectivity-based boundary extraction algorithm for 3D sensor networks 3D boundary extraction algorithm is used in sensor network 1) boundary node identification 2) critical node identification 3) landmark selection 4) coarse boundary extraction and 5) boundary refinement [Hongbo Jiang , April 2014].

A) Boundary node identification

In this step, every node p makes a decision as to whether itself is a boundary node, using connectivity information only. As mentioned earlier, previous 2D solutions based on boundary cycle generation cannot be used here. They use the traditional neighborhood size-based method based on the observation that nodes on the boundaries have much smaller neighborhood size than interior nodes. It does not offer a precise result, but here they only want a coarse sampling of the boundaries. This will suffice for triangulation scheme to be used later [Hongbo Jiang, April 2014].

B) Critical Node Identification

In this step, some nodes mark themselves as critical nodes based on local shape recognition. There are three types of such nodes: namely convex critical nodes, concave critical nodes, and saddle critical nodes. These nodes are especially important for capturing the distinct features of the geometric environment. Intuitively, nodes located at the area where boundary surface is locally flat are less important than those at corner areas [Hongbo Jiang, April 2014].

3D Skeleton Extraction Algorithm The knowledge of the skeleton (also called medial axis in of a sensor network can greatly improve routing performance. Skeleton can be used to achieve load balancing during geographical routing. Roughly speaking, each node, instead of greedy routing, forwards the packet to it neighbor, parallel along with the skeleton of the networking this scheme.

3D Segmentation Algorithm Many sensor network protocols, such as geographic routing and information gathering, implicitly assume a relatively dense and uniform sensor field in a simple geometric region. When applied to an irregular sensor field (e.g., with holes), their performance may degrade significantly. The segmentation algorithm in sensor networks is used to partition an irregular sensor field into nicely shaped pieces where protocols relying on a regular field tend to work well. Prior work has considered only 2D networks and cannot be used in a 3D space.3D skeleton extraction algorithm provides a possible way to fulfill this task.

3.2 Connectivity-Based Skeleton Extraction

Skeleton Extraction Algorithm to determine whether a node is a skeleton point, the corresponding nearest boundary point should be determined. To that end, the first step is to detect boundary points. While skeleton extraction algorithm is derived from the boundary, the boundary construction is out of the scope of this work. Numerous recent studies, for instance, have provided boundary detection and recognition algorithms. They bear this in mind and state that many of these algorithms can be used in conjunction with approach. Author assumed that boundary points are given as a system input in algorithms. Overall, the CASE algorithm includes five main building blocks:

1. Find corner points on the boundary such that the whole boundary can be decomposed into a finite number of boundary segments.
2. Identify the skeleton points such that they form a connected component.
3. Generate a set of skeleton arcs by connecting the skeleton points.
4. Generate a coarse skeleton result by connecting skeleton arcs and corner points.
5. Refine the coarse result to obtain the final skeleton

3.3 A Unified Framework for Line-like Skeleton Extraction

Boundary information is taken as an input, there are many boundary extraction algorithms in 2D/3D sensor networks [Theynping Liu, 2013].

1) Skeleton Node Identification: The node, which satisfies that the geodesic shortest paths (for 3D sensor networks) or shortest paths (for 2D sensor networks) between feature nodes decompose the boundary into 2 or more connected components, marks itself as Skeleton node

2) Importance Measure Computation and Skeleton: Tree Construction: The *importance measure* of each skeleton node is then derived from the computation of the number of nodes in the connected components. After that, each skeleton node chooses the neighboring skeleton node with the largest importance measure as the parent node, and accordingly, a skeleton tree is constructed following the direction of the monotonically increasing importance measure to derive a self-connected skeleton

3) Refinement: The skeleton tree may contain redundant skeleton branches, owing to the discrete nature of sensor networks. They trim the skeleton tree according to the proposed *branch similarity*. As a result, the final skeleton is obtained.

3.4 Boundary Recognition in Sensor Networks

The shape of the sensor field, i.e., the boundaries, indicates important features of the underlying environment. These boundaries usually have physical correspondences, such as a building floor plan, a map of a transportation network, terrain variations, and obstacles (buildings, lakes, etc). Holes may also map to events that are being monitored by the sensor network. If they consider the sensors with readings above a threshold to be invalid, then the whole boundaries are basically isos-contours of the landscape of the attribute of interest. Examples include the identification of regions with over-heated sensors or abnormal chemical contamination. Holes are also important indicators of the general health of a sensor network, such as insufficient coverage and connectivity [Y. Wang, J. Gao,2006].

4. Existing Boundary Value Strategies

The Medial Axis Construction Protocol (MACP) runs as follows:

1. Detect boundaries of a sensor field
2. Construct the medial axis graph, and broadcast it to every node in the network
3. Name each node by only localized computation.

A. Detect boundaries of a sensor field

The construction of the medial axis requires a sampling of nodes on the boundaries of the sensor field, including the outer boundary and the boundaries of interior holes. Each sample node knows to which hole boundary or outer boundary it belongs. These can be realized in different ways, either by manual identification of boundary nodes during deployment, or by automatic detection of holes. In particular, there are ways to detect some samples of sensors on the boundaries of holes by only the connectivity of the network. If the sensors are deployed uniformly densely in a field with large holes, sensors on the boundaries of holes usually have much smaller sensor density and can be detected [Y. Liu,2011]

B. Construct the medial axis graph

For a communication network represented by an un weighted graph $G = (V;E)$ and a subset $S \mu V$ on the boundaries of the sensor network, we define a node to be on the medial axis if it has equal hop counts to two closest boundary nodes. This node is called a *medial node*. The medial axis in the discrete case is defined as the sub graph $GM \mu G$ spanned by the medial nodes M.

C. Assign names to sensors

The medial axis of a sensor network is used as a reference to name every sensor node. In a continuous domain, a node is named by which chord it stays on. In a discrete sensor field, we name a node by a shortest path forest rooted at the medial axis that is, shortest path trees rooted at medial nodes. A node is named by which shortest path tree is stays on. To build the shortest path forest rooted at the medial axis, we start from the medial axis and progressively compute the closest medial node for each sensor. Every medial edge separates two canonical cells. S for a medial node, v in the interior of a medial edge. v should have at most two shortest path trees rooted at itself, one on each side of the medial edge.

5. Comparison Carried Out

5.1 Algorithm correctly identifies meaningful boundaries for networks with reasonable node density (average degree 6 and above) and distribution (e.g., uniform). The algorithm also works well for non uniform distributions. The algorithm is efficient. The entire procedure involves only three network flooding procedures and greedy shrinkage of paths or cycles. Further, as a theoretical guarantee, they prove that for a continuous geometric space bounded by polygonal obstacles the case in which node density approaches infinity the algorithm correctly finds all of the boundaries [Y. Wang, 2006].

5.2 CASE only introduces a little higher communication cost (around two to five times compared with MAP despite the network scale). It is noted that in Butterfly map, the communication cost using CASE is around five times than that using MAP. The reason is that, in this case, the number of boundary nodes is considerable and the average degree is high. Thus, the total traffic incurred by the identification of corner points using CASE is significant compared to others. Besides, noted that in the map of Hexagon, the communication cost using CASE is close to that using MAP as MAP [H. Jiang, May2010]. An augmented landmark selection procedure and the matching routing algorithm to be essentially the same as in the base case. This is possible because the algorithms operate only on shortest paths.

6. Proposed Approach

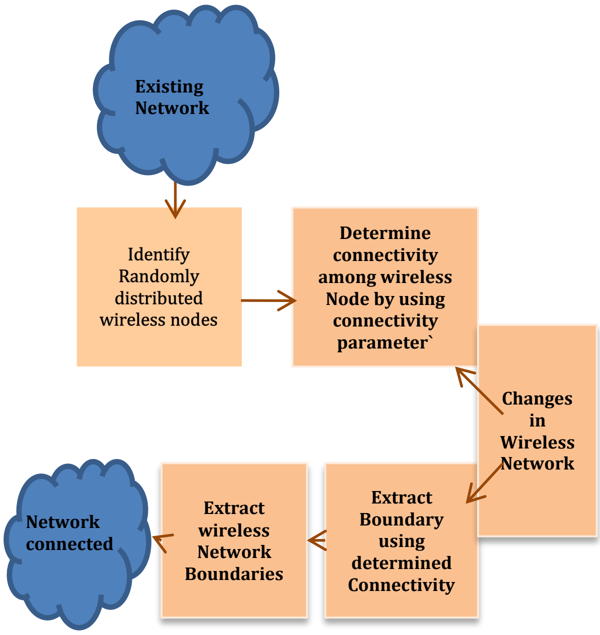

Fig.1 Proposed Approach of Boundary Extraction

Identify randomly distributed wireless nodes

Identify the nodes whether it is wireless or wired node; find randomly distributed wireless nodes in a given network.

*Determine connectivity among wireless Node by using connectivity parameter.*By using different parameters find connectivity between wireless nodes

- *Extract Boundary Using determined Connectivity*

Extract boundary using determined connectivity

Extract wireless Network Boundaries: The goal of boundary extraction is to find the nodes that are on the boundary of one is interacted with each other nodes. Boundaries is of great importance in the design of basic networking operations

Connect all nearest nodes: At the end, after finding all nodes in a network. Connect inner and outer nodes which are in a given area.

Conclusions

1) Boundary detection scheme which detects the boundaries within a sensor network using connectivity information
2) Proposed is a distributed boundary detection algorithm, for wireless sensor networks.
3) It can effectively identify boundaries in both uniformly and non-uniformly distributed sensor networks, exhibiting excellent robustness to sensor distribution
4) It can effectively identify boundaries in both uniformly and non-uniformly distributed sensor networks, exhibiting excellent robustness to sensor distribution
5) The sensor's topology-related applications such as segmentation, routing, and localization, which can benefit from the extraction

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