

# Skeleton representation for Wireless Sensor Networks

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**ABSTRACT:** Sensor networks today are widely used as they are able to capture the phenomena of the physical world that were originally difficult or impossible to obtain by traditional techniques. Sensor network applications are tightly coupled with the geometric environment where the sensor nodes are deployed. The skeleton extraction has a great impact on the performance of location, routing, and path planning in sensor networks. Present studies focus on using skeleton extraction for various applications in sensor networks. To achieve a better skeleton extraction has not been studied completely. The study on skeleton extraction from the computer vision community; their centralized algorithms for frequent space, however, are not immediately applicable for the discrete and distributed sensor networks. In this paper Connection oriented Skeleton Extraction algorithm to compute skeleton graph that is robust to noise, and accurate of the original topology. No centralization is needed. The skeleton graph is extracted by partitioning the boundary of the sensor network to identify the skeleton points, then generating and connecting the arcs, and finally refining the coarse skeleton graph. Our evaluation shows that is able to extract a well-connected skeleton graph in the presence of significant noise and shape variations, and state-of-the-art algorithms.

**KEYWORDS:** Sensor Networks-Centralised & Distributed, Skeleton extraction, WSN.

## I. INTRODUCTION

A wireless sensor network (WSN) consists of spatially distributed autonomous sensors to cooperatively monitor physical or environmental cases, such as temperature, sound, vibration, pressure and pollutants. Wireless sensor networks was motivated by military applications such as battlefield surveillance and it is now used in many industrial and civilian application areas like industrial process monitoring and health monitoring, environmental monitoring and habitat monitoring, healthcare applications, home control automation, and traffic control.

WSN represent a new paradigm for extracting data from the environment for many agricultural and scientific applications. The performance of the sensor network, e.g., the efficiency of routing of data, localization, and path planning, heavily depends on the sensors and the overall network topology. The topological skeleton also-called medial axis information of the sensor network can greatly improve routing performance [2].

In this paper [3], the routing efficiency is compared with GPSR, another wireless routing scheme where only local neighbor information is available; and great improvement is observed. Follow-ups have used skeleton information for

landmark selection to provide location service [8], segmentation [7], and navigation algorithms [5]. We argue that geometric skeleton information can be useful far more than routing, location, segmentation, and path design. For instance, for a mobility-assisted sensor network for field coverage, the skeleton can be used for path planning since the nodes in the skeleton represent a medial axis, and thus, cover most area where all nodes are observing. Thus, to understand the characteristics of the sensor topology and extract some important geometric information is essential to the sensor networks.

The previous works focus on the application of the skeleton information for various purposes in the sensor networks. The performance of the skeleton extraction, however, is not the focus of these studies. In this paper, we present a novel distributed Connectivity-bAsed Skeleton Extraction (CASE) algorithm which can better represent the topological shape of the sensor network than previous studies while incurring comparable communication cost.

A simple example is shown in Fig. 1 illustrated with a Maple leaf. Fig. 1a gives the boundary of the structure. Fig. 1b shows the medial axis in the network. Fig. 1c shows the medial axis graph computed using MAP and Fig. 1d shows the skeleton graph computed using CASE.

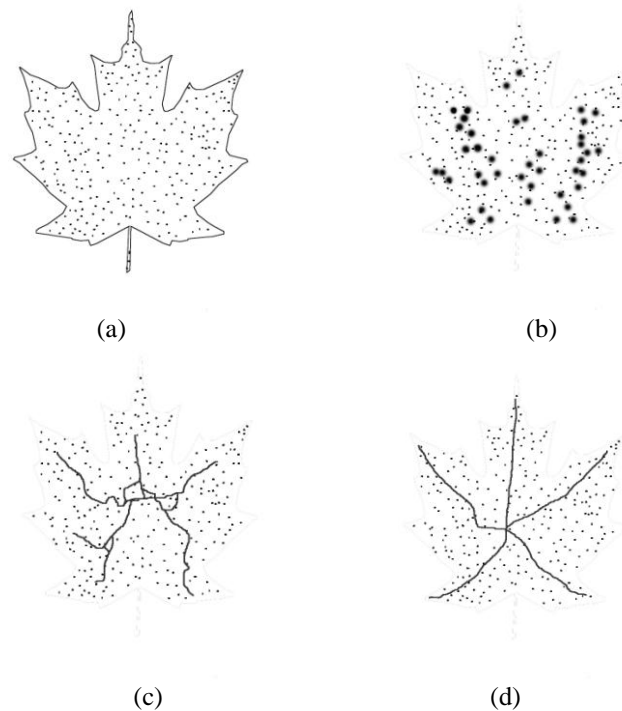


Fig. 1(a) Boundary of network, 1(b) Medial axis points, 1(c) Medial axis graph computed by MAP, 1(d) Skeleton graph computed by CASE.

Skeleton or medial axis extraction schemes have been studied in computer. While our proposed algorithm carries some of their advantages, there are some intrinsic differences due to the unique characteristics of the wireless sensor networks; for example, the sensor networks are discrete and the skeleton should be computed given only local connectivity information. Thus, we face numerical challenges in designing an efficient skeleton extraction algorithm. First, sensor nodes randomly deployed often have no location information or distance information. This makes topology recognition difficult as various techniques widely used in computer vision fields for skeleton extraction that request centralized computation are not suitable for a sensor network. Second, in a discrete network, the definition of the distance between skeleton nodes has to use hop-count distance instead of euclidean distance. This will result in noise, e.g., incorrect estimation of boundaries. It has been shown that a little noise or deformation at the boundary often seriously disturbs the topology of the skeleton graph [3]. As a result, many well known algorithms [8], [1], [14] applied in other fields to extract skeleton cannot be used directly. Effective elimination of the unstable segments in skeleton to keep the genuine geometric features is challenging. Third, even after the skeleton nodes are identified, connecting all nodes in a proper way is not as straightforward as that in the continuous case. In many cases, there are not enough skeleton nodes that can be extracted to construct a connected skeleton. In addition, the paths generated to connect skeleton nodes may either not be the shortest paths or introduce a cycle as shown in Fig. 1c. Toward taming these challenges, in this paper, we propose a novel skeleton extraction approach—CASE, and make the following contributions:

- . We present the design and implementation of a practical and distributed skeleton extraction algorithm which requests only connectivity information and preserves the topology well.
- . Based on boundary partition techniques, our proposed algorithm is robust against noise, and thus, capable of keeping the genuine geometric features of the sensor network.
- . We have proved that CASE is a scalable algorithm as its time and message complexity are linearly proportional to the network size.
- . Our work has implications for topology recognition in general. The results suggest that the user should keep track of the importation points such as skeleton joints and corner points in order to better understand the topology.

II. SKELETON EXTRACTION ALGORITHM

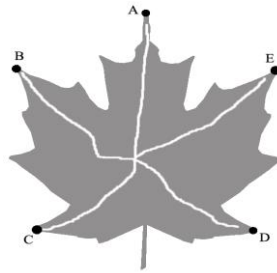
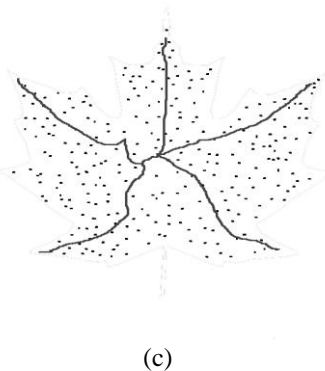
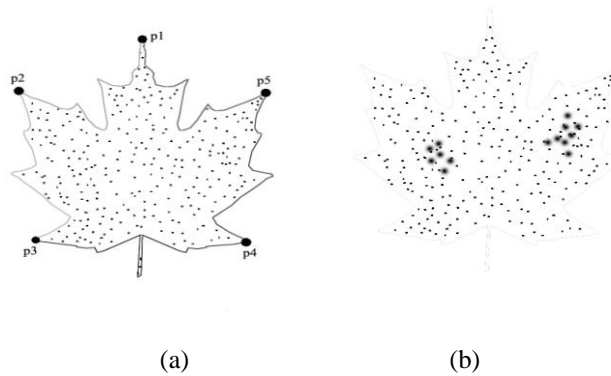


Fig. 2. (b) Boundary partitioned by five corner points on the boundary of maple leaf.

In computer vision [14], [1] studies have obtained good skeletons with the aid of the boundary corner points. We purposely delay the definition of corner points. Intuitively, it is one kind of critical points and using them as the endpoints of the skeleton allows explicit preservation of the topological information of the shape. As shown in Fig. 2b, the boundary of the maple leaf is partitioned by five corner points A;B;C;D;E; which leads to five boundary segment points having their generated points on these segments. As such, via boundary partition, the topology can be fixed and redundant arcs of skeletons can be disregarded [1]; leading to good skeletons.

Overall, the CASE algorithm includes five main steps:

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.



Shape of Network	Nodes	Boundary	Medial axis	Map	CASE
Maple Leaf	1,012	112	266	2,156	9,086
Man	2,056	387	452	3,206	6,984
Pentagon	1,412	286	398	895	4,546
Spring	1,891	345	423	1,918	7,578

Fig. 3. Skeleton extraction algorithm of Maple leaf network with the average degree of 19.3.

(a) Boundary segments. (b) Skeleton points. (c) Skeleton arcs.

### III. MULTIREOLUTION SKELETON

Our skeleton result is based on the threshold  $\delta_p$  for identifying corner points to partition the boundary. The corner points naturally provide a good partition of the boundary into segments. The points in the corner identifies, by providing a threshold can be considered to be the process of DCE [1], [16]. There exists a subset of sample points that lie on the boundary that constitutes a polygon result approximating the underlying geometric environment. The DCE process performs by recursively removing polygon points with the smallest shape contribution [16]. After the process of DCE, subsets of points (corner points) are accordingly extracted to provide a good approximation of the shape of a given boundary. This subset can also be viewed as a partitioning of the original boundary polygon into boundary segments. A multi resolution skeleton structure obtained by providing different thresholds is shown in Fig. 7. One desirable characteristic of DCE is the boundary partition stability [1]. Multi resolution representations are desirable, as they provide a flexible tool that fits the user's needs better than single-resolution systems. In sensor's applications, they can also be useful for location, navigation, and path planning.

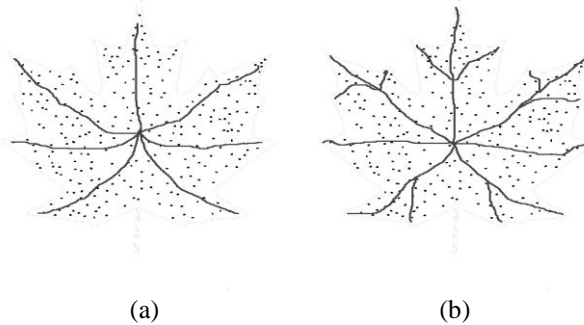


Fig. 4. Multi resolution skeletons when we set (a)  $\delta_p = 0.60$  and (b)  $\delta_p = 0.90$

### IV. CONCLUSION

We first identify the skeleton points by partitioning the boundary. These skeleton points are then connected to form the skeleton arcs, each of which corresponds to two boundary segment. All Skeleton arcs are connected and conduct a refinement to achieve the final skeleton. We have demonstrated that CASE provides more accurate skeleton results, and is robust against boundary variations. It outperforms a state-of-the-art algorithm under various configurations. Algorithm is scalable since its traffic complexity is linearly proportional to the network size. The experimental results demonstrate its scalability as it only causes a little higher traffic than previous algorithm while providing more accurate skeleton results.

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