Cut-And-Sew: A Distributed Autonomous Localization Algorithm for 3D Surface Sensor Networks

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AUTONOMOUS LOCALIZATION IN WIRELESS SENSOR NETWORKS

□ Location awareness is of significant importance

- □ Sensor deployment
- □ Position-aware sensing
- □ Geometric routing
- □ In-network data storage and retrieval
- □ Global Navigation Systems
 - □ Unaffordable due to high cost and lavish energy consumption
 - □ Unavailable without line-of-sight satellite signals

□ Autonomous localization

- \Box GPS-less
- □ GPS-free

2D PLANE, 3D VOLUME, AND 3D SURFACE SENSOR NETWORKS

□ Sensor network settings

- □ 2D plane: crop sensing in fields or wildlife tracking on plains
- □ 3D volume: underwater or space reconnaissance
- 3D surface: seismic monitoring on ocean floors or in mountainous regions







AUTONOMOUS LOCALIZATION ON 2D PLANE

□ Input: Euclidean distance

- Principle: search the solution space to discover optimal sensor coordinates that minimize the average distance error
- Methodology: multidimensional scaling, neural networks, nonlinear optimization, differential geometry
- Bottom line: distance information is sufficient to localize sensor nodes on a 2D plane (except for non-rigid shapes)



AUTONOMOUS LOCALIZATION IN 3D VOLUME

- Introducing the third dimension does not substantially increase the hardness of the problem
- It is straightforward to extend most 2D localization algorithms to 3D volume



CHALLENGES IN 3D SURFACE LOCALIZATION

- □ First glance: a 3D surface appears to be a special case of 3D volume or a generalization of 2D plane
- □ Surprising challenges: existing algorithms not applicable
 - Hardness: lack of correct Euclidean distance estimation between remote nodes



CHALLENGES IN 3D SURFACE LOCALIZATION

Proven result: a general 3D surface network is not localizable, given surface distance constraints only

Y. Zhao, H. Wu, M. Jin, and S. Xia, "Localization in 3D Surface Sensor Networks: Challenges and Solutions", in IEEE INFOCOM'12.

(c) A 3D surface network.

(d) MDS result of (c).

(b) Deformation of the surface.

(a) A 3D surface.

CHALLENGES IN 3D SURFACE LOCALIZATION

- □ Practical problem formulation:
 - □ Inputs: local distances and nodal height measurements
- □ First glimpse: the problem seems to become trivially easy
 - □ Height: Z-coordinate
 - □ Project sensors to X-Y plane and then apply 2D algorithms
- □ This naive approach often fails
 - □ Projection of a general 3D surface is non-planar
 - 2D localization algorithms either fail or result in extraordinarily large errors in a significantly non-planar graph



PROPOSED APPROACH

□ Observation:

- □ Sensor network on single-value (SV) 3D surface is localizable
- □ Proposed approach: divide-and-conquer
 - □ Partition a general 3D surface network into SV patches
 - □ Localize individual patches
 - □ Merge them into unified coordinates system



OPTIMIZATION GOAL

□ Observation:

- Many options to partition a network
- □ Theoretically infinite solution space to be explored
- □ Optimization goal: discover the minimum SV partition
 - □ All patches must be SV to ensure their localizability
 - The number of patches should be minimized to avoid unnecessary partitioning and merging, which are subject to linear transformation errors
- □ How to achieve minimum SV partition?
 - □ Identify Non-Single-Value (NSV) edges
 - □ Partition the network according to NSV edges
 - □ Proven to be minimum SV partition

NSV EDGES

Establish a triangular mesh structure (or triangulation) based on local connectivity and distance information [27]



NSV EDGES

If an edge in the triangular mesh is not on the boundary, it must be shared by two and only two triangles.

In the triangulation of a 3D surface network, an edge is locally NSV (or NSV for short) if the projection of its two associated triangles overlap on the X-Y plane.

LEMMA 1. Given an edge in the triangular mesh of a 3D surface sensor network, its associated local distance information is sufficient to determine whether it is a NSV edge.





network if it contains (or does not contain) NSV edges.



NSV EDGES

- THEOREM 1. The minimum SV partition is achieved by dividing the network along NSV edges.
 - □ Follow a partitioning strategy:
 - □ Start from any node on an arbitrary NSV edge and cut the network along all of its connected NSV edges
 - NSV edges must connect to each other or to boundary, the cutting process will either form a loop or stop at the boundaries of the network. In either case, the network is partitioned into two or more separated patches.

□ Repeats until no NSV edges exist in the entire network

- □ The network is partitioned into patches
- □ Patches are SV: none of them contain a NSV edge
- Partition is minimum: all NSV edges must be cut open, otherwise a patch containing NSV edges must be NSV patch

LOCALIZATION AND COMBINATION

□ For each SV patch

- □ Project to X-Y plane
- □ Apply 2D planar localization to obtain X-Y coordinates
- □ Add Z to yield 3D coordinates
- □ Use distributed least square to "sew" the patches



PRACTICAL SOLUTION WITH NOISY INPUTS

- □ Distance and height measurements can be noisy
- □ Inaccurate inputs directly affect identification of NSV edges
 - □ NSV edges become isolated, deviating from true NSV edges
 - □ Impossible to partition the network directly



PRACTICAL SOLUTION WITH NOISY INPUTS

□ Coalescence of isolated NSV edges

- □ If a triangle contains a NSV edge, the triangle marked NSV
- □ If two NSV triangles are one-hop away, the edges between them are marked as NSV
- □ Two closest clusters are connected by their shortest path



PRACTICAL SOLUTION WITH NOISY INPUTS

□ Formation of NSV band

- □ Marks the edges within 1-hop of existing NSV edges as NSV
- □ Partition along medial axises of NSV band
 - □ Two closest clusters are connected by their shortest path



COMPLEXITY AND OVERHEAD

\Box Overall observation

- NSV edge identification, network partitioning and projection are all done locally by the individual nodes
- Complexity and overhead are dominated by localization in each patch and the merge of patches
- \Box Computation complexity: O(Max{m³,n})
 - \Box n is the number of nodes in the network
 - \square m is the maximum number of nodes in a patch.
- \Box Overall communication overhead: O(n)

PROTOTYPING

- □ Built indoor testbed models
- □ Forty eight Crossbow MICAz motes are attached to its surface
- □ Sensors use close to minimum radio transmission power
- □ RSSI is used to estimate the length of links (about 20% errors)
- □ Ground truth is manually measured



EXPERIMENTAL RESULTS

- □ NSV edges are identified correctly
- □ Network is thus partitioned into two SV patches
- □ MDS is applied to localize each of them
- □ Combined patches largely restore the original 3D surface network
- □ Average location error around 14%



- □ Three network models, each simulated with 1k, 2k and 4k nodes
- \Box NSV edge detection error
 - Average minimum hop-distance between true NSV edges and identified NSV edges
 - □ Increases dramatically with higher measurement errors



- □ Network partition error
 - Defined as the maximum deviation between the ideal partition and the identified medial axis of NSV band
 - □ Insensitive to measurement errors
 - □ A higher sensor density helps reduce localization errors in stadium model. The effect is not observed in other models.



\Box Average location error

□ The localization result is not significantly affected by inaccurate distance and height measurements



- □ Comparison with a slice-based approach [25]
 - □ Cut the network into layers
 - □ No guarantee to localize all nodes in the network

Table 1: Localizable Rate			
	Stadium	Sea Cave	Mine Pit
Slice-Based [25]	98.8%	90.8%	81.3%
Cut-and-Sew	100%	100%	100%

CONCLUSIONS

- □ Unique challenge in 3D surface localization
- □ A divide-and-conquer approach, named cut-and-sew
 - □ Achieve minimum SV partition
 - □ Localization individual patches
 - \Box Merge patches
- Introduce a practically-viable solution for real-world sensor network settings where the inputs are noisy
- Implement and evaluate via simulations and indoor testbed experiments