Location Based Distributed Spectral Clustering for Wireless Sensor Networks

Gowtham Muniraju, Sai Zhang, Cihan Tepedelenlioglu, Mahesh K. Banavar, Andreas Spanias, Cesar Vargas-Rosales and Rafaela Villalpando- Hernandez

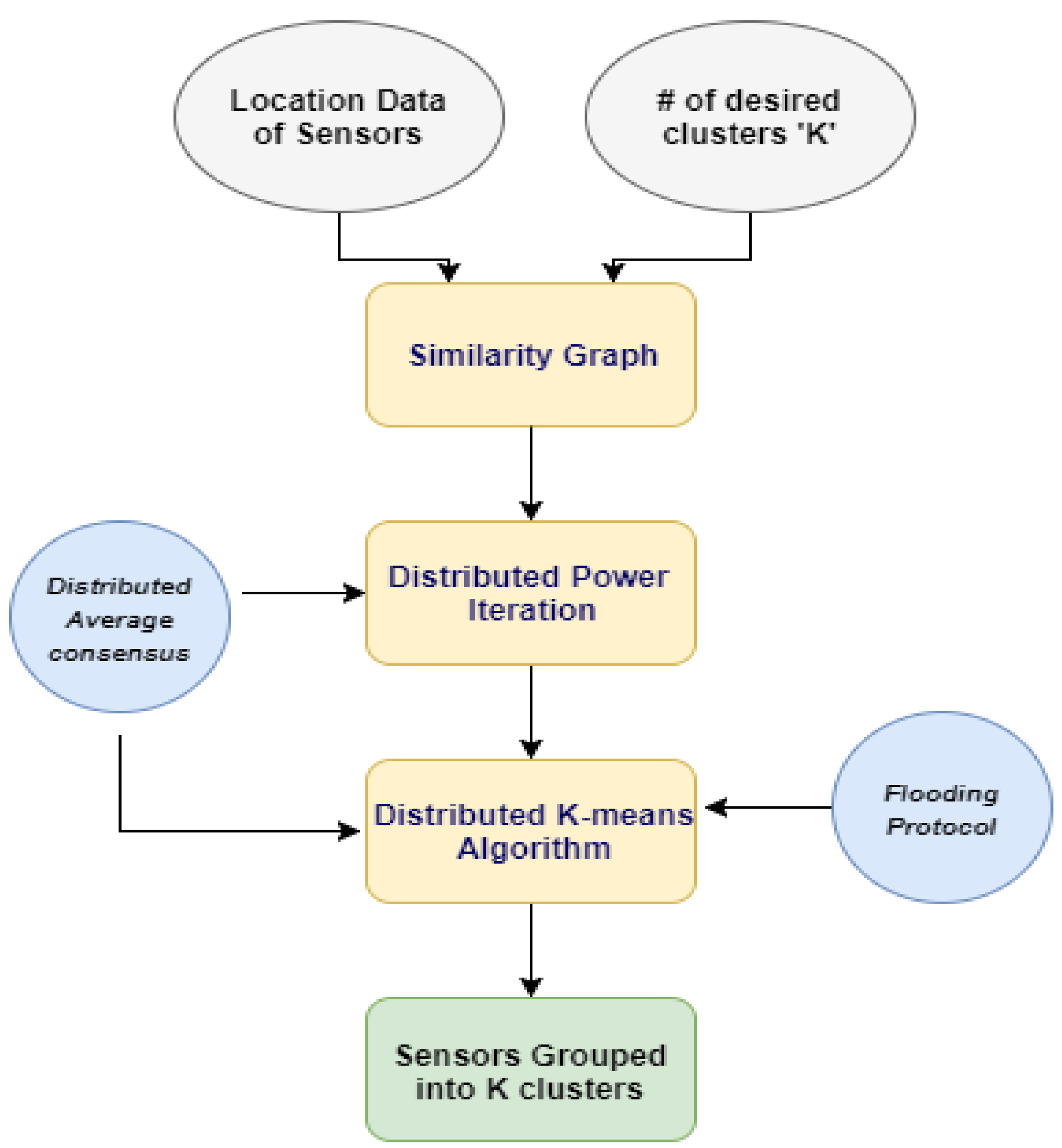
SenSIP Center, Arizona State University, Clarkson University, Technologico de Monterrey

SenSIP
Sensor, Signal and Information Processing Center

MOTIVATION & APPLICATIONS

- ❑ Data aggregation for machine learning and data mining applications in WSN creates a bottle neck at fusion center.
- ❑ Fully Distributed processing is effective in terms of
  - Memory and power management
  - Communication Bandwidth and Fault tolerance
- ❑ Applications
  - Environmental monitoring
  - Military and surveillance
  - Habitat monitoring & precision agriculture
  - Data Labeling

ALGORITHM FLOWCHART



FIEDLER VECTOR COMPUTATION

- ❑ Matrix transformation : $W = I - \alpha L$
- ❑ Matrix Deflation : $Z = W - \frac{1}{N} 1 1^T$
- ❑ Power Iteration : $u^{t+1} = Z u^t / ||Z u^t||$

DISTRIBUTED SPECTRAL CLUSTERING

- ❑ Input for the algorithm is the Location co-ordinates of sensors and number of clusters K
- ❑ Similarity Graph : Naturally induced by communication radius of the nodes $\in$ and location of the nodes.
  - All nodes whose pairwise Euclidean distance is less than are assumed to be connected.
- ❑ Distributed Power Iteration : To compute the Fiedler vectors of the graph Laplacian of the similarity graph in a distributed way.
  - $g_i^t = u_i^t - \alpha \sum_{j \in N_i}(u_i^t - u_j^t) - u_{avg}^t$
  - $u_i^{t+1} = g_i^t / ||g^t||$
  - All the nodes converge to the Fiedler vector of L.
- ❑ Distributed K- Means : To cluster the N nodes into K groups by taking Fiedler vector as the input.
  - $\rho_{ki} = |u_i - \mu_k|$
  - Assignment Step : $index = \operatorname{argmin}_i(\rho_{ki})$
  - $C_k = \{u_i \mid i \in index = k\}$
  - Update Step : $\mu_k = avgconsensus(C_k)$
  - Flooding protocol is used to broadcast the centroids

ACKNOWLEDGEMENTS

The authors from Arizona State University are funded in part by the NSF award ECSS 1307982, NSF CPS award 1646542 and the SenSIP Center, School of ECEE, Arizona State University.

SIMULATION RESULTS

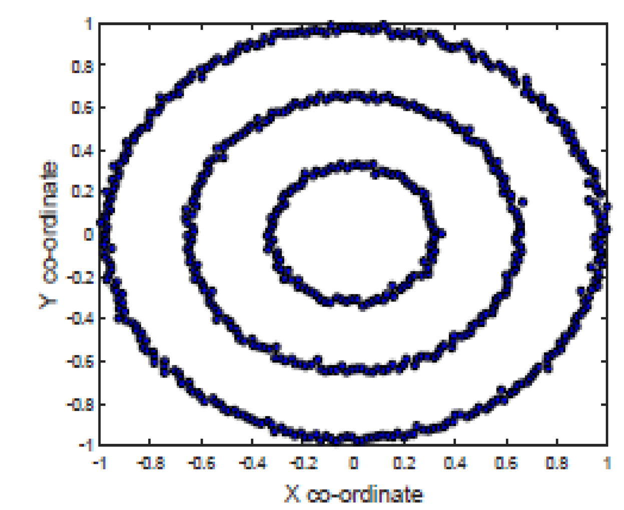


Figure 1: Synthetic data of 2-D sensor locations.

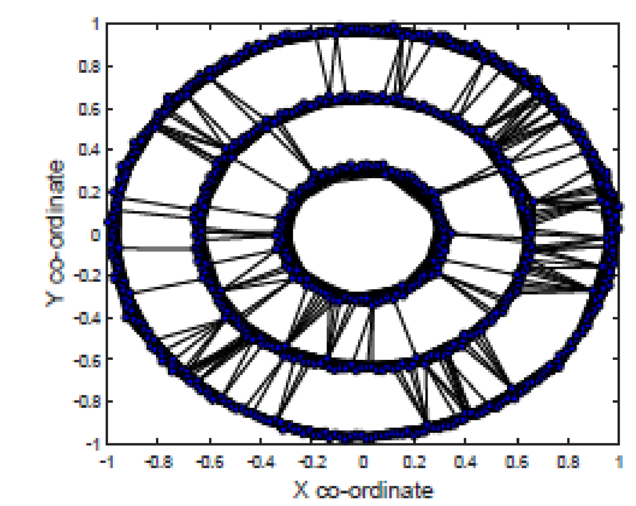


Figure 2: Similarity graph, $\epsilon = 0.3$.

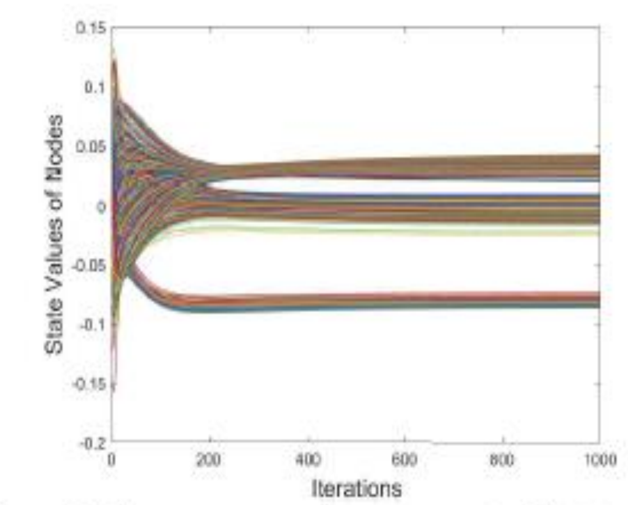


Figure 3: Convergence of nodes to the Fiedler vector.

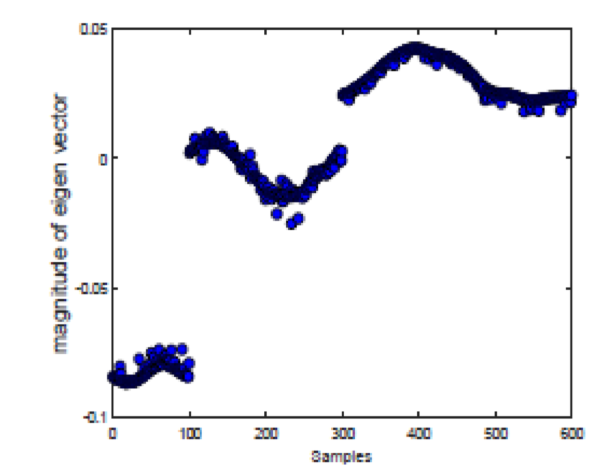


Figure 4: Fiedler Vector computed by Algorithm 1, $\alpha = 0.02$.

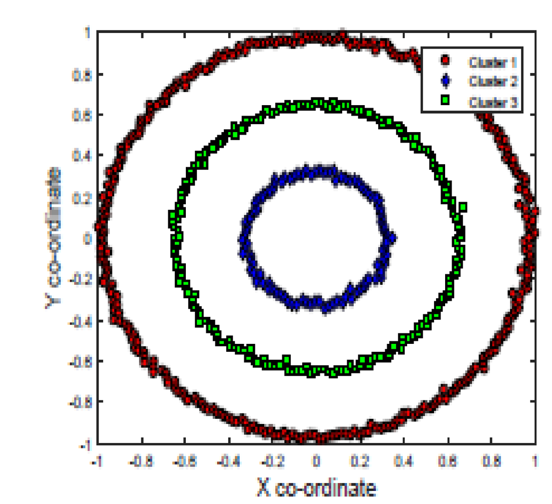


Figure 5: Result of distributed spectral clustering, $K = 3$.

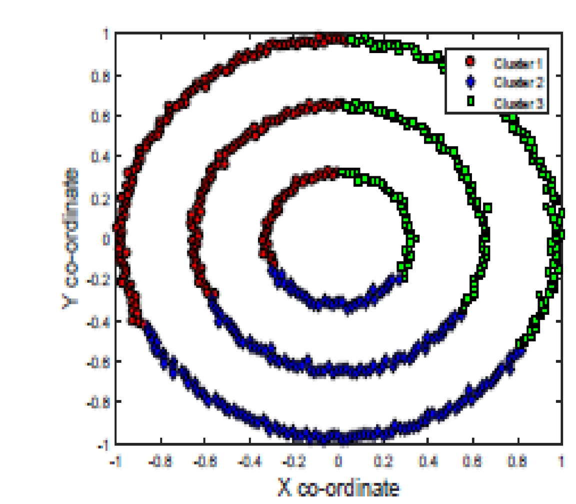


Figure 6: K-means clustering on the dataset in Fig. 1, $K = 3$.

REFERENCES

[1] X. Zhang, C. Tepedelenlioglu, M. Banavar, and A. Spanias, "Node Localization in Wireless Sensor Networks," *Synthesis Lectures on Comms*., vol. 9, no. 1, pp. 1–62, Morgan & Claypool Publishers, 2016.

[2] S. Zhang, C. Tepedelenlioglu, M. Banavar, and A. Spanias, "Distributed node counting in wireless sensor networks in the presence of communication noise," *IEEE Sensors Journal*, vol. 17, pp. 1175–1186, 2017.

[3] S. Dasarathan, C. Tepedelenlioglu, M. K. Banavar, and A. Spanias, "Robust Consensus in the Presence of Impulsive Channel Noise." *IEEE Trans. Signal Process*., vol. 63, no. 8, pp. 2118–2129, 2015.

Ira A. Fulton Schools of Engineering
ARIZONA STATE UNIVERSITY

Sensor Signal and Information Processing Center
http://sensip.asu.edu

NATIONAL SCIENCE FOUNDATION

Net-Centric I/UCRC