

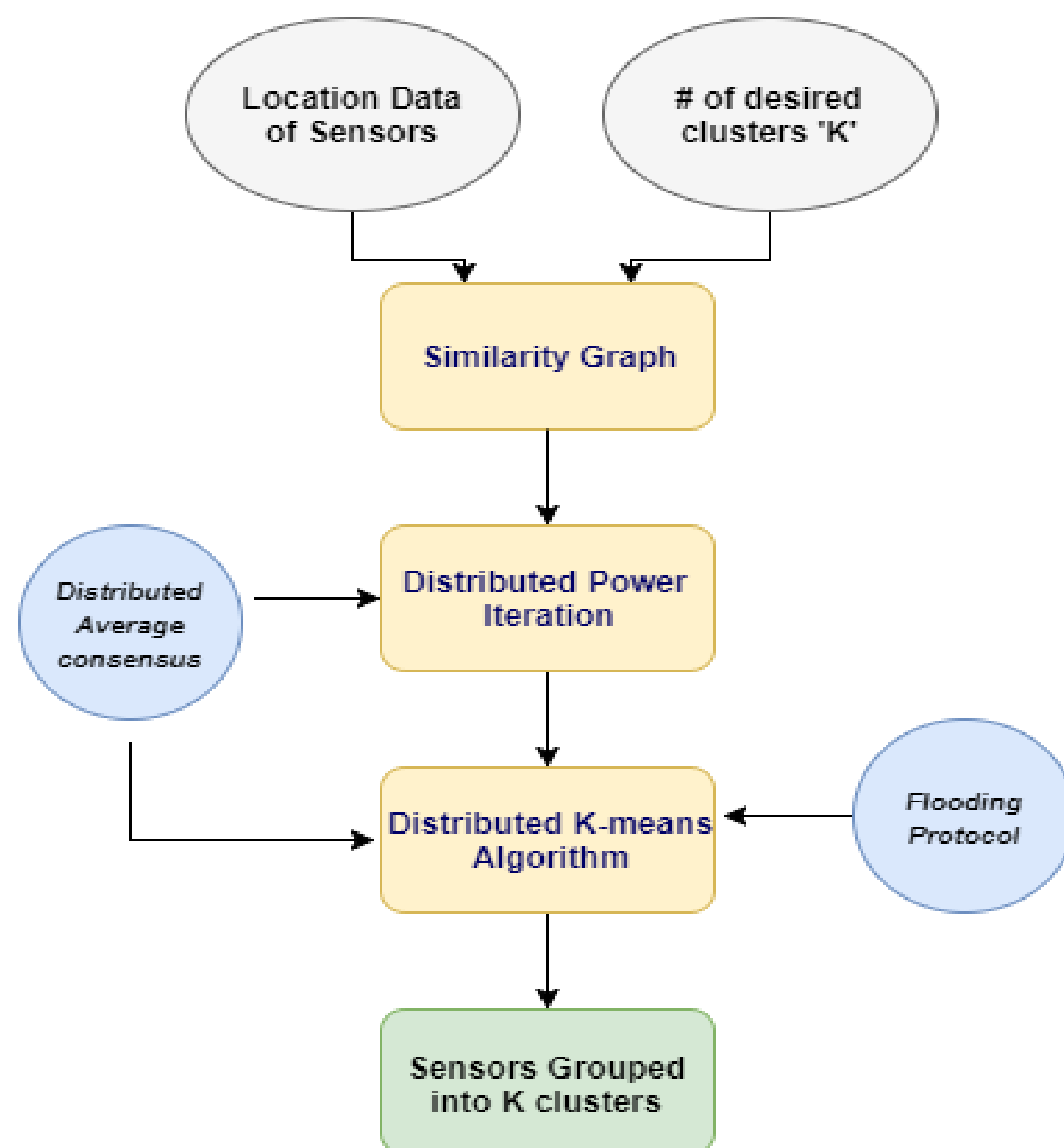
# Location Based Distributed Spectral Clustering for Wireless Sensor Networks

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## 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 :  $Z = W - \frac{1}{N} \mathbf{1}\mathbf{1}^T$
- 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  $\epsilon$  and location of the nodes.
  - All nodes whose pairwise Euclidean distance is less than  $\epsilon$  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.
  - $g_i^t = u_i^t - \alpha \sum_{j \in N_i} (u_i^t - u_j^t) - u_{avg}^t$
  - $u_i^{t+1} = g_i^t / \|g_i^t\|$
  - 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 :  $index = \underset{i}{\operatorname{argmin}}(\rho_{ki})$
  - $C_k = \{u_i \mid i \in index = k\}$
  - Update Step :  $\mu_k = \operatorname{avgconsensus}(C_k)$
  - Flooding protocol is used to broadcast the centroids

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## SIMULATION RESULTS

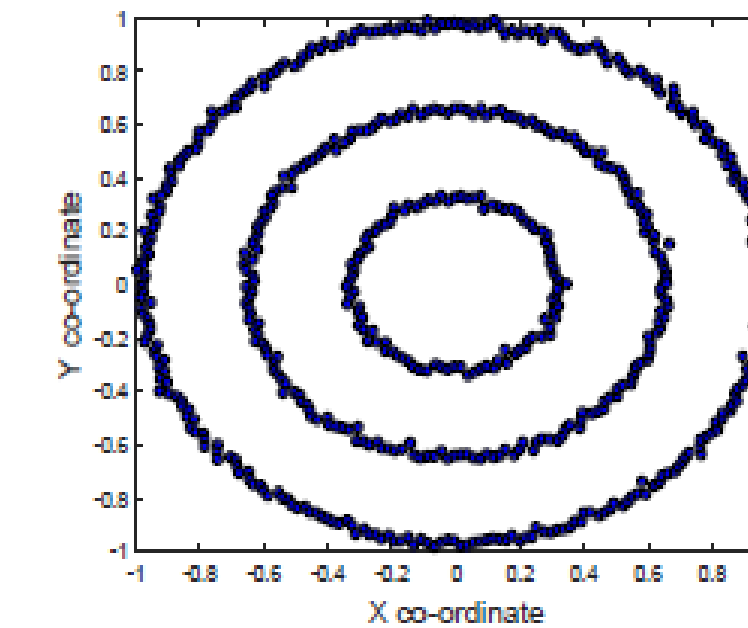


Figure 1: Synthetic data of 2-D sensor locations.

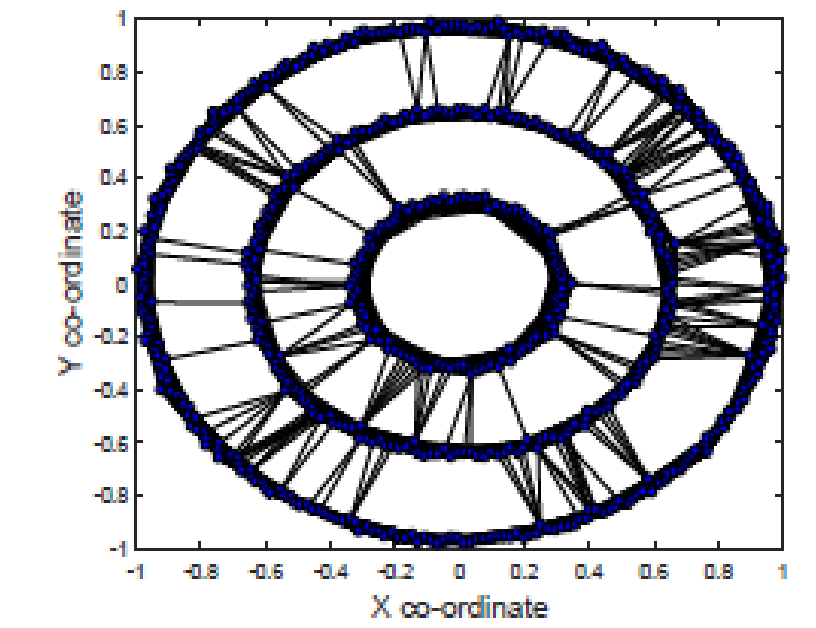


Figure 2: Similarity graph,  $\epsilon = 0.3$ .

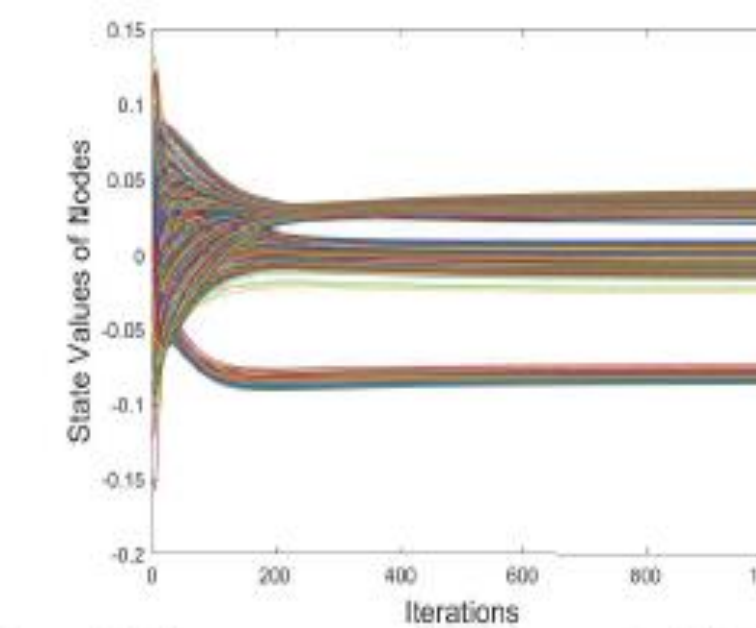


Figure 3: Convergence of nodes to the Fiedler vector.

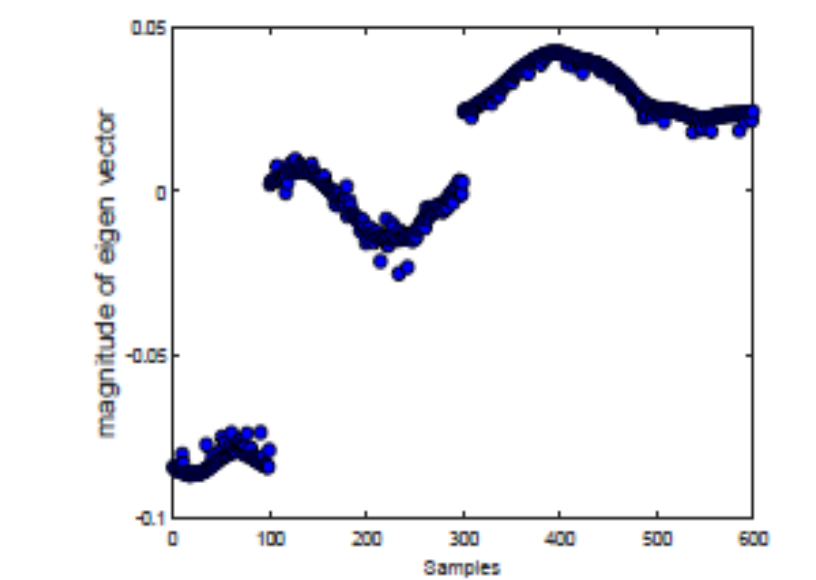


Figure 4: Fiedler Vector computed by Algorithm 1,  $\alpha = 0.02$ .

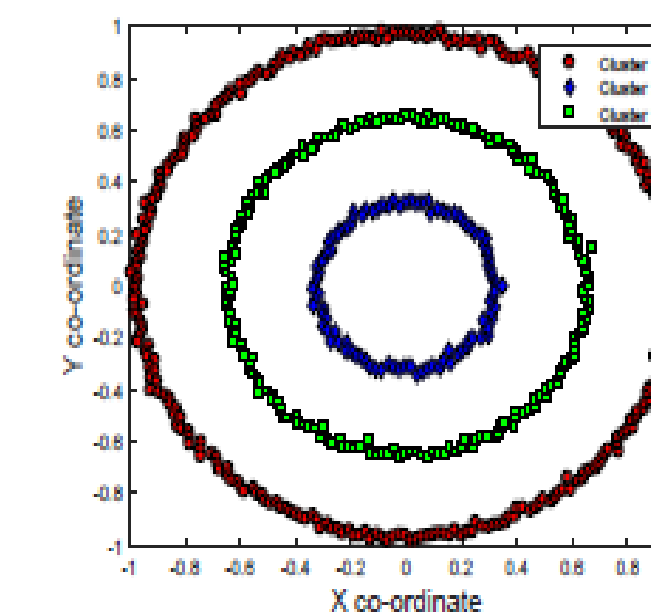


Figure 5: Result of distributed spectral clustering,  $K = 3$ .

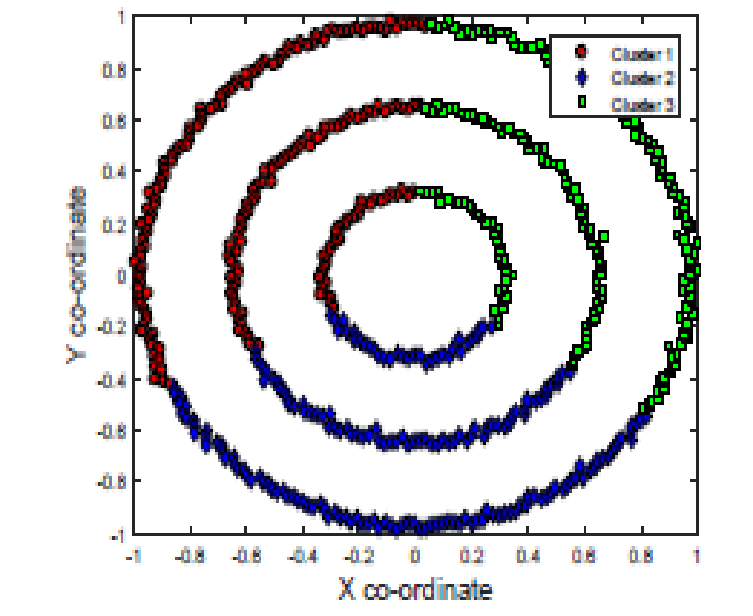


Figure 6: K-means clustering on the dataset in Fig. 1,  $K = 3$ .

## REFERENCES

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- [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.