# A Conditional Clustering Approach For Improved Network Lifetime In Wireless Multimedia Sensor Networks

P.X.Britto[1], Dr.S.Selvan[2]
[1]*Assistant Professor, Department of Electronics and Communication Engineering,*
*Mahakavi Bharathiar College of Engineering and Technology*
[2] *Principal, St.Peter's College of Engineering and Technology*

***Abstract - The transmissions of audio and video data in sensor networks are made possible by the evolvement of multimedia sensors which is more advantageous than scalar sensors. Hence the sensor network with multimedia sensors are called as Wireless Multimedia sensor networks (WMSN). In WMSN the battery energy and network lifetime are the major constraints of research since the transmission of multimedia data needs more energy. In this paper a conditional clustering approach based on spectral graph partitioning (SGP) for WMSN is proposed to increase the lifetime of the network. The efficient strategies for CH selection and rotation also proposed as a part of clustering approach. Simulation results show that our approach is better than existing approach.***
***Keywords: SGP, WMSN, Eigen values and Eigen vectors.***

## I. INTRODUCTION

The technological advancements in low power hardware design in wireless communication have led to the development of tiny, low cost and low power sensor nodes which have capability to sense and compute physical parameters, and are able to communicate with each other [1]. A wireless sensor network (WSN) consists of large number of sensor nodes where each node is equipped with processor, storage and radio capabilities. The sensor networks have various applications like monitoring temperature, pressure, light intensity, movement of object, etc. The WSNs in which the sensor node uses cheap CMOS (Complementary Metal Oxide Semiconductor) camera and microphone sensors to retrieve scalar data, video, audio streams and still images from the physical environment are called wireless multimedia sensor networks. WMSN uses both camera sensors and scalar sensors. [5]

WMSN can retrieve more detailed information in the form of multimedia data like audio and video streams and hence gives the detailed and interesting information about the environment than the scalar data. The multimedia sensor instigation enabled the WMSN for new applications such as traffic monitoring, border surveillance, smart homes, and environment and habitat monitoring. The multimedia data collected in the environment are processed and sent to the sink via multi hops.

The scalability of WMSN depends on the high energy efficiency and prolonged network lifetime in large scale networks. Battery power consumption is the constraint which is to be concentrated while designing of protocols and applications to improve the energy efficiency and network lifetime. Clustering is one solution adopted by the resources to improve the network life time.

The clustering is a process that leads to a two-level hierarchy where the CH (cluster head) nodes form the higher level and the cluster-member nodes form the lower level. Nodes communicate their data over shorter distances to their respective cluster head (CH) as shown in Figure 1.1. The cluster head aggregates these data into a smaller set of meaningful information and transmit them to the base station (BS) either directly or through the intermediate communication with other CH nodes. Not all nodes, but only the cluster heads need to communicate with their neighbouring cluster heads and sink/base station. However, because the CH nodes send all the time data to higher distances than the common nodes, they naturally spend energy at higher rates. [3]

A common solution in order balance the energy consumption among all the network nodes is to rotating the CH role among all the nodes over time in each cluster. It saves energy and reduces network contention by enabling locality of communication. [4]

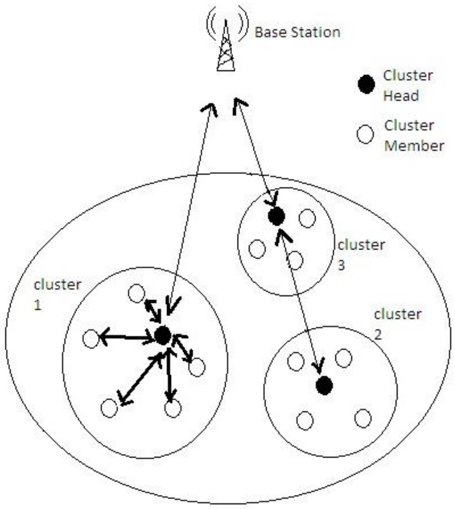



Figure 1.1

In this paper, we have utilized spectral graph partitioning (SGP) technique based upon Eigen values to form clustering in WMSN with the condition of zero single node clusters. Instead of the distance between CH and nodes, we consider the distance between the CH and sink for CH rotation with the residual energy of the node.

The rest of the paper is organized as follows. Section II contains the System model and Section III contains the previous work. Our proposed method of SGP strategy for clustering with a condition zero single node clustering has been presented in Section IV. In Section V we present the performance evaluation of the proposed method and Section VI concludes the paper.

## II. SYSTEM MODEL

Consider a wireless multimedia sensor network (WMSN) consisting of sensor nodes fitted with micro cameras to capture image data from the physical environment.

It is assumed that all the nodes have the same initial energy. In the proposed method, clustering of WMSN has been done on the basis of Spectral Graph Partitioning technique with the condition of zero single node clusters. Each node sends short message to sink which contains the location information of the node. On the basis of this information, the sink constructs the adjacency matrix and degree matrix and then the Laplacian matrix. The eigenvector corresponding to second smallest Eigen-value is used to partition the WMSN. [3]

Let G (V, E) is an undirected graph where V represents the set of vertices (sensor nodes) and E represents the set of edges connecting these vertices as shown in Figure 2.1. Each vertex is identified by an index . The edge between node i and node j is represented by eij. The graph can be represented as an adjacency matrix. The adjacency matrix A of graph G having N nodes is the N × N matrix where the non-diagonal entry aij is the number of edges from node i to node j, and the diagonal entry aii is the number of loops at node i. [3, 21]

The adjacency matrix $A$ is defined as

$$A = [a_{ij}] = \begin{cases} 1 & \text{edge weight between node } i \text{ and node } j \\ 0 & \text{otherwise} \end{cases}$$

The degree matrix D for G is a N × N square matrix and is defined as

$$D = [deg_{ij}] = \begin{cases} \text{total weight of edges incident to node } i \\ 0 \end{cases}$$

The Laplacian matrix is formed from adjacency matrix and the degree matrix. The Laplacian matrix of the graph $G$ having $N$ vertices is $N \times N$ square matrix and is represented as

$$L = D - A$$

The normalized form of Laplacian matrix can be written as

$$\gamma(i,j) = \begin{cases} 1 & \text{if } i = j \text{ and } degj \neq 0 \\ -\dfrac{1}{\sqrt{deg_i deg_j}} & \text{if } i \text{ and } j \text{ are adjacent} \\ 0 & \text{otherwise} \end{cases}$$

The Eigen values of matrix are denoted by $\lambda_i$, $i = 1, 2, \ldots, N$ such that $\lambda_1 \leq \lambda_2 \leq \cdots \leq \lambda_n$ Laplacian matrix has the property where $X$ is the Eigen vector of the matrix and $\lambda$ is the Eigen value of the matrix. [3]

$\lambda_1$ represents the number of sub-graphs in the network. The second smallest Eigen value $\lambda_2$ is referred to the algebraic connectivity and its corresponding eigenvector is usually referred to as the Fiedler Vector [19, 23].

We choose the eigenvector values corresponding to the second highest Eigen value $\lambda_2$. Second highest Eigen value ($\lambda_2$) divides the graph into two sub-graphs. $G$ is divided into two sub-graphs $G^+$ and $G^-$. $G^+$ contains nodes corresponding to positive Eigen values and $G^-$ contains nodes corresponding to negative Eigen values.

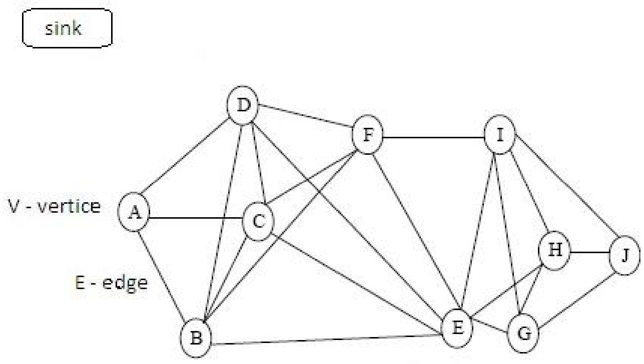



Fig. 2.1 System Model

## III. PREVIOUS WORK

The sensor nodes are often grouped into individual disjoint sets called a cluster. Clustering is used in WSNs, as it provides network scalability and resource sharing. Clustering schemes offer reduced communication overheads, and efficient resource allocations thus decreasing the overall energy consumption and reducing the interferences among sensor nodes. [2].

HEED (Hybrid Energy-Efficient Distributed Clustering) is a hierarchical, distributed, clustering scheme in which a single-hop communication pattern is retained within each cluster; where as multi-hop communication is allowed among CHs and the BS. In HEED, each node is mapped to exactly one cluster and can directly communicate with its CH. Also, energy consumption is not assumed to be uniform for all the nodes. The CH nodes are chosen based on two basic parameters, residual energy and intra cluster communication cost. Residual energy of each node is used to probabilistically choose the initial set of CHs. On the other hand, intra cluster communication cost reflects the node degree or node's proximity to the neighbor and is used by the nodes in deciding to join a cluster or not [1].

Spectral graph partitioning algorithm partitions the graph using the eigenvectors of the matrix obtained from the graph. SGP obtains data representation in the low-dimensional space that can be easily clustered. Eigen values and eigenvectors provide a penetration into the connectivity of the graph. Spectral graph partitioning technique is based on Eigen-values and eigenvector of the adjacency matrix of graph to partition the graph. The methods are called spectral, because they make use of the spectrum of the adjacency matrix of the data to cluster the points [3].

Spectral methods are widely applied for graph partitioning. Spectral graph partitioning is a powerful technique and also is being used in image segmentation and social network analysis. SGP divides the graph into two disjoint groups, based on eigenvectors corresponding to the second smallest Eigen value of the graph.

After the first iteration of above method, the whole network is divided into two clusters based on the Eigen values of the nodes. Table 3.1 shows the two partitions/ clusters for a given graph shown in Figure 3.1. After the first iteration cluster 1 contains all the nodes with positive eigenvector values and another cluster 2 contains nodes having negative eigenvector values. Cluster 1 has five nodes with positive value of eigenvector and the nodes are A, B, C, D and F. Cluster 2 has five nodes that have negative eigenvector values and the notes are E, G, H, I and J.

Table 3.1

<table>
<tr><th rowspan="2">Node</th><th colspan="2">Second iteration</th><th rowspan="2">Clusters</th><th rowspan="2">Cluster Head</th></tr>
<tr><th>Eigenvalue</th><th>Eigenvector</th></tr>
<tr><td>A</td><td>0</td><td>-0.7071</td><td rowspan="4">Cluster 1</td><td rowspan="4">A</td></tr>
<tr><td>B</td><td>1</td><td>-0.00001</td></tr>
<tr><td>C</td><td>1.25</td><td>-0.00001</td></tr>
<tr><td>D</td><td>1.25</td><td>-0.00001</td></tr>
<tr><td>E</td><td>1.5</td><td>0.7071</td><td>Cluster 2</td><td>E</td></tr>
<tr><td>F</td><td>1.33</td><td>-0.3017</td><td rowspan="2">Cluster 3</td><td rowspan="2">F</td></tr>
<tr><td>I</td><td>0</td><td>0.7475</td></tr>
<tr><td>G</td><td>0.7257</td><td>0.4101</td><td rowspan="3">Cluster 4</td><td rowspan="3">G</td></tr>
<tr><td>H</td><td>1.33</td><td>-0.3017</td></tr>
<tr><td>J</td><td>1.607</td><td>-0.3017</td></tr>
</table>

Only two clusters are formed in first iteration. The larger size clusters can be further divided into two different clusters by applying the algorithm recursively. This process continues until maximum intra-node distance within a cluster is less than $R/2\sqrt{2}$ where R is the transmission range of the sensor node.

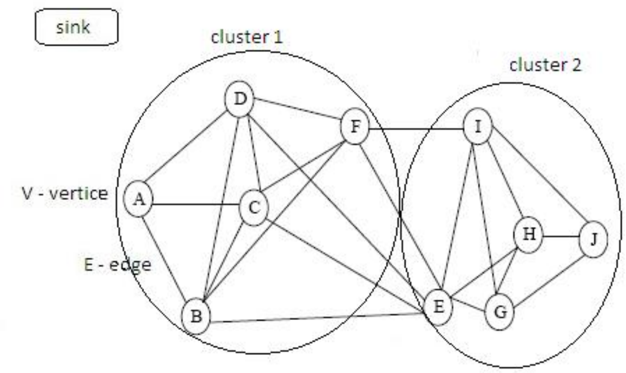



Figure 3.1

When intra- node distance is remaining $R/2\sqrt{2}$ two nodes in neigh-bouring clusters can communicate in one hop. After applying the algorithm recursively, the given network is divided into four clusters as shown in Figure 3.2. Table 3.2 shows the formed cluster after second iteration. After applying the algorithm cluster 1 is portioned into two different clusters. This algorithm is also applied to cluster 2 also.

Table 3.2

| Node | Degree | First iteration | | Clusters |
|---|---|---|---|---|
| | | Eigenvalue | Eigenvector | |
| A | 3 | 0 | 0.3235 | Cluster 1 |
| B | 5 | 0.2448 | 0.3155 | |
| C | 5 | 0.8987 | 0.3155 | |
| D | 5 | 1.076 | 0.3155 | |
| F | 5 | 1.2 | 0.1592 | |
| I | 5 | 1.378 | -0.3293 | Cluster 2 |
| E | 7 | 1.2 | -0.019 | |
| G | 4 | 1.25 | -0.3853 | |
| H | 4 | 1.263 | -0.3853 | |
| J | 3 | 1.488 | -0.407 | |

The clustering algorithm divides the whole network into clusters. The next step is election of cluster head for each cluster. As per the property of SGP, the least eigenvector value of node signifies that the node is well connected to the other nodes within the cluster as well as it is connected to cluster [26].

For initial cluster head election, we chose the least eigenvector value among the nodes within cluster, Table 3.2 represents the eigenvector values of the cluster and the elected cluster heads in different clusters on the basis of eigenvector values. Therefore, we compare the eigenvector values of the cluster and choose the least eigenvector node as a cluster head.

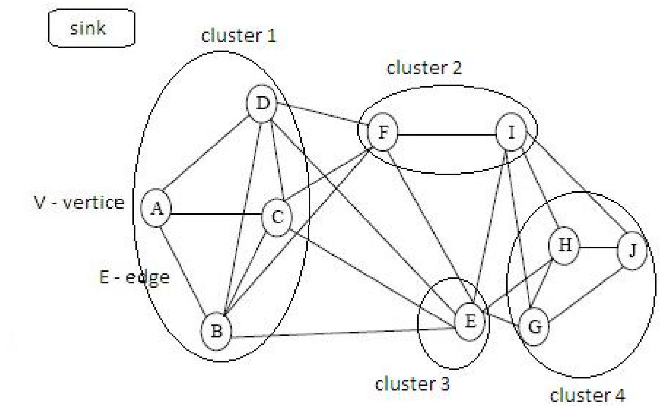



Figure 3.2

$$\text{Cluster Head} = \text{Least } |\text{Eigenvector}|$$

Cluster head rotation must take place when residual energy ($E_{res}$) of the cluster head node falls below the threshold value ($E_{th}$). The present cluster head declares the election process by sending a message that contains its Eres to all the cluster members. The cluster members whose residual energy is greater than Eres responds to this message by sending the residual energy to the cluster head.

The new cluster head is elected based upon CH Candidacy Factor (CF) defined as

$$CF_i = E^i_{res} / D_i$$

where is the residual energy of node i,

$$D_i = \sqrt{(x_{ch} - x_i)^2 + (y_{ch} - y_i)^2}$$

If $(x_{ch}, y_{ch})$ and $(x_i, y_i)$ are the location coordinates of current CH and node i, respectably, distance between sink and node is calculated by the above formula.

## IV. PROPOSED METHODOLOGY

In the previous work, they had used Spectral Graph Partition for cluster formation with the condition of maximum intra-node distance within a cluster is less than $R/2\sqrt{2}$. Because of this, there is a possibility of the ratio of single cluster in the network is high; it may lead to early energy dissipation. Ratio of single node cluster indicates that the ratio of number of clusters having single nodes to the total number of clusters. High single node cluster (the cluster head) may lead to reduce the network lifetime. Single node cluster arise when a node is forced to represent it-self.

In our proposed method, we use SGP with a condition in cluster formation to avoid single node cluster. We use a constant L to decide the cluster formation further, where L is the number of nodes present inside a cluster. We use Eigen values to form the cluster in SGP. In the first iteration, the whole network is divided into two clusters based on the Eigen values of the nodes. To form a next level of cluster or for further division of large size cluster, we use a condition that, Number of nodes inside the cluster should be greater than 1, i.e

$$L > 1$$

L – Number of Nodes inside a cluster

As shown in Figure 4.1 Cluster, which satisfy the above condition will go for further cluster formation; otherwise it will remain the same. The larger size clusters can be further divided into two different clusters by applying the algorithm recursively.

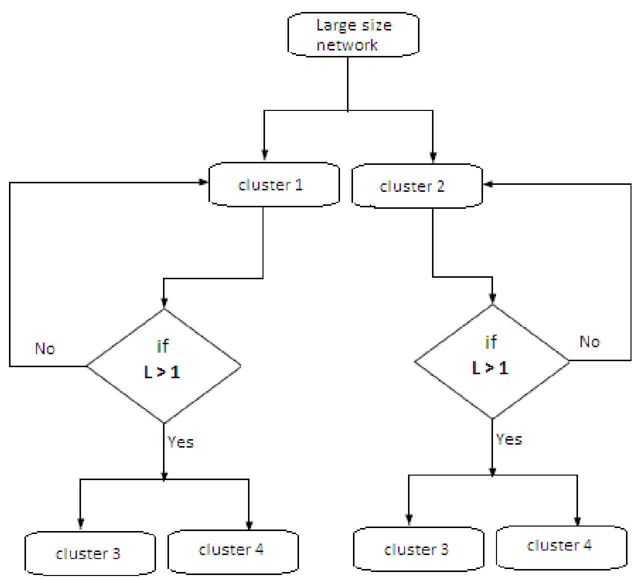



Figure 4.1

Cluster Head Election

The clustering algorithm divides the whole network into clusters. The next step is election of cluster head for each cluster. As per the property of SGP, the least eigenvector value of node signifies that the node is well connected to the other nodes within the cluster as well as it is connected to cluster [26].

For initial cluster head election, we chose the least eigenvector value among the nodes within cluster. Therefore, we com-are the eigenvector values of the cluster and choose the least eigenvector node as a cluster head.

$$\text{Cluster Head} = \text{Least}\,|\text{Eigenvector}|$$

Cluster head rotation must take place when residual energy ($E_{res}$) of the cluster head node falls below the threshold value ($E_{th}$). The present cluster head declares the election process by sending a message that contains its *Eres* to all the cluster members. The cluster member whose residual energy is greater than *Eres* responds to this message by sending the residual energy to the current CH. Then the Ch send these data to the sink and the sink will elect the next cluster head by the factor(F).

The new cluster head is elected based upon the below factor,

$$F_i = E^i_{res} / D_{si}$$

$E^i_{res}$ - Residual energy of node i

$D_{si}$ - Distance between node i and sink

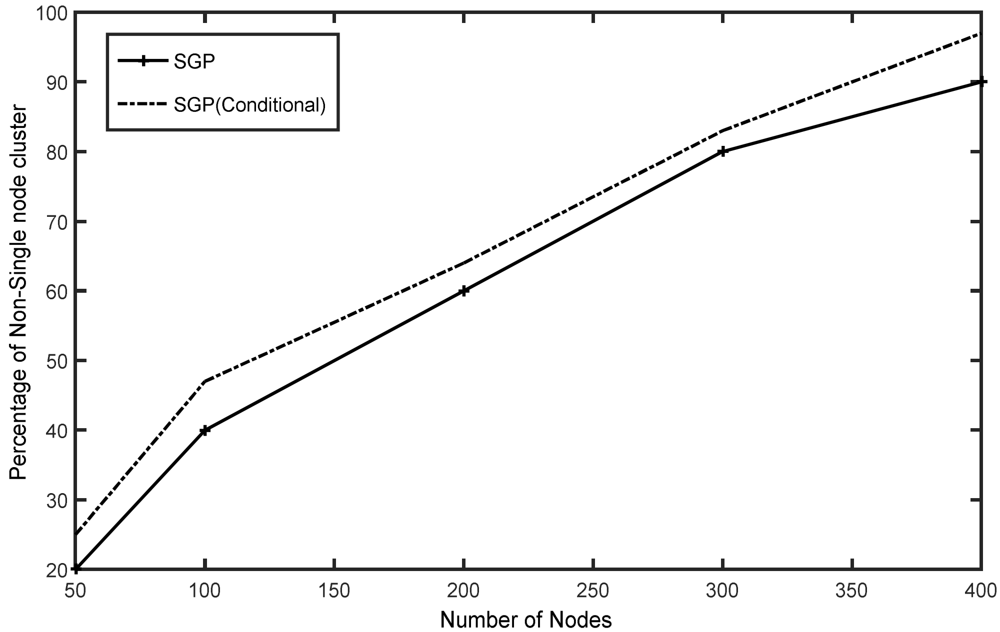
If ($x_s$, $y_s$) and ($x_i$, $y_i$) are the location coordinates of sink and node i, respectably, then distance between sink and node is calculated as,

$$D_{si} = \sqrt{(x_s - x_i)^2 + (y_s - y_i)^2}$$

Then a node with highest value of F is elected as next cluster head by the sink. Sink will send this information to every node present inside the cluster. Since we are including the sink and node distance it will give better performance than the previous work in terms of minimum amount of energy consumption because of shorter distance between cluster head and sink.

## V. PERFORMANCE EVALUATION

Simulation results demonstrate that our proposed method produces more Non-single node clusters compared with the previous one. Hence, it improves the network lifetime by avoiding single node clusters.




## VI. CONCLUSION

This paper has proposed the clustering in a given wireless multimedia sensor network using SGP method with the condition of no single node cluster or zero single node cluster to improve the Network Lifetime. The details of the proposed clustering algorithm are explained. It divides the network into two clusters and partitions the network without single node cluster. The cluster head elections technique is based on eigenvector initially and cluster head rotation is based on residual energy and Sink-Node distance. Simulation results show that our proposed algorithms perform better than the previous algorithm.

## REFERENCES

[1] Pushpender Kumar, Narottam Chand, "Clustering in Wireless Multimedia Sensor Networks, Journal of Sensor Technology, 2013.

[2] Vinay Kumar, Sanjeev Jai n and Sudarshan Tiwari, "Energy Efficient Clustering Algorithms in Wireless Sensor Networks: A Survey", IJCSI International Journal of Computer Science, September 2011.

[3] Ossama Younis and Sonia Fahmy, "HEED: A Hybrid, Energy-Efficient, Distributed Clustering Approach for Ad-hoc Sensor Networks", IEEE Transactions on Mobile Computing, October 2004.

[4] Zhang, "RFID and Sensor Networks", Page 323, 2009.

[5] Narottam Chand, "Energy Efficient Cooperative Caching inWireless Multimedia Sensor Networks", Advances in Information Science and Applications.

[6] F. Akyldiz, W. Su, Y. Sankarasubramaniam and E. Cay-irci, "Wireless Sensor Networks: A Survey," Computer Networks, Vol. 38, No. 4, 2002, pp. 393-422.

[7] S. Taruna and M. R. Tiwari, "An Event Driven Energy Efficient Data Reporting System for Wireless Sensor Net-works," Vol. 2, No. 2, 2013, pp. 70-75.

[8] I. F. Akyildiz, T. Melodia and K. R. Chowdhury, "A Sur- vey on Wireless Multimedia Sensor Networks," Computer Networks, Vol. 51, No. 4, 2007, pp. 921-960.

[9] P. Kumar and N. Chand, "Clustering in Wireless Multi- media Sensor Networks Using Spectral Graph Partition- ing," International Journal of Communication, Network and System Sciences, Vol. 6, No. 3, 2013, pp. 128-133.

[10] M. Demirbas, A. Arora, V. Mittal and V. Kulathumani, "A Fault-Local Self-Stabilizing Clustering Service for Wire- less Ad Hoc Networks," IEEE Transactions on Parallel and Distributed Systems, Vol. 17, No. 9, 2006, pp. 912- 922.

[11] B. Auffarth, "Spectral Graph Clustering," Course Report. http://wwwlehre.inf.uos.de/~bauffart/spectral.pdf

[12] B. Elbhiri, S. El Fkihi, R. Saadane and D. Aboutajdine, "Clustering in Wireless Sensor Network Based on Near Optimal Bi-partitions," 6th EURO-NF Conference on Next Generation Internet (NGI), 2010, pp. 1 -6.

[13] M. Qin and R. Zimmermann, "VCA: An Energy Efficient Voting Based Clustering Algorithm for Sensor Networks,"

Journal of Universal Computer Science, Vol. 13, No. 1, 2007, pp. 87-109.

[14] M. Chatterjee, S. K. Das and D. Turgut, "WCA: A Weight- ed Clustering Algorithm for Mobile Ad hoc Networks," Journal of Cluster Computing (Special Issue on Mobile Ad hoc Networks), Vol. 5, No. 2, 2002, pp. 193-204.

[15] S. Banerjee and S. Khuller, "A Clustering Scheme for Hierarchical Control in Multi-Hop Wireless Networks," IEEE INFOCOM, 2001, pp. 1028-1037.

[16] S. Bandyopadhyay and E. Coyle, "An Energy Efficient Hierarchical Clustering Algorithmfor Wireless Sensor Networks," 22nd Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM), Vol. 3, 2003, pp. 1713-1723.

[17] C. Li, M. Ye, G. Chen and J. Wu, "An Energy Efficient Unequal Clustering Mechanism for Wireless Sensor Networks," 2nd IEEE International Conference on Mobile Adhoc and Sensor Systems (MASS), 2005, pp. 125-132.

[18] Y. He, Y. Zhang, Y. Ji and S. X. Shen, "A New Energy Efficient Approach by Separating Data Collection and Data Report in Wireless Sensor Networks," International Conference on Communications and Mobile Computing, 2006, pp. 180-192.

[19] A. Bertrand and M. Moonen, "Distributed Computation of the Fiedler Vector with Application to Topology Infer- ence in Ad Hoc Networks," Internal Report KU Leuven ESAT-SCD, 2012.

[20] Laplacian Matrix Wikipedia. http://en.wikipedia.org/wiki/Laplacian_matrix

[21] Adjacency Matrix Wikipedia. http://en.wikipedia.org/wiki/Adjacency_matrix

[22] Degree Matrix Wikipedia. http://en.wikipedia.org/wiki/Degree_matrix

[23] A. Savvides, C. Han and M. B. Srivastva, "Dynamic Fine-Grained Localization in Ad Hoc Networks of Sensors," 7th International Conference on Mobile Computing and Networking (MOBICOM), 2001, pp. 166-179.

[24] D. Lu, N. Nan and X.-X. Huang, "Clustering Based Spectrum Allocation Scheme in Mobile Ad Hoc Networks," Bulletin of Advanced Technology Research (BATR), Vol. 5, No. 12, 2011, pp. 37-41.

[25] N. Bulusu, J. Heidemann and D. Estrin, "GPS-Less Low Cost Outdoor Localization for Very Small Devices," IEEE Personal Communication Magazine, Vol. 7, No. 5, 2000, pp. 28-34.

[26] A. Savvides, C. Han and M. B. Srivastva, "Dynamic Fine-Grained Localization in Ad Hoc Networks of Sensors," 7th International Conference on Mobile Computing and Networking (MOBICOM), 2001, pp. 166-179.

[27] O. Younis and S. Fahmy, "Distributed Clustering in Ad- Hoc Sensor Networks: A Hybrid, Energy Efficient Ap- proach," IEEE Transactions on Mobile Computing, Vol. 3, No. 4, 2004, pp. 366-379.