VORONOI FUZZY CLUSTERING APPROACH FOR DATA PROCESSING IN WSN

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Abstract

Clustering for data aggregation is essential nowadays for increasing the wireless sensor network (WSN) lifetime, by collecting the monitored information within a cluster at a cluster head. The clustering algorithm reduces overall transmission of data from each sensor to the sink node thus energy spent by individual sensor node is minimized .The cluster heads collect all sensed information from their respective cluster members and performs data aggregation to transmit the data to the sink node. In this paper novel Voronoi Fuzzy multi hop clustering (V-FCM) algorithm is proposed for grouping the sensor node. This algorithm is a mixture of Voronoi diagram and modified Fuzzy C- Means clustering algorithm. In addition to clustering, data aggregation technique such as MAX, MIN and AVG is computed in each cluster head for further reduction of the number of data transmissions. Finally, the simulations are performed and the results are analyzed within the simulation set up to determine the performance of the proposed algorithm in Weather forecasting sensor network. Our proposed approach has achieved higher energy efficiency when compared with the Fuzzy C-Means algorithm.

Keywords: Clustering, data aggregation, Voronoi fuzzy clustering algorithm, energy, QoS, Delaunay triangulation, EMST.

1. Introduction

Cluster aggregation is an essential technique that naturally reduces energy costs in wireless sensor networks without compromising the quality of data delivery. The process of separating the sensor nodes into groups is called clustering. There are a number of challenges involved in clustering. Firstly, the clusters themselves have to be identified. Secondly, cluster heads have to be chosen. Thirdly, routes have to be discovered from every node to their cluster head, and finally, the cluster heads have to proficiently relay the data to the sink node. This paper focuses all the later four problems. The foremost problem is defined by the application domain.

Data aggregation is another vital function in WSN to reduce the consumption of energy. The key idea of this process is to eliminate redundancy in data, minimizing the number of transmissions via integrated all the incoming data in the cluster head from diverse sources and enroute it to the sink. This focuses on data-centric approach. Aggregation algorithms are limited to the application requirement that is either in time or energy performance.

A wireless sensor network consists of tiny sensing devices, which normally run on battery power. Sensor nodes are densely deployed in the region of interest. Each device is sensing and wireless communication capabilities, which enable it to sense and gather information from the environment and then send the data and messages to other nodes in the sensor network or to the remote base station [4]. Wireless sensor networks have been envisioned to have a wide range of application in both military and civilian domains [1]. Due to the less power of sensor node energy, researchers have designed a lot of energy-efficient routing protocols prolong the lifetime of sensor networks [2]. The energy source of sensor nodes in wireless sensor networks is usually bored by battery, which is undesirable, even impossible to be recharged or replaced. Therefore, improving the energy efficiency and maximizing the networking lifetime are the major challenges in sensor networks [3]. Considering the limited energy capabilities of an individual sensor, a sensor node can sense only up to a very limited area, so a wireless sensor network has a large number of sensor nodes deployed in very high density (up to 20nodes/m) [5, 6, 7], which causes severe problems such as scalability, redundancy, and radio channel contention [4].

In this paper, the fuzzy c-means clustering algorithm is modified by incorporating with Voronoi diagram, which is a special kind of decomposition of a given space. The Voronoi Fuzzy Clustering (V-FCM) technique is used to find the area coverage, to reduce the expected distance calculation, to reduce the number of data transmission and to balance the load. The cluster head selection is based on the centroid, if the centroid value is repeated in a single sensor coverage area (ie. Single V-FCM cell) then that sensor will act as a cluster head. The cluster head sends the data every time to the sink node through multi hop data communication model .This is done , because the energy of the cluster head is reduced massively, due to the fewer number of transactions and the least amount of data. In order to reduce the number of transactions, avoid data collision, here the data aggregation method is used and this eliminates the redundancy of data by the following three methods: MAX, MIN and AVG are computed in the cluster head and the computed values are sent to the sink node via multi hop data communication, thereby reducing the energy of individual sensor and increasing network lifetime.

2 The Proposed V-FCM Clustering Algorithm for Data Aggregation

The proposed Voronoi Fuzzy Clustering algorithm is executed in the base station for selecting the cluster heads and its members. The cluster member transmits the sensed data to the base station through their cluster head. If the data sensed by each sensor is sent directly to CHs or BS without any relay node, the sensor nodes located far away have higher energy consumptions due to long-range communication and these nodes may die out faster. To overcome this problem, multi hop clustering algorithm along with data aggregation is employed. The multi hop clustering algorithm is implemented for finding the shortest path between CHs and BS through Delaunay triangulation and Euclidean minimum spanning tree (EMST) algorithm. Once the Cluster heads are selected by the V-FCM algorithm then BS execute the short path algorithm for transmitting the routing information to each CH, then CHs allocates TDMA time slot to its cluster members for data transmission. During the allocated time slot, data are transmitted by taking a differential value between pervious sent data and current captured data for performing data aggregation in CH.

3 V-FCM Clustering algorithm

The wireless sensor nodes are deployed randomly in the given field and the sensors are clustered using the Voronoi Fuzzy Clustering algorithm. Initially, Voronoi diagram applies to the sensor nodes based on the position and energy of the sensor. Subsequently Fuzzy C-Means clustering algorithm is employed for selecting the optimal cluster head. In order to find the membership function, select ‘c’ number of Voronoi cells as a cluster head and calculate the membership for every Voronoi cell with the assumed cluster head. The Voronoi cell goes to the cluster which has a highest value membership function. With the help of the membership function, the cluster heads are selected. Next shortest path among the ‘c’ cluster heads to BS is obtained by applying Euclidean minimum spanning tree. It is a minimum spanning tree of a set of n points in the plane which is actually constructed upon the complete graph on n vertices, which has n (n-1) /2 edges, where each edge weight is computed by finding the distance between each pair of points, and then run a standard minimum spanning tree algorithm on it like Prim's algorithm or Kruskal's algorithm. Since this graph has O (n^2) edges of n distinct points, constructing it already requires O (n^2) time and O (n^2) space to store all the edges.

In order to reduce this time and space, it is better to construct Delaunay triangulation for n points. The Delaunay triangulation is a planar graph, in which there are no more than three times as many edges as vertices in any planar graph. Achieving this Delaunay triangulation is easier in our proposed algorithm because of Voronoi implied. It is obtained by drawing line segment between each pair of Voronoi points which generates only O (n) edges with edge weight as the distance between two Voronoi points. Since there are O(n) edges, this requires O(n log n) time and O(n) space using any of the standard minimum spanning tree algorithms.

Pseudo code:

Input:

No of sensor $S = \{s_1, s_2, .. s_i\}$, Position and energy of every sensor $s_i = (x_i, y_j, z_k)$

Algorithm:

step 1. Find the distance for each s_i with r: $d(s_i,r)=\sqrt{(x_s-x_r)^2+(y_s-y_r)^2+(z_s-z_r)^2}$

step 2. $\{r|d(s_i,r)\le d(s_j,r), i\ne j\}$,where r = set of neighboring sensor

step 3. $r=(r_1,r_2\ldots r_n)$

step 4. $V(s_i) = \dfrac{d(s_i,r_j)}{2}$

step 5. Get the value of "c"

step 6. Select cluster heads ch_y

step 7. Find the member ship function $\mu_{xy}=\dfrac{1}{\alpha+\beta}[\alpha(D_{xy})+\beta(Q_{xy})]$

step 8. Find distance membership function using $D_{xy}=\left(\dfrac{\|v_x-ch_y\|}{\sum_{k=1}^{c}\|v_x-ch_k\|}\right)$

step 9. Find QOS membership function using

$$Q_{xy}=\frac{\sum_{q=1}^{3}V_x^y(z^q)}{\left(\sum_{k=1}^{c}\sum_{q=1}^{3}V_x^k(z^q)\right)}$$

step 10.Find max of μ_{xy} for each s_i

step 11. s_i → max (μ_{xy})

step 12.Find $ch_y=\dfrac{\sum_{x=1}^{N}\mu_{xy}^m . s_i}{\sum_{x=1}^{N}\mu_{xy}^m}$

step 13.Update ch_y

step 14.Go to step 5 until ch_y is placed in same $V(s_i)$

step 15.Find shortest path between CHs and sink node using EMST algorithm through Delaunay triangulation

step 16.Each s_i send data $s_i(d)$ to corresponding cluster head

step 17.The cluster head ch_i receives $D=(d_1,d_2,\ldots,d_i)$

step 18.Select hope 1. Avg 2. Max 3. Min for data aggregation

$$avg=\frac{\sum_{n=1}^{n}(d_i)}{N}$$

$$\max=\max(d_i)$$

$$\min=\min(d_i)$$

step 19.The output of step 18 goes to sink node by the way of step 15.

Let assume that a set of sensor node S is defined by $S=\{s_1,s_2,\ldots s_i\}$, $(1\le i\le n)$ is the total number of sensors in the wireless network. Each sensor node is defined by the position values (x coordinate and y coordinate) and the energy value (z). The position and the energy of the sensor nodes are given by $s_n=(x_i,y_j,z_k)$. After that Voronoi diagram (Fig 1) is applied to decompose the given network. A set of triangles in Voronoi diagram is called Voronoi triangles. The Voronoi triangles generation is based on the distance of the sensor node and the energy of the sensor node. Finding the r neighbors of the each sensor node is based on the minimum distance as in algorithm steps 1-4 , where $d(s_i,r)$ is the distance from point s_i

to r .That is r is the set of sensors closer to s_i than to any other s_j .The calculation of distance is done by the Euclidean metric as step1.

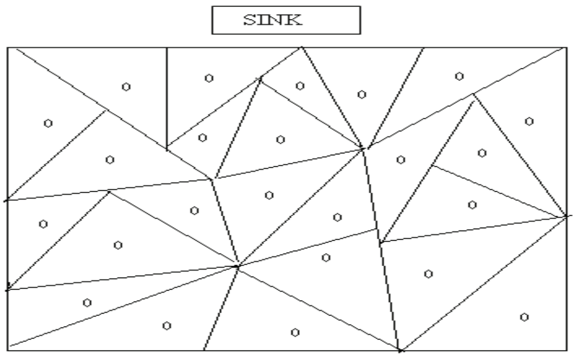

Fig 1: The Voronoi diagram for WSN.

3.1 Calculation of membership function

From the entire sensor nodes, clustering is performed on the sensor nodes based on the membership function. To find the membership function of each sensor node, let assume certain that the number of sensor node as cluster head. In order to find the membership function, first choose "c" cells as a cluster head (CH) that is $c = 2$ and assume any two cells as cluster head $y_1 = ch_1 = (x_{i'1}, y_{j1}, z_{k1})$ and $y_2 = ch_2 = (x_{i2}, y_{j2}, z_{k2})$. With the help of the assumed cluster head, calculate the membership function of each sensor point. Based on the membership function the nodes are clustered. In this paper, the membership function is attained based on two functions: first one is based on the distance and second one is based on the QoS values. The step 7 is used to find the membership function. In which

μ_{xy} → Membership function of x th sensor node with respect to the y th cluster head node

D_{xy} → Distance between x th sensor node to the y th cluster head node

Q_{xy} → Value of the QOS of x th sensor node with respect to the y th cluster head node

α → Weightage of distance (user defined)

β → Weightage of QOS (user defined)

3.1.1 Distance based membership function

Based on the distance between the cluster head and sensor node, the calculations are made through Euclidian distance method is employed to find the distance between the two points. This calculation describes, distance of the each cluster head node to the each sensor node. Then the sensor node moves to the nearest cluster head node. For calculating the distance based membership function step 8 in algorithm is used.

Running the example of Distance membership

Table 1 shows the positions of the each sensor node. From that table select 'C' number of the nodes as a cluster head first. Based on the selected cluster head the distance based membership function is found out. Here, C1= (9.5, 1.3), C2= (8.8, 2.5) are selected as a cluster head, based on that, the distance based membership functions are calculated.

	x	y
V1	2.5	2
V2	4.1	1.3
V3	5.4	0.8
V4	9.5	1.3
V5	8.8	2.5

Table: 1 shows that the positions of the sensor nodes

The distance membership calculation for V1 with respect to C1 and C2 is given below.

$$D_{11} = \frac{\|v1 - c1\|}{\|v1 - c1\| + \|v1 - c2\|}$$

$$D_{11} = \frac{\sqrt{(2.5-9.5)^2 + (2-1.3)^2}}{\left(\sqrt{(2.5-9.5)^2 + (2-1.3)^2} + \sqrt{(2.5-8.8)^2 + (2-2.5)^2}\right)}$$

$$D_{11} = 0.52$$

$$D_{12} = \frac{\|v1 - c2\|}{\|v1 - c1\| + \|v1 - c2\|}$$

$$D_{12} = \frac{\sqrt{(2.5-8.8)^2 + (2-2.5)^2}}{\left(\sqrt{(2.5-9.5)^2 + (2-1.3)^2} + \sqrt{(2.5-8.8)^2 + (2-2.5)^2}\right)}$$

$$D_{12} = 0.47$$

Likewise the distance membership function for each sensor with respect to the C1 and C2 is calculated and the results are shown in table 2.

	V1(2.5, 2)	V2(4.1, 1.3)	V3(5.4,0 .8)	V4(6. 8,3.0)	V5(8.8, 2.5)
V1(2.5,2)	0	0.2	0.3	0.4,	0.6
V2(4.1,1.3)	0.2	0	0.1	0.2	0.4
V3(5.4,0.8)	0.3	0.1	0	0.1	0.3
V4(6.8,3.0)	0.4	0.2	0.1	0	0.2
V5(8.8,2.5)	0.6	0.4	0.3	0.2	0

Table: 2 shows that the distance membership of the sensor node

3.1.2. QoS based membership

The values of the QoS of the each node with respect to each cluster head is given in table 3. Each of the sensor nodes has different quality parameter with respect to application where the sensors are applied. Here QoS functions are throughput, delivery ratio, delay time are taken. Based on those QoS values of the nodes with the cluster head, cluster can be obtained. Each of the nodes has the time slots at the beginning time, after generation of data packet the nodes are sent to the cluster head within the next time slot, if the packets are not delivered in the particular time period then it marked as the delayed packet. The calculation of the delay time is computed by the ratio of the received time to the sending time of the node; the result of this subtracted from 1 is the delay time. The following equation helps to find the delay time of the each node with respect to the each cluster head.

$$\left(z_{xy}^{1}\right)=\left[\left(\frac{receiving\ time}{sending\ time}\right)-1\right]$$

So each node has the number of packets to send to the cluster head, while sending the data packet to the cluster head some of the packets are not received in the cluster head because of the interruption and noise. The ratio is calculated by number of receiving data packets in the cluster head to the number of sent data packets from the node. The delivery ratio varies from node to node with respect to the cluster heads. The delivery ratio of the node of is obtained by the equation.

$$\left(z_{xy}^{2}\right)=\left[\left(\frac{numberof\ received\ packets}{numberof\ sent\ \ packets}\right)\right]$$

Each of the nodes generates the data packets and sends it to the cluster head. The flow of the data packet varies from node to node with respect to the cluster head. Number of packets send to the cluster head in a particular time interval is different for each node with respect to the cluster heads is given the below equation which helps to find the throughput of a node.

$$\left(z_{xy}^{3}\right)=\left[\left(\frac{numberof\ received\ packets}{time\ period}\right)\right]$$

Nodes	V1	V2	.	Vn
V1	$z_{11}^{1},z_{12}^{1},z_{13}^{1}$	$z_{11}^{2},z_{12}^{2},z_{13}^{2}$	.	$z_{11}^{n},z_{12}^{n},z_{13}^{n}$
V2	$z_{21}^{1},z_{22}^{1},z_{23}^{1}$	$z_{21}^{2},z_{22}^{2},z_{23}^{2}$	.	$z_{21}^{n},z_{22}^{n},z_{23}^{n}$
.	.	.	.	.
Vn	$z_{n1}^{1},z_{n2}^{1},z_{n3}^{1}$	$z_{n1}^{2},z_{n2}^{2},z_{n3}^{2}$	.	$z_{n11}^{n},z_{n2}^{n},z_{n3}^{n}$

Table: 3 contain QoS values of the all sensor node with all possible cluster heads.

The membership value based on the QoS values of the node with respect to the cluster heads are discovered by the step 9.

The running example of QoS membership function

	V1(2.5,2)	V2(4.1,1.3)	V3(5.4,0.8)	V4(6.8,3.0)	V5(8.8,2.5)
V1(2.5,2)	0,0,1	0.6,0.4,0.7	0.2,0.6,0.8	0.5,0.8,0.3	0.4,0.4,0.5
V2(4.1,1.3)	0.2,0.5,0.8	0,0,1	0.4,0.8,0.2	0.3,0.5,0.6	0.7,0.4,0.5
V3(5.4,0.8)	0.4,0.8,0.2	0.4,0.5,0.6	0,0,1	0.2,0.5,0.8	0.4,0.4,0.5
V4(6.8,3.0)	0.4,0.2,0.8	0.5,0.5,0.4	0.4,0.5,0.4	0,0,1	0.4,0.2,0.8
V5(8.8,2.5)	0.4,0.8,0.2	0.3,0.4,0.5	0.6,0.4,0.5	0.4,0.2,0.8	0,0,1

Table: 4 show that the QOS values of each node with all possible cluster heads.

QoS values of each node with all possible cluster heads are represented in table 4. Based on 2 cluster heads C1 (9.5, 1.3) and C2 (8.8, 2.5), the subsequent manipulation shows how to calculate the QoS value of the first node V1.

$$Q_{11} = \frac{1.6}{(1.6 + 1.3)} \qquad Q_{11} = 0.55$$

$$Q_{12} = \frac{v_1^2 (z_1 + z_2 + z_3)}{\left(v_1^1 (z_1 + z_2 + z_3) + v_1^2 (z_1 + z_2 + z_3)\right)}$$

$$Q_{12} = \frac{1.3}{(1.6 + 1.3)} \qquad Q_{12} = 0.44$$

Similarly, the calculated QoS membership function for the other nodes with cluster heads C1 and C2 are given in table 5.

	C1	C2
V1	0.55	0.44
V2	0.46	0.53
V3	0.48	0.51
V4	0.51	0.48
V5	0.45	0.54

Table: 5 shows that the QoS membership of the nodes

With the help of table 2 and 5, the membership function is calculated and that is described below.

Running the example of membership functions

The membership function of each node with respect to cluster heads is calculated using the step 7. Here; the same weightage is given for the distance and the QoS. The values of the weightage is depends on the user. If the user wants to group the sensor nodes mainly based on distance then the user gives the value of the α is greater than the β, if the user wants to group the sensor node based on the QoS then the value of β is greater than α. Here, the equal importance is given to both values as the same values are given for α and β .the values of α and β varies from the range [0-1].

$$\mu_{11} = \frac{1}{0.5 + 0.5}\left[0.5(0.52) + 0.5(0.55)\right]$$

$$\mu_{11} = 0.535$$

$$\mu_{12} = \frac{1}{0.5 + 0.5}\left[0.5(0.47) + 0.5(0.44)\right]$$

$$\mu_{12} = 0.455$$

Same as the membership function for all nodes with respect to cluster head C1 and C2 is calculated and shown in table 6.

	μ_{11}	μ_{12}
V1	0.535	0.455
V2	0.49	0.50
V3	0.50	0.48
V4	0.25	0.74
V5	0.72	0.27

Table: 6 contains the values membership function of the sensor nodes

Consider the two membership function's value: μ_{xy1}, μ_{xy2} , where x be the sensor node, $y1$ and $y2$ be the cluster heads then find which cluster head have maximum membership function value by taking max (μ_{xy1}, μ_{xy2}) and then assign the sensor node x to that cluster head y.

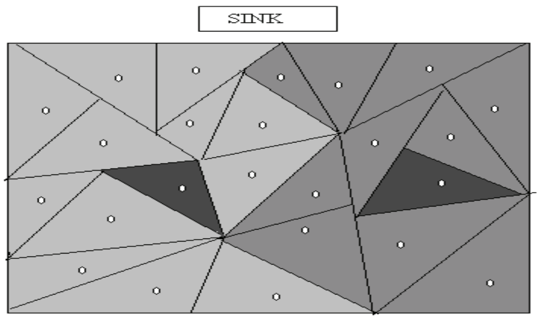

Fig 2.Cluster using V-FCM in WSN

By applying the membership functions; the clusters are obtained in which the first cluster has the following nodes V1. V3, V5 and the second has the nodes of V2 and V4. Then step 12 is used to find the adapted cluster heads with the calculated membership function.

3.1.3 Finding the cluster head

With the help of step 12, the cluster centroid points (3.15, 5.48) and (8.02, 4.9) are achieved. Both points are plotted in the following Fig 2 and the corresponding Voronoi cell is treated as cluster head. After the selection of the cluster head, the cluster head transmits the received data to the sink .And this process will consume high energy of the cluster head node. To solve this problem, Multi-hop data communication model and data aggregation are employed. Multi-hop data communication is implemented by finding the shortest path between CHs and the BS through Delaunay triangulation and Euclidean minimum spanning tree (EMST) algorithm. Once the Cluster heads are selected, BS executes short path algorithm for transmitting the routing information to each CH, then CHs allocates TDMA time slot to its cluster members for data transmission. During the allocated time slot data are transmitted to CHs for performing data aggregation in CH. Data fusion function like MAX, MIN, SUM, COUNT are used for data aggregation to reduce the number of data transmission in the network, eliminates redundant data, avoid collision thereby reducing the energy of individual sensor and increasing network lifetime.

Weather forecasting application's dataset is used for data aggregation where the temperature of the environment need to be sent periodically to basestaion for further decision making purposes. Each cluster will have the number of sensor nodes then $ch \in s_i$, the sensor nodes s_i transmit its sensed data $s_i(d)$to the corresponding cluster head ch_i, the $s_i(d)$ consists of the value of temperature, id, date, time. The data aggregation process is based on the three methods by taking the average of temperature and maximum of data and minimum of data.

Consider a set of data is received by the cluster head $D = (d_1, d_2, ..., d_i)$ where $(1 \le i \le n)$, here n be the total number of data received in the cluster head. For finding the average, maximum, minimum of data the step 18 is used.where n = number of data in the cluster head

N = Total number of received data.

The process of aggregation is done in three ways they are: 1) Taking average temperature, 2) Taking maximum temperature of the cluster, and 3) Taking minimum temperature. Equation (9) is used to find the average temperature of the clustering sensor node, equation (10) is used to find the maximum temperature of the clustering sensor node and the equation (11) is used to find the minimum temperature. Likewise all the sensor nodes in the cluser transmits their sensed data to the cluster head, here it uses the aggregation process based on the average value of the all temperature received in the cluster head ch_i and this $avg(tmp)$ value sends to the sink node by means of multi hop data communication as in Fig :3.This Multi hop data commnication is obtained by EMST and

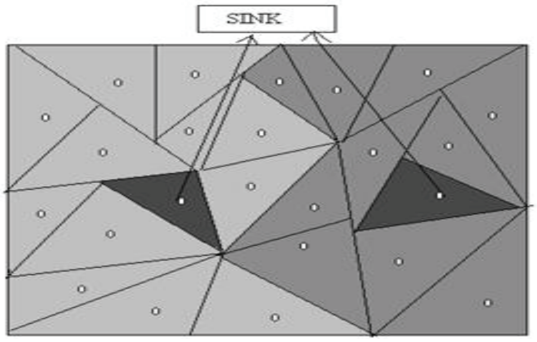

Fig: 3 Transmisson of aggregated

4 Results and Discussion

The experimental results of the proposed approach to cluster head selection is described in this section. The comparative analysis of the cluster head selection approach is with the previous algorithm Fuzzy C-Means algorithm is presented.

Experimental design

The proposed content cluster head selection for data aggregation in wireless sensor network has been implemented using MATLAB (Matlab7.10) and the performance of the proposed system is analyzed using the evaluation metrics including running time and size of received data in the sink node based on the number of cluster head in the wireless sensor network.

Evaluation of running time by varying the number of the sensor nodes

The V-FCM algorithm is compared with the Fuzzy C-Means algorithm in order to evaluate the performance of the proposed V-FCM algorithm. The following Fig 6 shows that the running time of the V-FCM algorithm and FCM algorithm. To evaluate the graph, change the number of sensor nodes at each execution and evaluate the time of the both algorithms, the value of the cluster head is constant for both algorithms to find the execution time. Then take the number of cluster heads as 10 for all executions. The following Fig 6 describes that, V-FCM algorithm needs less time to execute when compared with the Fuzzy C- Means algorithm. The reason behind is the if the membership function value of the sensor node is repeated in a single Voronoi cell then the execution of the membership function for that sensor node get stop since the running time of the V-FCM algorithm get reduced.

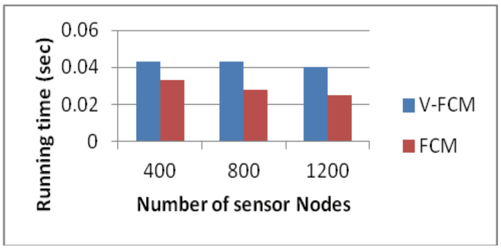

Fig: 5 Running time VS number of nodes

Evaluation of running time by varying the number of cluster heads

Here, the running time is evaluated by keep the number of sensor nodes (1000) at constant and varying the number of cluster heads for each time. The following Fig 7 shows that the running time of V-FCM algorithm and FCM algorithm and when seeing that graph we conclude the V-FCM algorithm takes less to execute when compare to the FCM algorithm. The running time of the both algorithm is directly proportional to the number of cluster heads. The calculation of the membership function for each point with respect to the each cluster head takes more time since the running time is increase when the number of cluster head increase.

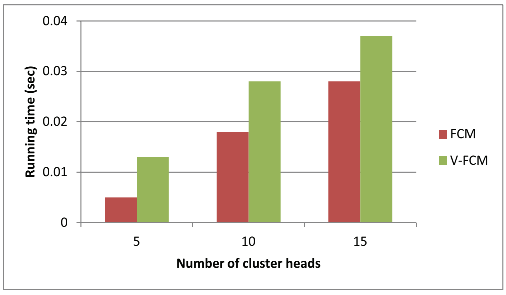

Fig :6 Running time VS No of clustering head

Number of received data in sink node by varying the number of the sensor nodes

After the selection of cluster head, then each of the sensor nodes sends their sensed data to the cluster head. The cluster head had received many data's from the sensor nodes, as per the user suggestion (data aggregation or data compression) the cluster head operates the received data and send that data to the sink node. The sink node has received the data from the cluster heads, the following graph (figure: 13) shows that the number of received data in a sink node for different number of sensor nodes. Based on the position of the cluster head, the received data of the sink node get varied since the position of the cluster head is different for both V-FCM algorithm and FCM algorithm. Hence, take the number of received data in a sink node as a parameter. The following graph describes, the sink node receives more number of data's by using V-FCM algorithm rather than using the FCM algorithm.

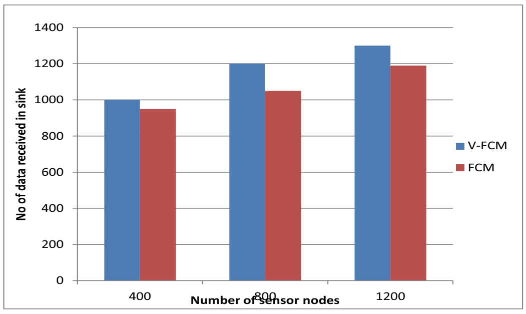

Fig: 7 No of data received data in sink node VS number of nodes.

Number of received data in sink node by varying the number of the cluster heads

The number of receiving data in a sink node varies based on the number of cluster heads in a sensor network. Fig 8 shows that the number of receiving nodes in a sink node based on different number cluster heads for both V-FCM algorithm and FCM algorithm, the sink node receives more number of data's by using V-FCM algorithm rather than using the FCM algorithm.

Fig: 8 size of data received data in sink node Vs No of cluster head

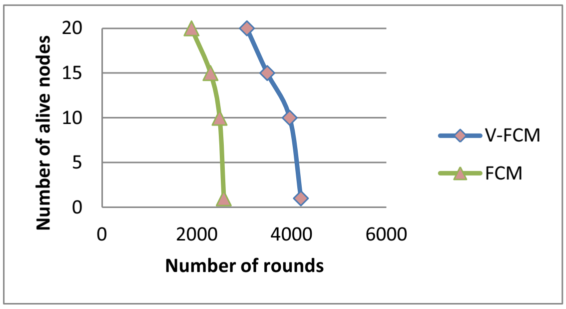

Fig: 9 Number of alive nodes VS Number of rounds

The proposed algorithm is made to run for determining the simulation time taken by the number of rounds VS first node dead for FCM and Voronoi fuzzy clustering algorithm. The measured performance evaluation is shown in figure 9 for twenty nodes, it's emphasized that at first round, first node starts dying at time 3056 for V-FCM and 1887 for FCM. Hence the number of nodes alive in V-FCM is longer than FCM algorithms.

5 Conclusions

In this paper, the energy efficient Voronoi Fuzzy Clustering algorithm for data aggregation in WSN is presented. The objective this algorithm is attained incorporating Voronoi diagram in distributed clustering algorithms .Applying Voronoi diagram is robust and its main benefit is to reduce the number of Euclidean distance calculations in fuzzy clustering algorithm and to find the shortest path for data communications . The Euclidean minimum spanning tree is used with the support of Delaunay triangulation in path identification for sending the data communication .This shortest path algorithm finds the path in O (n log n) time and O (n) space. Thus when executing V-FCM algorithm its simulation results shows, that the proposed Voronoi based clustering algorithm increases the energy of the network when compared to the existing algorithm.

6 References

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