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# Enhancing Fuzzy C-Means by Grid-Density Clustering for Distributed WSN Data Stream

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**Abstract:** Recent years witnessed an interest in the use of Wireless Sensor Networks (WSNs) in a widespread range of applications in many field related to military, surveillance, monitoring health, observing habitat and so on. WSNs contain individual nodes that interact with the environment by sensing and processing physical parameters. Sensor nodes usually generate a big amount of sequential tuple-oriented and small data that is called data streams. Data streams usually are huge data that arrive in an online mode, flowing rapidly in a very high speed, unlimited and there is no control on the arrival processing order. Due to WSN limitations, some challenges are faced and need to be solved. Such challenges include extending network lifetime and reducing energy consumption. Data mining could deal with WSN challenges. Clustering is a data mining technique that plays an important part in organizing WSNs. It has proven its efficiency on network performance by extending network life time and saving energy of sensor nodes. This study develops a grid-density clustering algorithm that enhances clustering in WSNs by combining grid and density techniques. The algorithm helps to face limitations found in WSNs that carry data streams. By using MATLAB, the grid-density clustering algorithm is compared with another clustering algorithm in WSNs that manipulate with data streams called k-means algorithm. The simulation results prove that the grid-density algorithm outperforms FCM by 17% in network lifetime and 11% in energy consumption performance metrics.

**Key words:** WSNs, data mining, clustering, data stream, fuzzy clustering, grid, density

## INTRODUCTION

In recent years, a widespread use of WSNs are found in various applications. A WSN is a specific kind of ad-hoc networks that is able to sense and process information. They can be used in many areas such as environmental, industrial, military and agriculture fields. WSNs consist of built-in, independent and tiny equipment's called sensor nodes. Sensor nodes contain four main components, energy source, processing unit, sensing unit and transducer (Aquino *et al*., 2007a, b). Sensor nodes are mainly used in processing data and report parameters continuously. The reports are transferred by sensor nodes and collected by special controllers called Base Stations (BSs). A WSN has many resource constraints including high computational power and limited energy source. WSNs depend on their nodes that consumes battery energy. Unfortunately, the WSNs nature makes it difficult to recharge sensor nodes batteries. Therefore, energy efficiency is an important design objective in WSNs (Younis *et al*., 2006) and their algorithms should be accurately designed based on energy saving. In some WSN applications, data that WSNs process usually contain a large amount of data sets that flow rapidly in a very high speed and arrive in an online fashion. Data are considered to be unlimited and the arriving order of elements being processed is out of control. Such data are called data streams (Aquino *et al*., 2007a, b).

The widespread deployment of WSNs and the need for aggregating data streams requires an efficient organization of network topology to reach load balancing and extension of network life time. This is performed by using mining techniques. Clustering is a data mining technique that is considered to be an efficient tool in WSNs to solve the problem of network life time, energy consumption, data aggregation, load balancing, scalability (Abdullah *et al*., 2015), delay and delivering data stream packets. It organizes WSNs into a connected hierarchy. In general, two categories of network structure are found in WSNs, flat and clustered (i.e., hierarchical) (Liu, 2012). At any case, clustering plays an important part in network organization and also affects network performance. Owing to obtain many advantages, clustering is preferred in

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mining WSNs data. In a clustered WSN, the network is divided into groups called clusters, each cluster has a leader elected from sensor nodes called Cluster Head (CH). Data streams are aggregated from nodes by their CH inside a cluster. Then it is transmitted from CHs to the BS. Transmitting streaming data in the wireless medium by a multi-hop communication to reach the BS resumes nodes energy leading to shorten the lifetime of a network. As mentioned previously, a WSN suffers from power consumption during data stream transmission. Sensor nodes should be energy efficient. Energy efficiency affects the entire WSN lifetime. Therefore, to gain the WSN's operational long-lasting, consuming energy is considered during designing WSNs algorithms. Furthermore, since, sensor nodes are in difficult-to-reach locations, replacing batteries is unpractical (Alia, 2014). A WSN can achieve energy saving from clustering algorithms. However, to achieve better energy conservation, data stream mining must be formed in a distributed manner due to their resource constraints (Sabit and Anbuky, 2014). Clustering algorithms are designed to obtain load-distribution between CHs, high connectivity, saving energy and fault tolerance. In WSNs, using resources and reducing energy is provided in clustering technique by decreasing number of nodes that transmit data streams through long distance transmission. Clustered WSN algorithms running streaming data are usually partitioned in two main steps, cluster formation step and data transmission step (Zhong *et al*., 2012). But specifically, the cluster based operation of clustered WSN algorithms consist of rounds. Rounds involve cluster creation, CH-election and data transmission to the BS. Grid-based clustered WSNs are type of networks where a sensed area is partitioned into a number of equally sized of small cells called grids. Grid-based clustering scheme has proven to have a fast processing time compared to other types of clustering algorithm schemes due to clustering operations are performed on grid cells instead of the whole dataset stream (Abdullah *et al*., 2015).

This study develops a distributed grid clustering algorithm for WSNs based on density. The algorithm is a clustering algorithm based on combining a grid technique and a density technique. Beside the advantages of clustering listed above, the density technique can find arbitrary shaped clusters with noise while the grid technique is used to avoid clustering quality problems by discarding the boundary nodes of grids. This combination of techniques decrease the algorithm computational time, reduce energy consumption and thus increasing network lifetime resulting the desirable simulation results. To reach the aim of this study, the algorithm must converge the limited dataset streams as fast as possible to ensure that a processor can take on next set of streams. The study provides an evaluation of our grid-density clustering algorithm to prove its efficiency among another stream mining clustering algorithm called Fuzzy C-Means (FCM) to enhance WSNs performance.

**Literature review:** Clustering algorithms could be classified into three main types. First, clustering algorithms in WSNs running normal data. Second, clustering algorithms running data streams not applied on WSNs. Third, clustered WSNs running data streams. The following study describe briefly the main three classifications.

**Clustering algorithms in WSNS not involving data streams:** This study presents the first classification of clustering algorithms. Based on network structure, algorithms found in WSNs can be divided into two classes, algorithms for either flat networks or hierarchical networks. In a flat network structure, all nodes has the same tasks and perform exact functionalities. Data transmission is done in a hop-by-hop manner using flooding. Some clustering algorithms in flat WSNs include Directed Diffusion (DD) and Greedy Perimeter Stateless Routing (GPSR). These clustering protocols are efficient in networks with a small-scale. However, flat WSN algorithms are unfavorable in networks with large-scale due to resource limitation but nodes such networks preform more data processing (Liu, 2012). Otherwise, in a hierarchical structure, nodes has different functions and are organized into groups according to specific requirements or metrics. Generally, each cluster has a specific CH and other sensor nodes. In general, CHs have the highest energy inside clusters to perform processing and transferring data while other nodes with low energy perform sensing (Liu, 2012). Some clustering algorithms in a hierarchical WSN topology include Low-energy Adaptive Clustering Hierarchy (LEACH) and Hybrid Energy-Efficient Distributed clustering (HEED). Clustering technique is an important scheme in hierarchical WSNs due to many advantages such as data aggregation, scalability, less load, low energy consumption and more robustness (Liu, 2012).

**Clustering algorithm sinvolving data streams:** This study presents the second classification of clustering algorithms. It presents some common clustering algorithms involving data streams not applied on WSNs. In 2006, Feng Cao proposed the DenStream algorithm for clustering dynamic data stream (Jia *et al*., 2008). It is an effective method that can discover clusters with arbitrary format in data streams but it is insensitive to noise. Heng

Zhu Wei proposed a density and space clustering algorithm called CluStream (Jia *et al*., 2008). CluStream is a clustering data stream algorithm based on k-means that is inefficient to get clusters of arbitrary formats and cannot process outliers. Further, they have to predetermine a parameter k (i.e., number of clusters) (Chen and Tu, 2007). k-means is used in an offline phase of some algorithms such as CluStream. It is a divide and conquer schemes that partition data streams into segments and discover clusters in data streams. k-means has a number of limitations. Firstly, it doesn't reveal clusters with arbitrary formats and usually identifying spherical clusters. Secondly, it is unable to discover outliers and noise. Thirdly, k-means requires multiple scans of data, making it impractical for huge data stream (Jia *et al*., 2008; Chen and Tu, 2007). Stream and CluStream are data stream clustering algorithms that are extensions of k-means (Amini *et al*., 2013).

Localsearch, stream, DenStream and CluStream are clustering algorithms involving data streams. They disregard grid border problems. Data streams come with a large number in chronological order and makes original grids no longer adapt to new data mapping, so, a large number of data is likely to fall on grids borders. But if the data is simply discarded, it affects the clustering quality. If grids are updated in time, cost is greatly increased and the clustering efficiency is affected greatly (Jia *et al*., 2008).

D-Stream is a real-time density-grid stream data clustering algorithm where nodes are assigned to grids and grids are gathered to form clusters based on their density. D-Stream clustering quality depends on the lowest grid structure level. This may reduce the clusters accuracy despite the technique processing time speed (Amini *et al*., 2013). The D-Stream assigns input data into grids by using an online component. It also computes the density of each and clusters grids based on their density by using an offline component (Chen and Tu, 2007). MR-Stream is an algorithm that can cluster data streams at various resolutions. It divides a given data space to cells and a data structure tree that keeps the space dividing. MR-Stream increases the clustering performance by determining the exact time to generate clusters (Amini *et al*., 2013).

Flock stream is a density clustering algorithm that is based on the concept of bio-inspired model. It uses the flocking model where independent micro-cluster agents form clusters together. FlockStream combines online and offline components where agents form clusters once required. It can get clustering results without performing offline clustering. DenStream, MR-Stream, D-Stream and FlockStream are density based clustering algorithms evolving data streams. They can affectively reveal clusters with arbitrary shapes and handle noise but their quality decrease when using clusters with variant densities. Local search algorithm uses dividing and conquering to partition data streams into segments and discovers clustering of data streams in finite space by using the k-means algorithm (Jia *et al*., 2008). An Online Divisive-Agglomerative Clustering (ODAC) algorithm was also proposed to use a top-down organization to create clusters with a tree hierarchy. The previous techniques assumes that all data streams are collected at a centralized location before being processed (Yin and Gaber, 2008). Many density-based clustering algorithms for multi density datasets are not suitable for data stream environments. First, they need two-pass of data and this condition is impossible for data streams where they arrive continuously and need a single scan to be performed. GMDB scan and ISDB scan use a two-pass data. Second, some multi-density clustering algorithms require using the whole data. Third, other algorithms have a high execution time which makes them unsuitable when applying data streams. DSCLU is considered to be a density clustering algorithm runs streaming data in multi-density environments (Amini *et al*., 2013).

**Clustered WSNS involving data streams:** This study presents the third classification of clustering algorithms. It is divided into two subsections, algorithms based on FCM algorithm and algorithms for multimedia streaming data. Our proposed density-grid clustering algorithm belongs to research study scope of algorithms presented in this section. Fuzzy C-means or Fuzzy Clustering Means (FCM) is a widely used data mining clustering algorithm when involving data streams in WSNs. Most clustering algorithms are descendant from FCMs when solving data stream problems in WSNs. FCM requires prior information about how many needed clusters C to divide the data space. The clusters number C is unknown previously (Sabit *et al*., 2009). Figure 1 represents examples of some algorithms based on the FCM and k-means.

An algorithm based on FCM, a distributed WSN data stream clustering algorithm called SUBFCM (Subtractive Fuzzy Cluster Means) is proposed to decrease nodes energy consumption and extend network lifetime in WSNs involving data streams. The SUBFCM focuses on the clustering problem on data streams. Simulations show that the energy efficient algorithm SUBFCM can obtain clustering with less energy than the FCM. SUBFCM reduces the overall data transmission needed without affecting vital information in data streams (Sabit *et al*., 2009). SUBFCM is a result of blending a subtractive clustering algorithm with the FCM. For algorithms based

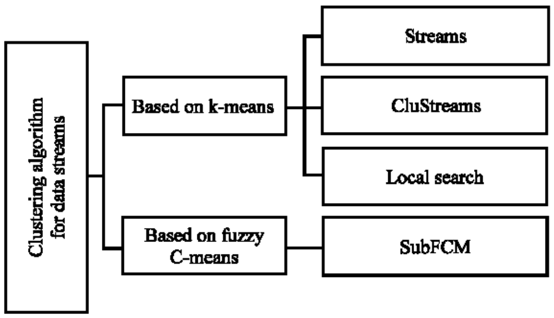


Fig. 1: Clustering protocols for data streams

on multimedia streaming data, in Wireless Multimedia Sensor Networks (WMSNs), multimedia clustering protocols use the Quality of Service (QoS) parameters (Diaz *et al*., 2014). The requirements of QoS differ based on to the multimedia applications type. QoS has several metrics such as jitter, delay, band width, reliability (Abazeed *et al*., 2013) and packet loss (Diaz *et al*., 2014). A lot of multimedia applications are time critical, they require to be managed with a limited time. Sensors in multimedia are able to grab image, audio, video and so on. Then, send the multimedia content by sensors (Abazeed *et al*., 2013). FoVs is a wireless multimedia sensor network clustering algorithm proposed based on Overlapped Field of View (FoV) areas. FoVs prolongs network life time and saves energy (Kumar *et al*., 2011).

## MATERIALS AND METHODS

### Fuzzy C-Means (FCM)

**Overview on fuzzy C-means algorithm:** The most wide spread fuzzy clustering algorithm is the standard FCM algorithm (Seth and Khan 2014; Thangavelu and Pathak, 2014) . FCM was developed by Dunn and later improved by Alia (2014) and Sabit and Anbuky (2014). It is used in cluster analysis, image processing and pattern recognition. In WSNs, FCM assigns each point into a specific cluster based on a degree of membership (Alia, 2014). In k-means, data is divided into distinguished clusters where every node belongs to only one cluster, this is called hard clustering. In fuzzy clustering, nodes are allowed to be found in several clusters at the same time. It is done with different degrees of membership. Fuzzy clustering is a soft clustering and considered to be more natural than hard clustering. In soft clustering, common nodes between several clusters aren't forced to belong to one of the clusters. In fact, they are assigned to a membership degrees between 0 and 1 that indicates partial membership (Sabit and Anbuky, 2014; Seth and Khan, 2014; Thangavelu and Pathak, 2014). Figure 2 shows a simple structure about the types of clustering algorithms based on network topology.

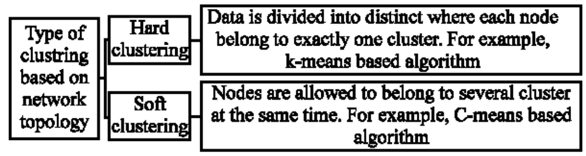


Fig. 2: Types of clustering based on network topology

In real-life applications, neighboring clusters do not have sharp boundaries. This makes soft fuzzy clustering more suitable for streaming data (Sabit and Anbuky, 2014). In the soft FCM, degree of belongingness is given within the range between (Aquino *et al*., 2007a, b). Each node calculates the degree of belongingness by using the Euclidean distance (Sabit and Anbuky, 2014; Keerthi and Babu, 2012). The Euclidean distance is used to compute distances between sensor node and their CHs. Similar to K-means, a main drawback of FCM is to predetermine number of clusters within data space (Sabit and Anbuky, 2014). Moreover, in FCM, computing the distance between each sensor node to other CHs is time-consuming, thus, effecting execution time and clustering process efficiency (Keerthi and Babu, 2012). Hence, in our proposed density-grid base clustering algorithm there is no predetermination of clusters number in the sensed area. In addition, using gridded network sensed area is better to eliminate empty spaces, thus, reducing energy consumption and prolonging network lifetime.

**Algorithms based on FCM for streaming data in WSNs:** This study provides an overview on FCM-based clustering algorithms that are used to improve FCM network life time. Generally, clustering algorithms in WSNs involving data streams are classified into distributed, centralized and hybrid clustering algorithms (Seth and Khan, 2014). In distributed clustering, any node can elect itself to be a CH (Seth and Khan, 2014). In centralized techniques, global network information are required to provide BSs the abilities to manage the whole network. CHs are selected by the BS in this approach. Hybrid techniques are a combination of centralized and distributed approaches. In a hybrid environment, distributed schemes are responsible for coordinating between CHs while centralized schemes are used to build individual clusters (Seth and Khan, 2014). Based on the previous network topologies, clustering algorithms must include a technique to compute similarities or distance between vectors. Distance is considered to be the most natural method used to represent numerical data similarity measurement. Low values denote more similarities. The most common distance metrics is the Euclidean distance. However, the distance metric does not research properly with non-numerical data. FCM use the Euclidean distance and considered to be the most suitable algorithm for WSNs involving streaming data due to its soft clustering

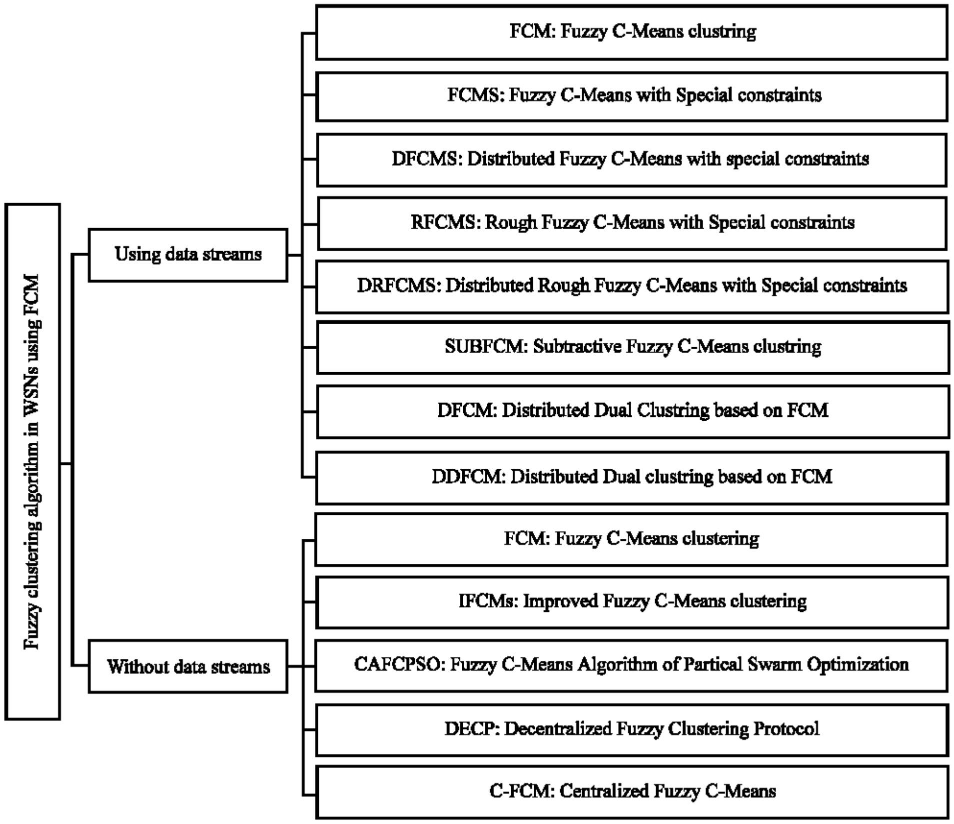


Fig. 3: Classification of FCM-based clustering algorithms in WSNs

nature. Figure 3 shows some FCM-based algorithms such as SUBFCM, DFCM, IFCMs and FCMS. Most algorithms listed in Fig. 3 are FCM-based clustering algorithms. They introduce the Subtractive Clustering algorithm (SUBFCM) to predetermine number of clusters and their cluster centers, then apply the FCM to manipulate data streams in WSNs. As known, FCM requires a pre-knowledge of number of clusters and each cluster center, since, the output rules depend hardly on the initial values (Huang and Zhang, 2011). Cluster formation at SUBFCM assumes each node is a potential cluster center. Then a calculation is done to measure possibilities that each node would define a cluster center.

**Grid-density based clustering algorithm:** Clustering WSN algorithms could be considered under specific schemes such schemes are hierarchical scheme, grid scheme, heuristic scheme, weighted scheme, PSO-Based scheme. The developed grid-density algorithm is a grid scheme. Figure 4 summarizes the clustering schemes in WSNs with examples of each clustering scheme. The grid-density clustering algorithm is a clustering algorithm that forms clusters based on the density of each grid in a gridded WSN. Grid-density algorithm is proposed to

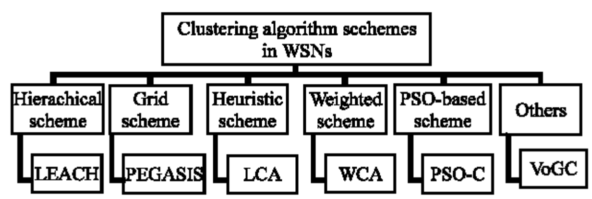


Fig. 4: Clustering algorithms schemes in WSNs

enhance the standard FCM. It solves the same problems that FCM and FCM-based clustering algorithms solve. Grid-density clustering algorithm forms clusters in a different manner where cluster formation is not based on the Euclidian distance calculation. Cluster formation is based on finding the density of each grid. Additionally, it doesn't require a predetermination of number of clusters.

To form the network clusters, the developed scheme is done by dividing a sensor network area into equal size of grids. The area is divided by a value called grid size g where g∈X and g∈Y. Grids then are classified based on their densities by using a specific value called threshold σ. By using the suggested algorithm and both values g and σ, grids close to each other are combined after finding

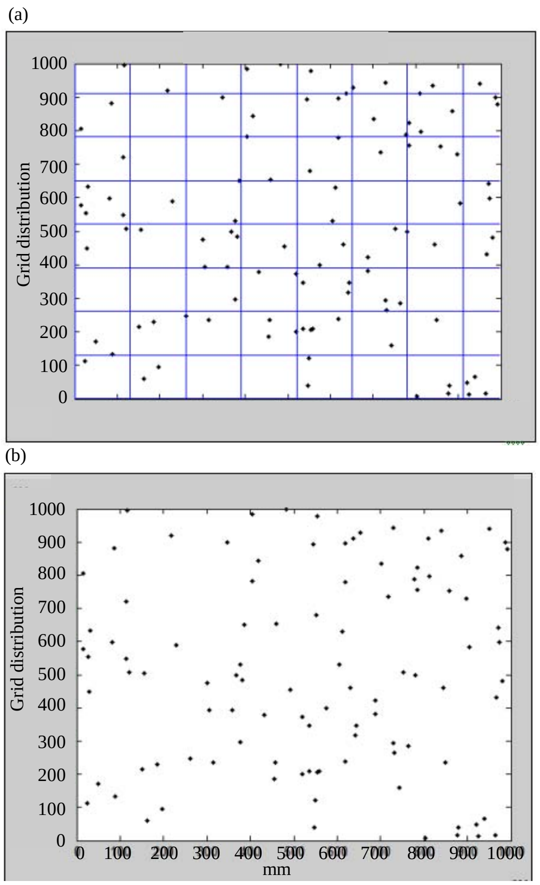


Fig. 5: a) Gridded WSN in grid-densityclustering algorithm and b) Sensed area in FCM

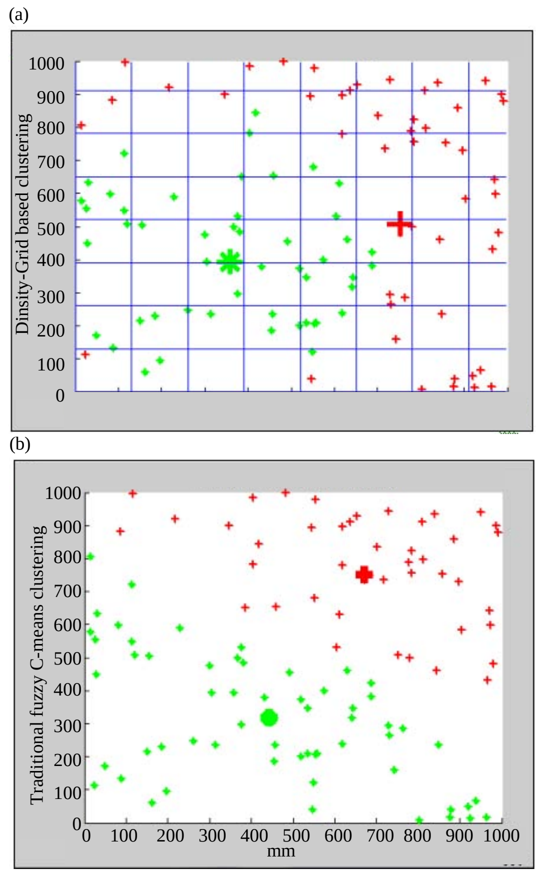


Fig. 6: a) Cluster creation in grid-densityclustering algorithm and b) Cluster formation in FCM

their density to form arbitrary shaped clusters. Empty grids are discarded to minimize algorithm time execution. Cluster formation process in the grid-density algorithm is based on g and σ to find number of clusters C. After forming clusters, the grid-density selects a CH for each cluster based on nearest distance to the BS. Figure 5a shows a sensed area that is already divided to grids assuming that g = 130 and σ = 5 by using the grid-density algorithm. In contrast, Fig. 5b presents the same sensed area in FCM that is not gridded.

After forming network clusters and choosing CHs initially, the network is ready to stream data. To stream data, the algorithm goes through several rounds until the end of network life time. Each round consists of two steps, transmitting data and choosing CHs. First step is responsible for transmitting sensed streaming data from source nodes to the final destination at the BS through CHs. The second step it to rotate the role between CHs based on nodes highest residual energy. Figure 6 represents grid-density clustering algorithm pseudo code.

**Algorithm 1; Grid-density clustering algorithm pseudo code:**

```
Pseudocode of grid-density clustering algorithm
Input: n, g, σ
Output: C
Initialize
Create a grid sensed area based on g
Randomly scatter n nodes inside grids
Classify each grid based on its density Start clustering based on σ and grids
densities
Select a CH for each cluster based on nearest distance to BS
Start streaming data streams
while (n>0)
    {Transmitting data streams from SN-CHs to BS
        Choose CH based on highest residual energy}
```

The procedure used to obtain the final experimental results for both competitors is by running the grid-density algorithm first to form its clusters, then gain number of clusters C. After that FCM is run individually using the predetermined value C gained from the grid-density algorithm. Comparisons between competitors is done based in network life time and energy consumption for the entire network.

## RESULTS AND DISCUSSION

To build and evaluate the grid-density algorithm, MATLAB Simulator Version R 2008 b was used. In our research experiments, MATLAB is used in a machine with Windows 7 service pack 1 with 1TB disk space, 64 bit operating system, Intel ® Core ™ i7 processor and 8 GB RAM.

After several simulation experiments, the following experiment has the best results and is chosen to compare between the two competitor's final performance metrics results in terms of network lifetime and energy consumption. Assuming that grid size $g = 130$ andthreshold $\sigma = 5$. Both algorithms in their experiment are streaming the same dataset stream packet with size 126 byte/message in a $(1000\times1000)$ $m^2$ sensed area and BS located at the center with $n = 100$ node scattered randomly each with an initial energy equal to 1 Joule. At cluster formation process in the grid-density algorithm, clusters number obtain from this experiment is $C = 2$. Figure 6a represents two individual clusters formed in the grid-density algorithm, each with a clear CH. By using number of clusters $C = 2$, gained from the grid-density algorithm and then applying it in FCM on the given sensed area, Fig. 6b shows the cluster creation result in FCM each with a clear CH. It is clear from Fig. 6 that the sensed area is gridded in the grid-density algorithm while not gridded in FCM.

Figure 7a, b both graphs present network lifetime for grid-density algorithm and FCM consequently. X-axis presents the running time and Y-axis presents number of live nodes. It is clearly shown that the proposed algorithm extends network lifetime more than FCM where FCM nodes stats to die before the proposed algorithm nodes. From experimental results, the grid-density algorithm extends network lifetime by about 17% more than FCM.

Figure 8a, b present graphs of grid-density algorithm and FCM consequently for their energy consumption. X-axis presents the energy in percentage while Y-axis presents the running time. It is found that the proposed algorithm reduces energy consumption by about 11% less than FCM.

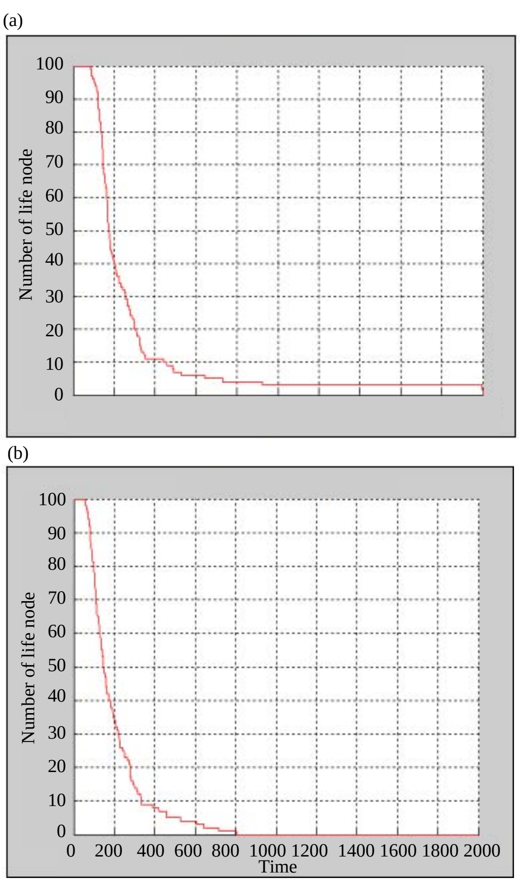


Fig. 7: a) Network lifetime in grid-density clustering algorithm and b) Network life time in FCM

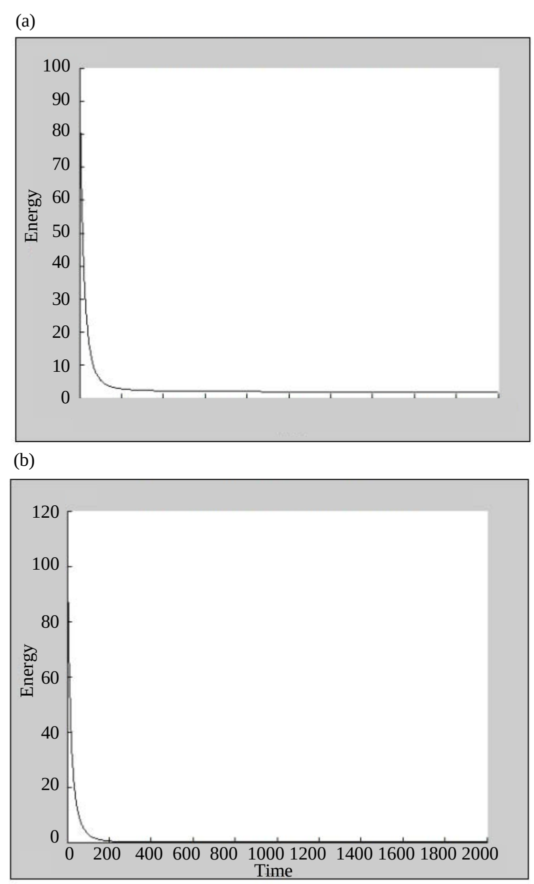


Fig. 8: a) Energy consumption in grid-density clustering algorithm and b) Energy consumption in FCM

The grid-density algorithm processes small grids were all operations are performed on grid cells rather than processing the whole sensed area space and exhaustion the network as found in FCM. Gridding reduces network exhaustion thus, reduces energy consumption that in turn extends network lifetime.

## CONCLUSION

Recent years witnessed a widely use of WSNs in several applications and it has become an interesting research area of study in data mining field. This study provided a classification for clustering algorithms based on the research study background. They were classified into three main types. Clustering algorithms in WSNs (without data streams), clustering algorithms for data streams and clustered WSNs for streaming data. The study focused in details on WSNs clustering algorithms involving streaming data that are called FCM-based clustering algorithms that are similar to the research area of our grid-density algorithm. The proposed grid-density based clustering algorithm is based on the concept of finding the density of each grid to form clusters in a WSN. The grid-density clustering algorithm results are regarding some performance metrics. Performance metrics are compared with its competitor (i.e., the traditional FCM algorithm). The simulation results prove that the grid-density algorithm outperforms FCM by 17% in terms of network lifetime and 11% in energy consumption.

## REFERENCES


Abazeed, M., N. Faisal, S. Zubair and A. Ali, 2013. Routing protocols for wireless multimedia sensor network: A survey. J. Sens., 2013: 1-11.

Abdullah, M., H.N. Eldin, T.A. Moshadak, R. Alshaik and I.A. Anesi, 2015. Density grid-based clustering for wireless sensors networks. Procedia Comput. Sci., 65: 35-47.

Alia, O.M., 2014. A decentralized fuzzy C-means-based energy-efficient routing protocol for wireless sensor networks. Scient. World J., Vol. 2014. 10.1155/2014/647281

Amini, A., H. Saboohi and T.Y. Wah, 2013. A multi density-based clustering algorithm for data stream with noise. Proceedings of the IEEE 13th International Conference on Data Mining Workshops (ICDMW), December 7-10, 2013, IEEE, Dallas, Texas, USA., ISBN:978-1-4799-3142-2, pp: 1105-1112.

Aquino, A.L.D., C.M. Figueiredo, E.F. Nakamura, L.S. Buriol and A.A. Loureiro *et al*., 2007b. Data stream based algorithms for wireless sensor network applications. Proceedings of the 21st International Conference on Advanced Information Networking and Applications (AINA'07), May 21-23, 2007, IEEE, Niagara Falls, Ontario, Canada, ISBN:0-7695-2846-5, pp: 869-876.

Aquino, A.L.D., C.M.S. Figueiredo, E.F. Nakamura, L.S. Buriol and A.A.F. Loureiro *et al*., 2007a. A sampling data stream algorithm for wireless sensor networks. Proceedings of the IEEE International Conference on Communications (ICC'07), June 24-28, 2007, IEEE, Glasgow, England, ISBN:1-4244-0353-7, pp: 3207-3212.

Chen, Y. and L. Tu, 2007. Density-based clustering for real-time stream data. Proceedings of the 13th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, August 12-15, 2007, San Jose, USA., pp: 133-142.

Diaz, J.R., J. Lloret, J.M. Jimenez and J.J. Rodrigues, 2014. A QoS-based wireless multimedia sensor cluster protocol. Intl. J. Distrib. Sens. Netw., 10: 480372-480389.

Huang, J. and J. Zhang, 2011. Distributed dual cluster algorithm based on FCM for sensor streams. Adv. Inf. Sci. Serv. Sci., 3: 201-209.

Jia, C., C. Tan and A. Yong, 2008. A grid and density-based clustering algorithm for processing data stream. Proceedings of the 2nd International Conference on Genetic and Evolutionary Computing (WGEC'08), September 25-26, 2008, IEEE, Hubei, China, ISBN:978-0-7695-3334-6, pp: 517-521.

Keerthi, M. and D.B.S. Babu, 2012. An improved FCM's clustering protocol for wireless sensor networks. Proceedings of the International Conference on Information Technology, Electronics and Communications (ICITEC-2012), February 1-3, 2012, Seoul National University, Seoul, South Korea, pp: 140-143.

Kumar, V., S. Jain and S. Tiwari, 2011. Energy efficient clustering algorithms in wireless sensor networks: A survey. Int. J. Comput. Sci. Issues, 8: 259-268.

Liu, X.X., 2012. A survey on clustering routing protocols in wireless sensor networks. Sensors, 12: 11113-11153.

Sabit, H. and A.A. Anbuky, 2014. Multivariate spatial condition mapping using subtractive fuzzy cluster means. Sens., 14: 18960-18981.

Sabit, H., A.A. Anbuky and H.G. Hosseini, 2009. Distributed WSN data stream mining based on fuzzy clustering. Proceedings of the Workshop on Ubiquitous, Autonomic and Trusted Computing (UIC-ATC'09), July 7-9, 2009, IEEE, Brisbane, Queensland, Australia, ISBN:978-1-4244-4902-6, pp: 395-400.

Seth, A. and J.M. Khan, 2014. Performance comparison of FCM and K-mean clustering technique for wireless sensor network in terms of communication overhead. Global J. Adv. Eng. Technol. Sci., 1: 26-29.

Thangavelu, A. and A. Pathak, 2014. Clustering techniques to analyze communication overhead in wireless sensor network. Intl. J. Comput. Eng. Res., 4: 75-78.

Yin, J. and M.M. Gaber, 2008. Clustering distributed time series in sensor networks. Proceedings of the 8th IEEE International Conference on Data Mining (ICDM'08), December 15-19, 2008, IEEE, Pisa, Italy, ISBN:978-0-7695-3502-9, pp: 678-687.

Younis, O., M. Krunz and S. Ramasubramanian, 2006. Node clustering in wireless sensor networks: Recent developments and deployment challenges. IEEE Network, 20: 20-25.

Zhong, S., G. Wang, X. Leng, X. Wang and L. Xue *et al*., 2012. A low energy consumption clustering routing protocol based on K-means. J. Software Eng. Appl., 5: 1013-1015.