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Clustering of Wireless Sensor Networks UsingHybrid Algorithm

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Abstract: It is commonly recognized that Wireless Sensor Networks (WSN) is the major sections of academic researches, but the activities' rate of WSN is always Low. Based on WSN' characteristics, in this paper attempt are made to present a model based on Hopfield– fuzzy CMeans clustering algorithm. Firstly, it is capable of identifying the reasons behind the emergence of the present status. Secondly, the suggested model must represent the clustering of the WSN in different levels. Finally, it tests the validity of the suggested model with comparing by other models (Hopfield–K-Means, K-Means, and fuzzyCMeans).

Key words: wireless Sensor Networks, Clustering, Learning Automata.

INTRODUCTION

Nowadays, one of the principle challenges of the networks is improving the performance of the WSN. It is commonly recognized that Wireless Sensor Networks (WSN) are the major sections of academic researches, but the activities' rate of WSN is always Low.Furthermore,Esnaashari and Meybodi (2008) describe wireless sensor network that it consists of many sensornodes.The sensors which are randomly deployed in theenvironment of a phenomenon play the role of gatheringspecific data from the environment, processing and finallysending it to the base station (sink).Sensor networks havecritical applications in the scientific, medical, commercial,and military domains.

Chen et al. (2002) and Bein (2009) explained that in WSN the channel contention is shared among the active nodes. Thus, self- organization of the nodes and adaptation to network dynamics, along with cooperation of nodes is essential. This extends the network lifetime and reduces congestion by avoiding redundant. If very few nodes are activated, the distance between them would be very large.

Since, goal of improving of the WSN is decreasing of distance between the activated nodes, to improve productivity it would be necessary to identify the present status at first and then the causes and the solutions are describe based on suitable algorithm. Thus, it needs to use ofa Learning Automata-based Clustering Algorithm for Wireless Sensor Networks.To study and analyze these problems, we should be able to answer some basic questions: What clustering algorithm type should be used? Also provides conditions for output quality. What factors affected on the conditions of improvement, and how they can identify and provide the appropriate response to them? There are severalalgorithms for clustering of WSN (such as the hierarchical clustering, K-Means, C-Means, Hopfield, SOM models). In this paper, we present the Hopfield– fuzzy C Means algorithm in order to overcome these limitations. This approach eliminates the randomness of the initial solution provided by fuzzy C-Means based algorithms and it moves closer to the global optimum.

The study is set seven major sections; the second part presents the related works. The third part presents WSN. The forth part describes the proposed algorithm based on the Hopfield– fuzzy C Means algorithm. The fifth part is expressed case study, and in the next sections, it will be discussed analysis and presentation of research findings and suggestions for future research results.

Related works:

Esnaashari and Meybodi (2008) describe wireless sensor network that it consists of many sensor nodes. The sensors which are randomly deployed in the environment of a phenomenon play the role of gathering specific data from the environment, processing and finally sending it to the base station (sink).Sensor networks have critical applications in the scientific, medical, commercial, and military domains.

Wang and Li (2002) proposed a sparse spanner for both the number of hop sand the length in a sensor network. The resulting sub graph has at the most O(n) edge sand communication cost of O(n) due to its algorithm. The dominators, better known as the cluster heads, are found using the maximal independent set. They used the local Delaunay graph on the CDS to form the backbone of the wireless network.

Karp and Kung(2000) had proposed the greedy perimeter stateless routing (GPRS), which guarantees the delivery of a packet, if a path exists.

Das and Bharghavan (1997) proposed a routing strategy using the minimum connected dominating sets (MCDS), the prime objective of which was to exploit the structure of the backbone of wired cellular networks (WCN), so that they could support flows, multi casting and fault-tolerant routing. Owing to the dynamic nature of

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the virtual back bone, on contrary to WCN, it concentrated more on finding and updating the routes, rather than routing data grams due to the environment dynamics.

Pottie and Kaiser (2000) proposed a TDMA protocol for wireless networks, in which nodes schedule their communication with their neighbors on a priori basis.

Chen et al. (2002) and Bein (2009) explained that in WSN the channel contention is shared among the active nodes. Thus, self- organization of the nodes and adaptation to network dynamics, along with cooperation of nodes is essential. This extends the network lifetime and reduces congestion by avoiding redundant. If very few nodes are activated, the distance between them would be very large. Thus, it needs to use of a Learning Automata-based Clustering Algorithm for Wireless Sensor Networks.

Tsai and Lin (2011) review Fuzzy C-means based clustering for linearly and nonlinearly separable data. In this paper, they present a new distance metric that incorporates the distance variation in a cluster to regularize the distance between a data point and the cluster centroid. It is then applied to the conventional fuzzy C-means (FCM) clustering in data space and the kernel fuzzy C-means (KFCM) clustering in a high-dimensional feature space. Experiments on two-dimensional artificial datasets, real datasets from public data libraries and color image segmentation have shown that the proposed FCM and KFCM with the new distance metric generally have better performance on non-spherically distributed data with uneven density for linear and nonlinear separation. The experiments on the 2D artificial datasets have shown that the kernel-based clustering methods can well partition nonlinearly distributed data, but only up to quadratic functions. It is worthy of further investigation for extending the kernel-based clustering to a higher polynomial function. A good computational strategy is also required in the future to use the kernel-based clustering for datasets with a huge number of data points, especially for color segmentation in a very large image.

Mingoti and Lima (2006) Compare SOM neural network with Fuzzy c-means, K-means and traditional hierarchical clustering algorithms. In this paper, they present a comparison among some nonhierarchical and hierarchical clustering algorithms including SOM (Self-Organization Map) neural network and Fuzzy c-means methods. Data were simulated considering correlated and uncorrelated variables, none overlapping and overlapping clusters with and without outliers. A total of 2530 data sets were simulated. SOM neural network did not perform well in almost all cases being very affected by the number of variables and clusters. The traditional hierarchical clustering and K-means methods presented similar performance. The results showed that Fuzzy c-means had a very good performance in all cases being very stable even in the presence of outliers and overlapping. All other clustering algorithms were very affected by the amount of overlapping and outliers.

Lopez et al. (2011) purpose Hopfield–K-Means clustering algorithm as a proposal for the segmentation of electricity customers. Customer classification aims at providing electric utilities with a volume of information to enable them to establish different types of tariffs. Several methods have been used to segment electricity customers, including, among others, the hierarchical clustering, Modified Follow the Leader and K-Means methods. These, however, entail problems with the pre-allocation of the number of clusters (Follow the Leader), randomness of the solution (K-Means) and improvement of the solution obtained (hierarchical algorithm). Another segmentation method used is Hopfield's autonomous recurrent neural network, although the solution obtained only guarantees that it is a local minimum. In this paper, they present the Hopfield–K Means algorithm in order to overcome these limitations. This approach eliminates the randomness of the initial solution provided by K-Means based algorithms and it moves closer to the global optimum. The proposed algorithm is also compared against other customer segmentation and characterization techniques, on the basis of relative validation indexes. Finally, the results obtained by this algorithm with a set of 230 electricity customers (residential, industrial and administrative) are presented.

According the Mingoti and Lima (2006), they say that Fuzzy c-means had a very good performance in all cases being very stable even in the presence of outliers and overlapping (rather than SOM, HC, K MEAN, …), and so according to Lopez et al. (2011), they say that the Hopfield–K Means algorithm has good performance rather than other algorithms. Therefore, in this paper, I claim that the Hopfield–fuzzy C Means algorithm has better performance than the Hopfield–K Means algorithm.

Therefore, I present the Hopfield– fuzzy C Means algorithm in order to overcome these limitations. This approach eliminates the randomness of the initial solution provided by fuzzy C-Means based algorithms and it moves closer to the global optimum.

The Hopfield–Fuzzy C Means Algorithm:

The algorithm that is presented in this paper has been developed to classify in an optimal manner a set X comprising a large number Q of Mean Load Curves (MLC) of electric energy customers previously characterized and standardized. The load curves are represented as follows:

$$x(i,j) = x_j^i \ \forall i = 1, \dots, Q; j = 1, \dots, v$$
$$x = \{x^{(i)}, i = 1, \dots, Q\}$$

$$c^{(X)} = \frac{1}{q}\sum_{x\epsilon X} X^{(I)}$$

Where x(i) represents a characterized and standardized node i and xij represents term j of node i. The value of v will depend on the characterization of node i. Finally, C(X) is the centroid of load curve set X. The objective of this segmentation algorithm is to form a certain number of clusters X(k) □X, k=1, . . ., K with a great deal of dissimilarity among the different classes and very little dissimilarity inside each class. H-ANN–K is a two-stage hybrid algorithm. In the first stage, an initial segmentation is obtained using the H-ANN algorithm. On the basis of the initial segmentation, in the second stage, the K-Means algorithm is applied to refine the solution obtained by H-ANN until the final segmentation is achieved. It is worth noticing that, as opposed to classical K-Means algorithms, the random formation of the initial cluster centroids is replaced with an initial assignment applying the H-ANN algorithm. The algorithm is robust since it always achieves the same solution. Distance is used as the measure of dissimilarity:

$$d\left(x^{(i)}, x^{(l)}\right) = \left\{\sum_{j=1}^{v} (x_j^i - x_j^l)^p\right\}^{1/p} \quad ; \forall (x^{(i)}, x^{l}) \epsilon X$$

-H-ANN algorithm: first stage: In general terms, a H-ANN is a complete graph G= (V, A) whose vertices (V) represent N neurons connected to each other by means of edges or arcs (A). A synaptic weight wij, which is a real number that represents the strength of the link between the neurons i, j, is associated to each axis or connection. Synaptic weights (SW) are the distances, and are represented as: SW(i, j) = wi,j □i, j = 1, . . . , N

This matrix is symmetric (wij = wji) and has zero diagonal (wii =0). In general terms, the basic computational element for a H-ANN network is a bipolar processing unit. Its mathematical function is defined in the set {−1,1}N, and can be described by means of the following expression:

$$f(x_1, x_2, \dots, x_N) = \begin{cases} 1 & if\ x_1 w_1 + \cdots + x_N w_N \geq \theta \\ -1 & if\ x_2 w_2 + \cdots + x_N w_N < \theta \end{cases}$$

WherexN represents the state of the network's N neurons. Furthermore, in the case of multi-valued recurrent networks, state xi of each N neuron will be characterized by its output si which, in a general formulation, can take any value from a set that we will call M. Said set can take values in R, or in a non-numerical (qualitative) set. Since the network evolves over time, the state of the ith neuron will be characterized by the value of its output at that instant si(t). The vector S(t) = [s1(t), s2(t), . . ., sN(t)], which describes the state of the network's neurons at the given instant t, will be called the state vector of the network at instant t. An energy function (E) is associated to this state vector and defined as:

$$E(t) = -\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} w_{i,j} f(s_i, s_j) + \sum\nolimits_{i=1}^{N} \theta_i s_i$$

Where function f is an application of M×M→R and measures the analogy or similarity between the outputs of ith and jth neurons. The network's dynamic evolution follows an asynchronous sequential procedure. The H-ANN begins with an initial state vector S(0). The states of all the neurons for instants 1, 2, . . ., t, t + 1 are calculated according to the following computation rule:

$$s_i(t+1) = \begin{cases} 1 & if \quad \sum_{j=1}^{N} w_{ij} s_j(t) \geq \theta \\ -1 & if \quad \sum_{j=1}^{N} w_{ij} s_j(t) < \theta \end{cases}$$

For each instant 1, 2, . . ., t, t + 1, there is a state vector S(1), S(2), . . ., S(t), S(t + 1); the union of which will represent the network's state space. The network evolves in such a way that at every instant the value of the energy function associated to its state vector decreases as much as possible. The final objective is to minimize the energy function E for the simulation interval considered, thus guaranteeing a local minimum. The final solution is the state vector for the minimum energy function value. For the purpose of segmentation, a multistate H-ANN network must be constructed taking into account the following considerations:

(1) Synaptic weights wij are calculated with distance p. Cases p=1 and p = 2 (Euclidean distance) have been considered.

(2) The output (si) of each neuron is a value of the set M= {1, 2, . . . K}, K being the number of clusters.

(3) The thresholds θi of all network neurons are considered null.

(4) The similarity function used is that of identity: f(x, y) = (x≡y), which can be expressed as:

$$f(x,y) = \begin{cases} 1 & if\ x = y \\ 0 & if\ x \neq y \end{cases}$$

(5) The energy function for an instant t will be determined by the following expression:

$$E(t) = -\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} w_{i,j}\left(s_i(t) \equiv s_j(t)\right)$$

Where (si ≡sj) will be equal to 1, if the states of ith and jth neurons coincide, and 0 if they do not.

(6) The solution obtained is the state vector S(t) that corresponds to the minimum energy function (E) of the simulation interval.

(7) Classes K, associated with the state vector S(t), are determined. The subset X(k)0□ X, k = 1, . . . , K contains the MLC whose neurons have the same output (si ≡sj).

(8) The centroids C(k)0 of the classes formed (X(k)0) are calculated, and will be used later in the K-Means algorithm for the final segmentation.

Fuzzy C-Means: second stage: FCM partitions the dataset X into C clusters by minimizing the errors in terms of the weighted distance of each data point xi to all centroids of the C clusters. The algorithm's steps are the following:

(1) The data set is randomly partitioned into C classes, calculating the initial centroids. In our case said initial _centroids are obtained by the H-ANN algorithm, C0 = (C(1)0 , C(2)0 , . . . , C(k)0 , . . . , C(K)0).

(2) For each element of set X, the distance (p = 1 and p = 2) of each element x(i) □ X(k)0 to its own centroid, and to the centroids of the other classes, is calculated. If any element is not currently in the class whose centre is the closest, change the sample class and recalculate the set of centroids. The new set of centroids will be C1 =(C(1)1 , C(2)1 , . . . , C(k)1 , . . . , C(K)1). After it, we should be obtaining followings:

E-step:

$$w_{ic} = 1/\sum_{j=1}^{c}\left(\frac{d_{ic}^2}{d_{ij}^2}\right)^{1/(p-1)} \quad for\ i = 1,2,\dots,N\ and\ c = 1,2,\dots,C$$

Where

$$d_{ic}^2 = \|x_i - v_c\|^2$$

M-step:

$$v_c = \frac{\sum_{j=1}^{N} w_{jc}^p . x_j}{\sum_{j=1}^{N} w_{jc}^p} \quad for\ c = 1,2,\dots,C$$

(3) Repeat step (2) until the algorithm reaches convergence, in other words, until there are no variations of class centroids in two consecutive iterations. In this case a subset X(k)f⊂ X, k = 1, · · ·,K and associated centroids Cf = (C(1)f , C(2)f , . . . , C(k)f , . . . , C(K)f)are obtained. This is the finalsolution obtained by the H-ANN–fuzzy C Mean algorithm.

Case Study:

The case study used consisted of information regarding nodes periodically report 250 bytes of data to the sink node, Directed diffusion is used as the multi-hop inter-cluster routing protocol. All simulations have been implemented using Matlab 2010. We use IEEE 802.11 as the MAC layer protocol. Nodes are placed randomly on a 2 dimensional area of size 50 (m) x 50 (m). The H-FCM segmentation method was compared with Hopfield's recurrent neural network (H), K-Means (K), SOM–K-Means (SOMK).

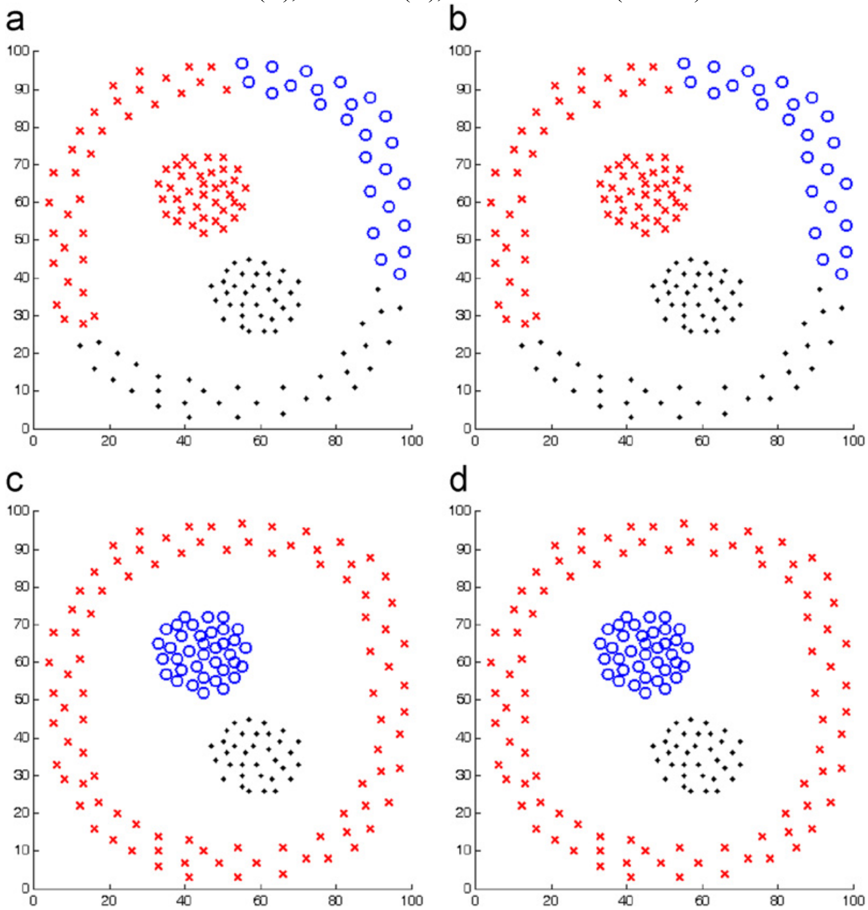

Fig. 1: Clustering results from (a) H, (b) SOMK, (c) FCM, and (d) H-FCM.

Results are shown the H-FCM is the better performance rather than H, SOMK and FCM (see fig.1 and table 1), therefore The performance of H-FCM in general situations has also to be better evaluated.

Table 1: Comparison between Clustering method

	Number of Variables						Number of clusters					
	3	6	9	15	30	40	Mean	2	3	4	5	10
Single	0.4012	0.4105	0.4223	0.4379	0.4496	0.4601	0.4303	0.4948	0.4568	0.4269	0.4008	0.3721
Complete	0.1379	0.1497	0.1680	0.1840	0.1941	0.1910	0.1708	0.2628	0.2048	0.1500	0.1283	0.1081
Centroid	0.1751	0.1878	0.1950	0.2062	0.2152	0.2256	0.2008	0.2824	0.2474	0.2039	0.1471	0.1234
SOMK	0.1550	0.1636	0.1750	0.1834	0.1930	0.2009	0.1785	0.2538	0.2112	0.1814	0.1316	0.1145
H	0.0966	0.1046	0.1173	0.1315	0.1385	0.1392	0.1213	0.1712	0.1530	0.1168	0.0948	0.0707
K-means	0.1464	0.1600	0.1679	0.1816	0.1860	0.1957	0.1730	0.2527	0.2081	0.1710	0.1239	0.1090
H-FCM	0.0542	0.0663	0.0749	0.0853	0.0912	0.0984	0.0784	0.1184	0.0899	0.0769	0.0640	0.0427
FCM	0.1991	0.2278	0.2424	0.2513	0.2654	0.2702	0.2427	0.3233	0.2760	0.2324	0.2025	0.1792

Conclusion:

We have defined the Learning Automata-based Clustering Algorithm for Wireless Sensor Networks based on Hopfield– Fuzzy C Means clustering algorithm. The proposed clustering algorithm, in an iterative process tries to find a policy that determines a cluster-head set with the minimum cardinality for the network. This approach eliminates the randomness of the initial solution provided by Fuzzy C-Means based algorithms and it moves closer to the global optimum.

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