Weighting for Mobile Ad Hoc Networks Clustering based on K-HPSO and its application in aircraft networks

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Abstract

Efficient Cluster schemes play an important role in the self-organizing Ad Hoc wireless networks, so the performance of this structure needs to evaluate specially for distance sensitive. In this paper, we present a distance we present a hybrid PSO approach that uses K-means algorithm to replace the refining stage in the PSO algorithm, weighted clustering algorithm (WCA), in ad hoc networks. One of the measures taken for the HKP process will underestimate the number of clusters compared with other algorithms.and also observed that the number of cluster head changes is less and the life time of the cluster head is more. Analysis and simulation of the algorithm have been implemented and validity of the algorithm has been proved.

الخلاصة

كفاءة المخططات تلعب دورا مهما في عمليه التنظيم الذاتي لشبكات المحمول المخصص وبالتالي فأن أداء هذه ألتركيبه يحتاج إلى حساب خاص للمسافات بين المخططات . في هذا البحث تم تقديم سرب الجسيمات الهجين (PSO) الذي يستخدم الخوارزمية (HKP) لتحل محل مرحله التكرارفى (PSO) الخوارزمية المضافة (WCA) تقلل من عدد المجموعات (المخططات) عند مقارنتها مع خوارزميات أخرى لنفس الغرض. ويلاحظ أيضا قله عدد المجموعات الرئيسية ومده فعاليتها أكثر .وقد تم تنفيذ التحليل والمحاكاة من الخوارزمية وثبت صحة الخوارزمية.

Introduction

A mobile ad-hoc network is used to provide mobile users with instant and seamless wireless communications and can be applied in many application environments. A MANET is of dynamic nature. A pair of nodes communicates by sending messages either over a shared direct wireless link or over a sequence of wireless links including one or more intermediate nodes, forming arbitrary ad hoc network topologies. One of important structures for Ad Hoc networks is clustering(Zhijun, 2003). There are a large number of clustering methods. The choice of clustering methods depends both on the type of data available and on the particular purpose and application(Gerla, 1995&Lin, 1997&Parekh, 1994&Bassagani,1999&Chatterjee, 2002&Wu Di, 2006). In general, major clustering methods can be classified into partitioning methods, hierarchical methods, density-based methods, grid-based methods and model-based methods. This domain has been intensively studied because it is very useful when you want to route a message through the network.

K-means algorithm and its variants were the one of the best known partitioning clustering algorithm (Hartijan, 1975). This algorithm is simple, straightforward and is based on the firm foundation of analysis of variances. In addition to the K-means algorithm, several algorithms, such as pso (pso)(Jones,1995).

In this paper, we investigate the weight clustering of mobile ad hoc via HKP correct convergence approach. That is, HKP is related with the minimization of the weight clustering on the weight vectors. We prove that when the weight clustering reduces to a local minimum. Moreover, it is further shown by the theoretical analysis and simulation experiments that if this minimum is global, the HKP process consists of first making a correct number of weight vectors

fall into the hypersphere and then further pushing them to approach each center of the clusters, in that order, with these extra weight vectors driven to perpetuity.

This paper is organized as follows. Section 2 describes the background and related work. Section 3, we revise the WCA to be suitable for dense mobile nodes, the HPSO clustering algorithms based on K-mean are described in Section 4. In Section 5, simulation and application experiments are demonstrated, and the conclusion is presented in Section 6.

Background and related work

An energy efficient design will prolong the lifespan of the network. A convenient approach for the maintenance of these networks is through the decomposition of a network into clusters. With a cluster scheme, the nodes in the ad hoc network are separated into groups called clusters. In each cluster, one node is elected as the CH to act as a local controller, while the restore normal nodes. The size of the cluster depend sent he RF range of the cluster. The structure of cluster scheme, shown in Figure 1, consists of three types of nodes: normal nodes, CHs and gate way nodes.
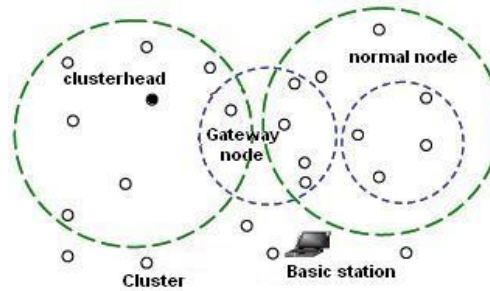

Figure1 Cluster Scheme

The normal node generates data, such as by sensing the environment, and sends or relays them to the CH. The CH not only generates data, but also collects the data from normal nodes and transfers them to the next hop. The gateway node, which belongs to more than one cluster, bridges the CHs in those clusters. The presence of gate way node is not compulsory in cluster schemes.

Cluster schemes are hierarchical. When a source node wants to send a packet to another network node that is not in the same cluster, the node uses a reactive routing protocol in order to discover the route. However, within the confines of the cluster itself, a proactive routing protocol is used since cluster connectivity is maintained by periodically exchanging information updates about any changing links among neighboring nodes (Fernandess, 2002).

The cluster scheme has many advantages, such as the following:

1) Within a cluster, all the normal nodes send their data to the CH. The resulting absence of flooding scheme, multiple routes, or routing loops result in energy saving.

2) The backbone network consists only of the CHs, which are far fewer in number than all the nodes in the entire network. Routing with the backbone network is therefore simpler, and requires less storage of routing information and less overhead of the ad hoc network.

3) The changes of nodes within a cluster affect only that cluster but not the entire backbone network, which will therefore be robust to these changes.

The degree of a node is computed based on its distance from others. The neighbors of a clusterhead become members of that cluster and can no longer participate in the election process. It can reduce the number of clusters, the mean-hop of source-destination pairs and delay of packet forward. However ratio which be used in space of channel is lower because of the fewer number of the cluster. Not having any restriction on the upper bound on the number of nodes in a cluster, the throughput drops and the system performance degrades gradually when the number of nodes in a cluster is increased. In Node-Weight heuristic (Bassajni, 1999), each node is assigned weights based on its suitability of being a clusterhead. A node is chosen to be a clusterhead if its weight is higher than any of its neighbor's weight; otherwise, it joins a neighboring clusterhead.

Weighted Clustering Algorithm (Wang, 2003) is depended on weight of the nodes in weight among the neighbors is selected as clusterhead. Although it can increase stability of the cluster, the proportion of every factor in the weight is uncertain. Furthermore calculation and storage of the weight are costly. Clustering algorithm based on global positioning system (Jain,2001) depends on the distance which is calculated according to the physical coordinate of the nodes in the network. This algorithm need not keep the topology information of the network. Owing to these, the cost of the network is fewer and it can fleetly adapt to the topology change of the network.

The weighted clustering algorithm WCA selects the clusterheads based on the weight of each node Wv of each node v. As detailed in [14], Wv is defined as

$Wv = w1\Delta v + w2Dv + w3Mv + w4Pv$ (1)

Where Δv is the degree-difference, Dv is sum of the distances of the members of the clusterhead, Mv is the average speed of the nodes, and Pv is the accumulative time of a node being a clusterhead. The corresponding weighing factors are such that $\Sigma wi = 1$. The node v with the minimum Wv is chosen to be the clusterhead. Once a node becomes the clusterhead, neither that node nor its members can participate in the cluster election algonthm.

The election algorithm will terminate once all the nodes either become a clusterhead or a member of a clusterhead. Refer to (Chatterjeee, 2002)for complete details of WCA. The degree difference Δv defined in (Robbins, 19951)seem not suitable when the mobile nodes is dense, since under such situation a potential clusterhead (e.g. centered nodes) with redundant neighbors may have a relative high Wv , leading to its fail in clusterhead competition. So in our solution, when the neighbors of node v ale less then the ideal cluster member number δ, we use Δv to evaluate Wv ; otherwise, we set Δv to zero and choose δ cluster members in a stochastic method, while being aware of the nodes weight. Therefore, two neighboring nodes can share the surrounding nodes and form two clusters, which can not be come up under previous WCA.

The hybrid pso with K-MEAN algorithms(HKP).

A.K-means cluctering algorithm,The K-means algorithm is simple, straightforward and is based on the firm foundation of analysis of variances. It clusters a group of data vectors into a predefined number of clusters. It starts with randomly initial cluster centroids and keeps reassigning the data objects in the dataset to cluster centroids based on the similarity between the data object and the cluster centroid. The reassignment procedure will not stop until a convergence criterion is met (e.g., the fixed iteration number, or the cluster result does not change after a certain number of iterations).

The K-means algorithm can be summarized as:

(1) Randomly select cluster centroid vectors to set an initial dataset partition.

(2) Assign each document vector to the closest cluster centroids.

(3) Recalculate the cluster centroid vector cj.

$$C_j = \frac{1}{n_j} \sum_{\forall d_j \in S_j} d_j \qquad (2)$$

where dj denotes the document vectors that belong to cluster Sj; cj stands for the centroid vector; nj is the number of document vectors that belong to cluster Sj.

(4) Repeat step 2 and 3 until the convergence is achieved.

The main drawback of the K-means algorithm is that the result is sensitive to the selection of the initial cluster centroids and may converge to the local optima (Selim,1904) for that reason, the initial selection of the cluster centroids affects the main processing of the K-means and the partition result of the dataset as well. The processing of K-means is to search the local optimal solution in the vicinity of the initial solution and to refine the partition result. The same initial cluster centroids in a dataset will always generate the same cluster results. However, if good initial clustering centroids can be obtained using any other techniques, the K-means would work well in refining the clustering centroids to find the optimal clustering centers (Anderberg, 1973)

B. PSO clustering Algorithm

Merwe's research (Merwe, 2003) indicates that utilizing the PSO algorithm's most advantageous ability, if given enough time, the PSO clustering algorithm could generate more compact clustering results from the low dimensional dataset than the traditional K-means clustering algorithm. However, when clustering large document datasets, the slow shift from the global searching stage to the local refining stage causes the PSO clustering algorithm to require many more iterations to converge to the optima in the refining stage than the K-means algorithm requiring. Although the PSO algorithm is inherently parallel and can be implemented using parallel hardware, such as a computer cluster, the computation requirement for clustering large document dataset is still high. In our experiments, it needs more than 500 iterations for the PSO algorithm to converge to the optimal result for a document dataset that includes 800 documents. The K-means algorithm only requires 10 to 20 iterations.

Although the PSO algorithm generates much better clustering result than the K-means algorithm does, in terms of execution time, the K-means algorithm is more efficient for large datasets (Al-Sultan, 1999), For this reason, we present a hybrid PSO approach that uses K-means algorithm to replace the refining stage in the PSO algorithm. In the hybrid PSO algorithm, the algorithm includes two modules, the PSO module and the K-means module. The global searching stage and local refine stage are accomplished by those two modules, respectively. In the initial stage, the PSO module is executed for a short period to discover the vicinity of the optimal solution by a global search and at the same time to avoid consuming high computation. The result from the PSO module is used as the initial seed of the K-means module. The K-means algorithm will be applied for refining and generating the final result. The whole approach can be summarized as (Xiaohui, 2005):

(1)Start the PSO clustering process until the maximum number of iterations is exceeded

(2) Inherit clustering result from PSO as the initial centroid vectors of K-means module.

(3) Start K-means process until maximum number of iterations is reached.

In this work, we give a framework of a novel model of PSO, Divided Range Particle Swarm Optimization (DRPSO) for distributed computing. In the DRPSO, the individuals are divided into sub-populations (groups) by the values of one objective function, e.g. Δv, Dv, or Mv, in WCA.

Simulation experance and results

Simulation Environment and performance index,we simulate our clustering algorithm by OMNET++. The random waypoint model (Chatterjee,2002)is used in the simulation runs. In this model, a node selects a destination randomly within the roaming area and moves towards that destination at a speed uniform distributed between 0m/s and Vmax m/s, where Vmax is the maximum speed of the node. Once the node reaches the destination, it selects another destination randomly and moves towards it after a predefined pause time. We simulate a system of N nodes was 40 and 80,on a 100m×100m area. Simulation time is 10000s.

Each clusterhead could at most handle 10 nodes in its cluster in terms of resource allocation are assumed . The values of wi are arbitrary at this time and should be adjusted according to the system requirements. The same values for all weighing factors are used both in the original and the optimized revised WCA.

Simulation Results

In this study, we employ two performance metrics:

i) the number of clusterheads,

ii) the number of reaffiliations.

The reaffiliation count is incremented when a node gets dissociated from its clusterhead and becomes a member of another cluster within the current dominant set. These parameters are studied for varying number of nodes in the system.
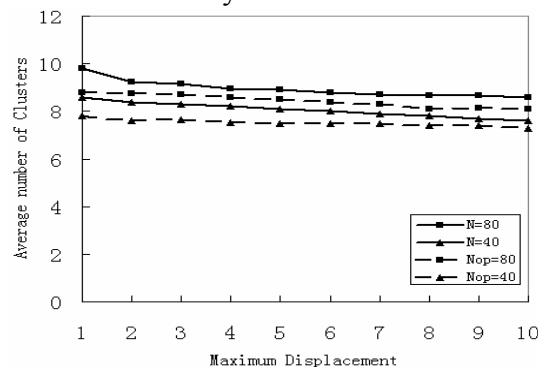

Figure 2 Average number of clusters

Where:

N: Average nubmer of Clusters

Nop: Optimized Average nubmer of Clusters

Figures 2 shows the average number of clusterheads with the varying Vmax for original WCA and optimized revised WCA respectively. We observe that the optimized WCA yields lower number of clusters.
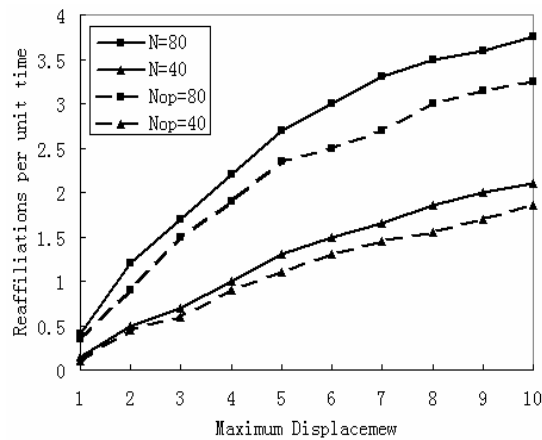
Figure3 Reaffiliations per unit time

Where:

N: Reaffiliations per unit time

Nop: Optimized Reaffiliations per unit time

Figures 3 shows the reafflliations per unit time with the varying Vmax for original WCA and optimized revised WCA respectively. As the displacement becomes larger, the nodes tend to move farther from their clusterhead, detaching themselves from the clusterhead and causing more reaffiliations per unit time.

Aircraft networks

Added the algorithm (WCA) can be applied to networks of the aircraft. Where possible to reduce a refining stage and to reduce the number of groups and their effectiveness .Almost all wireless networks hook up to the wired network at some point to provide access to files, databases, and the Internet. There are many ways these connections can be realized, depending on the circumstances. For example, in Fig. 4(a), we depict an airplane with a number of people using modems and seat-back telephones to call the office. Each call is independent of the other ones. A much more efficient option, however, is the flying LAN of Fig. 4(b). Here each seat comes equipped with an Ethernet connector into which passengers can plug their computers. A single router on the aircraft maintains a radio link with some router on the ground, changing routers as it flies along. This configuration is just a traditional LAN, except that its connection to the outside world happens to be a radio link instead of a ardwired line
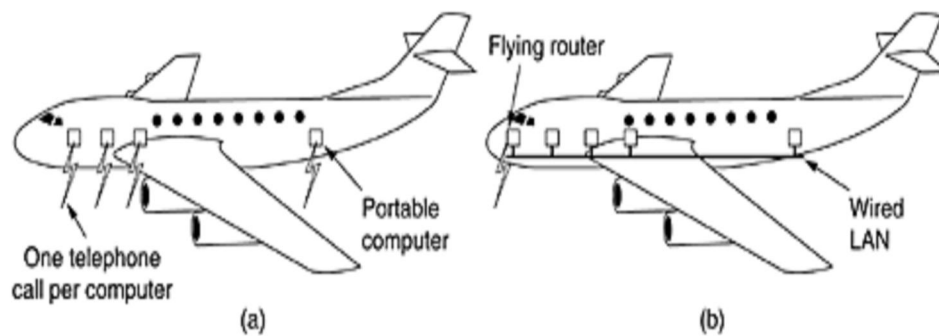
Figure4 (a), (b): The model of civil an aircraft

Conclusions

In this paper, the weighted clustering algorithm which the mean degree and distance of mobile nodes takes into consideration are proposed . It makes clusterhead's selection become reasonable. It also overcomes the limitation of most existing clustering algorithms which only take into consideration certain factor which affects network. It can improve its applicability and universality. As the weight clustering reduces to a local minimum, the HKP algorithm has the separation nature that a number of weight vectors converge within a hypersphere surrounding the nodes set, while the other weight vectors diverge to infinity. If we make the cost function reduce to the global minimum, the K-HPSO algorithm will allocate a correct number of weight vectors that will converge to each center of the clusters in the nodes set, respectively.

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