An Optimization Strategy for Mobile Ad-hoc Networks

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Abstract. For MANETs , topology control can enhance the stability of network topological structure. This paper proposes a hybrid strategy to construct a MANETs hierarchical structure, so as to enhance the stability of network topological structure. Simulation experiments show that our strategy performs better in the stability of hierarchical structure than the existing algorithms.

Introduction

A key concern in MANETs is the control of network topology. Characterized by a typical distributed system, the topology in a MANETs varies dynamically and massively. An effective solution is to construct a topology control strategy in a MANETs[1].

Hierarchy-partitioning in a MANETs can be attributed to build a hierarchical network based on a clustering algorithm. Clustering is then regarded as the issue to seek for the maximum independent set, also known as the NP-hard problem [2]. Therefore, a heuristic algorithm is adopted to form clusters in most of MANETs. According to different principles of cluster-head selection, various clustering algorithms are considered, such as the lowest-ID algorithm, the highest-connectivity degree algorithm, the maximum-weight algorithm, and etc [3]. The mobility-based d-HOP (MobDHop) algorithm proposed a clustering scheme, in which the received signal strength of each node can be measured. To substitute for the node weight, this signal strength is used as the selection criteria of the cluster head. The RWC algorithm [4] assumes five characteristics to identify a cluster head; however, as a centralized algorithm, it requires the network's global information and thus is not suitable for a large-scale MANETs, exhibiting a poor practicability. Although presented a distributed clustering algorithm, LDSD aims at the clustering in MANETs characterized by the cluster's movement, with a narrow applicability. As described in Ref. [5], an active-learning clustering algorithm based on CDMA/TDMA can achieve desirable clustering results. Nevertheless, the algorithm is quite tedious. Conclusively, the above-listed algorithms fail to take full advantage of the MANETs' multi-dimensional dynamic distributed characteristics, and the clustering are therefore not adaptive to the conditions of network and mobile nodes. More seriously, the cluster head is highly likely to be the bottleneck in the network.

In the present work, according to the conditions of network and nodes, several characteristics of node stability are taking into account, and a dynamic adaptive hierarchy-partitioning is achieved by perceiving the distributed dynamic network topology with the use of multi-feature fusion and GRF-MAP method. Moreover, the number of nodes and the size of cluster can be optimized by the maximum loads of the backbone nodes, leading to a balance adaptive to the actual capacity.

Topology control Strategy

At present the main means is low click type and the lever type, low click type is on the bottom of the ball through attack the ball flew over obstacles, this method is able to pick the ball's advantages and makes the energy loss in institutions least, the shortcoming is the ball high requirement of the shape of the electromagnetic valve [6]. Therefore, the development of a high-performance control system of soccer robot has become an urgent desire for soccer robot fans.

Problem description: Given a system topology G(S, E), composed of nodes and links, in which S denotes the set of nodes while E denotes the set of sides. Side (x, y) connects node x and node y, suggesting that x and y are the one-hop neighbor nodes which can be comminuted with each other. The distance between x and y, d (x, y), represents the number of minimum hops between two nodes. The goal is to select a set of cluster-head nodes which can cover the whole network, and then to constitute clusters with their one-hop neighbor nodes. By clustering, each node in the network becomes a cluster head or a cluster member.

Node stability

Regarding the node stability in a MANETs, several characteristics are selected to make a fusion; namely, the interestingness of a node to act as a backbone node, the remaining battery power, available memory and movement velocity of a node, combined with the degree to be a key node. All of these can measure the stability of a node, with the major reasons listed as follows.

(i) Interestingness of a node to act as a backbone node (I). A majority of clustering algorithms forcibly define the maximum-weight node as the cluster head. Actually, the node may be unwillingness to be the cluster head. If the interestingness is neglected, the node which is reluctant to be a backbone node cannot perform the backbone node's responsibility, resulting in a poor performance of network. Accordingly, the interestingness of the node should be included in the measurement of node stability.

(ii) The remaining battery power of a node (P). The backbone nodes should take on extra responsibility, and therefore their battery power consumptions far exceed the normal nodes'. The nodes with more remaining battery power should be given priority to be the backbone nodes.

(iii) Available memory of a node. Due to the fact that the backbone nodes should take the responsibilities to maintain the communications of their members and the communications between the intra-cluster and inter-cluster members, the nodes with a large memory are more suitable for the backbone nodes.

(iv) Movement velocity of a node. To avoid a declining network stability induced by the frequent changes of backbone nodes, the nodes with lower movement velocities are more inclined to be the backbone nodes.

(v) The degree to be a key node. In a large-scale MANETs, some edge nodes connected two or more regions alone are more likely to appear. These nodes exhibit more power consumptions. Once they are out of work, the network's topology will be partitioned and thus the communication is interrupted. The node satisfies a relationship Ni - Mi ≥ 2 can be defined as a key node, in which Ni and Mi are the node's neighbor degree and basic circuit degree, respectively. Moreover, the node whose key-node degree is greater than or equal to 2 can be regarded as the backbone node.

Related definitions

Definition 1 (Clique) Given a neighbor system η in the set of nodes S, the subset C composed of the single node and its neighbor nodes is then referred to as the clique corresponding to (S, η). As a subset of S, C should meet one of the following constraints:

C is based on the single node;

If i $\in$ C, j $\in$ C and i $\neq$ j, node i is the neighbor of node j, i.e., i $\in \eta_j$.

The concept of clique is an indicator of the interactions among the node's position. In terms of the accessible hops between the center node and the neighbor nodes, the clique can be classified as several types, such as the first-order clique C1, the second-order clique C2, the third-order clique C3, and so on.

Definition 2 (Cluster) Suppose node i is a backbone node, $\mathrm{N}_i = \{i' \in \mathrm{S} | d(i', i) \leq 1, i' \neq i\}$ represents a set of nodes composed of the members of a cluster in which node i acts as the cluster head. To be specific, N_i is referred to as a cluster, where $d(i', i)$ represents the hops between node i and nodei'.

(In references [7],the definition of node stability、random field and neighborhood system had be defined)

Construction of a prior energy function

Determination of the prior potential function of a clique. In accordance with the detection results in the initial label field, the nodes in a MANETs can be divided as the backbone nodes and the normal nodes, respectively, and then they obtained binarization results are denoted as $\hat{f}_k(\bullet)$.

$$\hat{f}_k(\bullet)=\begin{cases}0 & \text{label backbone node for } node \text{ i}\\ 1 & \text{label general node for } node \text{ i}\end{cases} \tag{1}$$

In which the prior energy function U (f) is the related energy in the initial label field. Given a label field f(•), the detection results at k-th time . $\hat{f}_k(\bullet)$ are treated as the initial label field.

Essentially, the potential function Vc(f) mirrored the dependence of the center node to its neighbor clique. The better the state of center node fits with the neighbor clique, the lower the potential Vc(f) is. The prior potential function is then constructed as follows,

$$V_c(f_k(i))=\frac{f(i)\neq f_k(j)}{\#C_i} \tag{2}$$

in which $\#C_i$ denotes the number of nodes in a clique which includes node i as well. Since the number of neighbors in the neighborhood system of a center node is different, serves as a normalization factor in the construction of the prior potential function. Moreover, is the label of the neighborhood system, j is the one-hop neighbor with node i in the clique Ci, and $f_k(j)$ is the label of node j at k-th time.

In line with the definition of energy function, the prior energy function of node i at k-th time can be described as

$$\boldsymbol{U(f)=\sum_{f_k\in L}V_c(f_k(i))} \tag{3}$$

in which L represents the set of labels of the neighborhood system which includes node i. When f is consistent with all nodes or most of nodes in the neighborhood system, U(f) turns lower, and the system can achieve a favorable consistency effectively. Additionally, due to the introduction of the normalization factor, the nodes with fewer neighbors can acquire a larger weight, contributing to a consistency of the system. U(f) is a data-driven item induced by the initial label, reflecting the consistency between the prior label and the required label. When the required label fits well with the prior label, the energy of this item reduces otherwise it increases.

Construction of a likelihood energy function

The likelihood energy function is referred to as the corresponding energy functions of the correlation between the nodes in the label field under the constraint conditions. The acquired multi-feature information are used as the constrain conditions, and the key features to constrain the node stability are then converted to the probability of each feature's occurrence. Due to the fact that the selection of the key characteristics of node stability is independent, i.e., the conditions are independent; the likelihood function can be expressed as

$$P(X\setminus f)=P(x_I,x_p,x_M,x_V,x_D\setminus f)=\prod_{j=1}^{5}P(x_j\setminus f) \tag{4}$$

The analysis results in Section **Node stability** indicate that xV and xD should be minimized for the maximization of node stability, and thus Eq. (4) can be written as

$$\max P(X\setminus f)=\max\frac{P(x_I\setminus f)P(x_p\setminus f)P(x_M\setminus f)}{P(x_v\setminus f)P(x_D\setminus f)} \tag{5}$$

Taking a positive logarithm on Eq. (5), we can obtain

$$\min[-\ln P(X\setminus f)]=\min[-\ln P(x_I\setminus f)-\ln P(x_p\setminus f)-\ln P(x_M\setminus f)+\ln P(x_v\setminus f)+\ln P(x_D\setminus f)] \tag{6}$$

Therefore, the defined likelihood energy function is given by

$$\boldsymbol{U(X/f)=U^I+U^p+U^M+U^V+U^D} \tag{7}$$

In which

$$U^I=-\ln P(x_I\setminus f),U^p=-\ln P(x_p\setminus f),U^M=-\ln P(x_M\setminus f),U^V=\ln P(x_v\setminus f),U^D=\ln P(x_D\setminus f).$$

'Multi-feature fusion', as mentioned in the present work, has two primary implications: (i) a multi-dimensional Gibbs random filed model is used to construct a GRF model; and (ii) when constructing an energy function, the obtained prior information in the multi-feature detection are considered comprehensively, and then serve as the constraint conditions. Consequently, Eq. (2) is also known as a multi-feature fusion model. The objective function $\hat{f}_{MAP}$ can be obtained by substituting Eq. (3) and Eq. (7).

Estimation of the probability density of the components in the stability vector

According to the Linderberg-Levy theorem, combined with the experimental results in a large number of literatures, the nodes' movement velocity, degree and the available memory are assumed to follow a Gaussian distribution, i.e., $x_V \sim N\left(u_V, \sigma_V{}^2\right)$, $x_D \sim N\left(u_D, \sigma_D{}^2\right)$, $x_M \sim N\left(u_M, \sigma_M{}^2\right)$; Besides, let x_I ～U[0，a], xp is exponentially distributed with a probability density p(pi) in the following forms $p(p_i) = \begin{cases} \lambda e^{-\lambda p_i} & p_i > 0 \\ 0 & p_i < 0 \end{cases}$

Then, the FGM clustering Strategy is constructed as follows:

Step 1: In the initial state, any node in the network broadcasts a 'Hello' message (the energy is measured with the node' movement velocity as the index).

Step 2: Each node broadcasts a 'Hello' package, and sends its label to the neighbor nodes.

Step3: The nodes which can receive the 'Hello' package with one hop are accepted as the member of the cluster, i.e., a cluster forms;

Step 4: The nodes which receive more than one 'Hello' package serves as the gateway nodes.

The clustering is finished.

Test results

Using the corresponding underlying codes of NS2, the Strategy in the present work was implemented, with the same simulation environments as introduced in Ref. [4]. The number of updated cluster heads per unit time is calculated and compared comprehensively with the related indexes in the simulations on the RWC algorithm, as presented in Fig. 1. It should be noted that the maximum load of the cluster head is selected to be 15 in the present work, i.e., C = 15.

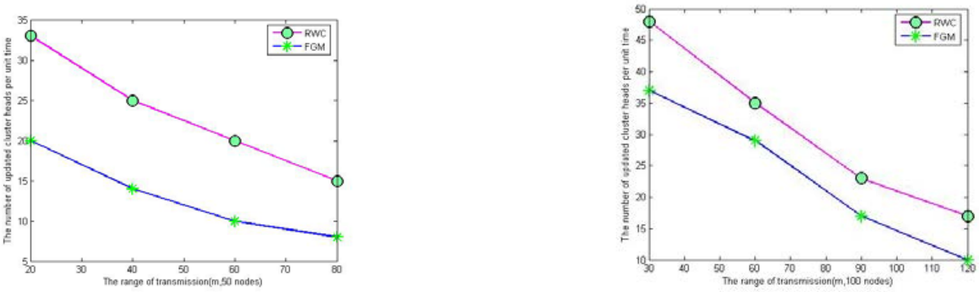

Fig.1 Number of updated cluster heads per unit time (at a maximum speed of 30m/s)

As observed from Fig. 1, the FGM clustering Strategy advanced in the present work exhibits a significant improvement compared with the RWC algorithm, in terms of the stability of hierarchies in a MANETs. Conclusively, the FGM Strategy is an appropriate hierarchical algorithm with favorable stability and strong robustness.

Conclusion

In the present study, using multi-feature fusion and GRF-MAP (FGM) method, a distributed clustering Strategy based on the node stability is proposed. The load can be balanced by imposing limitations on the number of nodes in a cluster, and moreover, the probability of variations in the cluster's relationship is reduced, leading to a decreasing expense on the cluster's configuration. The simulation results indicate that the network structure by performing the FGM Strategy exhibits preferable performance and stronger robustness.

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