NCD-TAP: A Tracking Area Planning Approach Based on Newman Community Detection for HCN

Shanshan Tu, Qiangqiang Lin, Weipeng Wang, Kaili Sun, Yao Huang, Hong Phong Nguyen

***Abstract*—**In heterogeneous cellular network (HCN), the cell is usually divided into tracking areas (TA) for better management of users' locations. The trade-off between location update signaling and system paging signaling is a core issue in TA planning. However, the existing TA planning solution aiming at large-scale deployment of small cell has the problems of uneven location updating signaling, ping-pong effect and so on. Against the above problems, this paper presents NCD-TAP, a novel TA planning method based on Newman fast community detection algorithm. Firstly, the TA planning problem is modeled as a complex network community detection problem and the Newman algorithm in the community detection is used to propose the TA planning scheme. Then, the modularity concept of community partition is introduced to measure the performance of TA planning scheme. Finally, the experimental simulation results show that the scheme proposed in this paper has obvious advantages in the case of large scale of small cell and high expectation of small cell Poisson distribution, and is suitable for massive cellular deployment environment.

***Keywords*—**Tracking Area Planning; Newman Algorithm; Community Detection; Heterogeneous Cellular Networks

I. INTRODUCE

RECENTLY the global mobile communication service business has developed rapidly. Cellular mobile communication technology has been upgraded from 2G voice and low-speed data service to present high-speed 4G data communication, and continuously to mobile broadband development [1]. Meanwhile, mobile services have diversified development, such as online video, online games, cloud services, mobile payment and other network applications, that help greatly enriching and facilitating the living standards of people. Due to the emergence of these network applications, users need numerous network data services, and there is a sharp growth demand for the transmission rate of real-time network data services. Therefore, it is an urgent issue problem to enhance cellular capacity in the areas with more mobile services, such as densely populated areas [2-3].

In order to solve the problem of the low Quality of Service (QoS) brought by explosive growth of data, it was proposed to deploy low power, low cost small cellular systems on the traditional macro cellular network architectures. For instance, the formation of a heterogeneous cellular network technology can provide more spectrum re-sources with larger network capacity [4-5]. According to the statistical results of data services and development experiment of existing communication networks, Small Cell (SC) technology is widely used to improve the network capacity [6].

The SC technology concentrates the whole base station functions on a single chip with the advantages of low cost and low power consumption and the disadvantage of smaller coverage. In addition, a large number of random deployment of SC make it possible for users move under their coverage to travel frequently in different cells, which may lead to frequent location update signaling then seriously reduce the system's operational efficiency [7], [8]. In order to better manage users' locations, the cells are divided into the tracking areas. The trade-off between location update and system paging signaling is needed in TA planning. Too large TA coverage leads to more system paging signaling, which exceeds the system paging load. By contrast, too small TA coverage may lead to frequent location update signaling operate and reduce system operation efficiency [9]. Therefore, the principal of the TA planning is to cover as many cells as possible in a specified TA to reduce the location updating signaling, and at the same time, it must be ensured that the maximum load of system paging signaling is not exceeded.

In the environment of large-scale SC deployments, many TA planning algorithms are proposed for better management of users' locations. One solution is static TA planning scheme. For example, it is both used in the GSM and IS-41 systems, in which the partition of TA is fixed. The static TA planning scheme can easily generate a large number of location update signaling when users move between adjacent TA, that is, the generation of ping-pong effect [10]. In order to solve this problem, another solution is the dynamic TA planning scheme

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Shanshan Tu, Qiangqiang Lin and Kaili Sun are with the Faculty of Information Technology, Beijing University of Technology and the Beijing Key Laboratory of Trusted Computing, 100124 Beijing, China.

Weipeng Wang is with the Beijing Electro-Mechanical Engineering Institute, 100074 Beijing, China.

Yao Huang is with the Chengdu University of Information Technology, 610225, Chengdu, China

Hong Phong Nguyen is with the Faculty of Civil Engineering, University of Transport and Communications, Hanoi 100000, Vietnam.

(Corresponding author: Qiangqiang Lin, e-mail: 969118264@qq.com)

which has three typical schemes: 1) Time-based [11-13], 2) Distance-based [14-16], 3) Motion-based [17-21]. Although the above three dynamic TA planning schemes can combine the mobility and service behavior characteristics of users and improve the TA planning efficiency, there are still some problems of uneven distribution of location update signaling.

In order to solve the deficiencies existing in the above schemes, this paper proposed a new type of TA planning based on the improvement in [7]. The specific contributions are as follows:

1) Apply the Newman algorithm [22] in community detection to quickly give TA planning scheme;

2) Introduce the concept of modularity [23] of community partition to measure the performance of TA planning scheme;

3) Comparison of simulation results shows that the modularity of the proposed TA planning scheme in this paper is the highest when the scale of SC and the expectation value of SC Poisson distribution are high, which indicates that the proposed TA planning scheme is suitable for massive cellular deployment environment.

II. RELATED WORK

TA planning scheme has been a challenge in HCN. With the deep and extensive study of the TA planning problem, many algorithms have been proposed by scholars, among which dynamic TA planning scheme has been a hot research topic.

There are three schemes for dynamic TA planning scheme: 1) Time-based; 2) Distance-based; 3) Motion-based dynamic TA planning scheme. The time-based TA planning scheme has a built-in time counter in the user terminal, which updates the location when the time counter exceeds the preset threshold. At the same time, the user's location information saved in the network is sent to the corresponding cell when the network calls the user.

For example, Li et al. [12] proposed a time-based location update scheme under the assumption that the paging interval and the user's resident cell time follow arbitrarily distributed. The time-based location update scheme is not a reasonable solution compared with the other two schemes. The main reason is that the user may have TA change within the preset time threshold, and then the user does not perform location update operation at this moment. The user location information previously saved in the network is invalid. If the network calls the user at this time, the call will fail. The distance-based TA planning scheme is similar to the time-based TA planning scheme. Similarly, a distance counter is built in the user terminal, and the user terminal performs a location update operation when the distance counter exceeds the preset threshold. For example, Li et al. [15] proposed a distance-based location update scheme. Compared with other schemes, although such scheme can effectively reduce signaling overhead of location update, it is difficult to implement because the user terminal must know the topology of the cellular network, which is extremely difficult for the massive SC deployment environment. The motion-based planning scheme built a counter in the user terminal to record the number of movement steps. When the counter exceeds the preset motion threshold, the position update is reported. The performance of this scheme is between the above two schemes. For example, Fu et al. [18] proposed a delay registration mechanism, in which users' location update operations perform only when entering cellular coverage to reduce signaling overhead. Deng et al. [24] calculated the user's activity characteristics in the scope of TA planning, and modeled the TA planning problem as the graph segmentation problem. Yu et al. [25] proposed a TA planning scheme assisted by the handover management algorithm, which greatly reduce the traffic capacity of SC transfer macrocell. Ko et al. [26] on the basis of it put forward the mobility-aware location management scheme in macrocell networks. Safa et al. [27], [28] figured out TAs reconfiguration problems in LTE networks. In addition, Ning et al. [7] proposed a location-based management approach based on community detection. In this method, the TA planning problem was modeled as a graph segmentation problem, and a TA planning method based on collaborative game was proposed. This planning scheme regards cellular base station as a rational individual in a complex network and cooperates with other individuals through profit decision. However, when the scale of SC in the scene is large, there will be more and more prisoners' dilemma. (In the game process, faced with common interests, a rational individual may not take a cooperative decision in decision-making of interests. And they are trapped in the prisoner's dilemma when there is a contradiction between individual rationality and collective rationality.) This will lead to the unreasonable phenomena that more and more communities are separately planned as the TA.

The above TA planning schemes have their own merits and demerits. They are mainly structured for the cellular deployment environment, and cannot face the massive SC deployment environment. Therefore, improved by [7], this paper proposes a TA planning scheme based on fast Newman community detection algorithm.

III. THE PROPOSED TA PLANNING SCHEME

Firstly, we model the TA planning problem as a graph segmentation problem and give the objective function. Then the problem is further modeled as community detection problem based on complex networks, and we introduce the modularity of the community partitioning to evaluate the performance of the TA planning scheme and the TA planning process based on the fast Newman algorithm, namely NCD-TAP.

A. Modeling of the TA planning problem based on Graph Segmentation

As shown in Fig. 1, a cellular network can be modeled as a network graph $G(V, E)$, where vertices V and edge E represent the adjacency relationship between cells and cells in the network respectively. The weight CR_i of the vertex i represents the time of user paging requests occurred in the cell i, and the weight LU_i of the edge represents the time of the user moving between the cell i and the cell j. Dividing the graph into a number of regions V_1, V_2, ..., V_k indicates that the cell partition corresponds to the TA partition in TA planning. Suppose the number of cells in the network is *n*, and the number of partition is *k*.

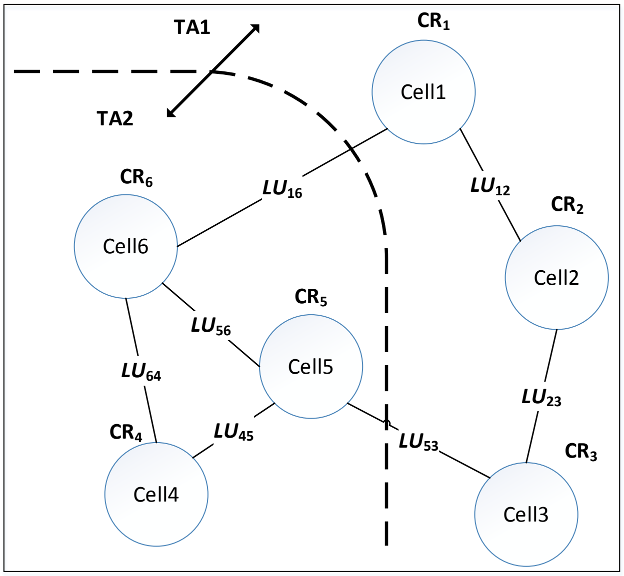

Figure 1. TA planning modeling based on graph segmentation

TA programming problem can be modeled as:

$$Min \sum_{(i,j)\in(V_1,V_2,\dots,V_k)} LU_{ij} \quad (1)$$

$$s.t. \sum_{i\in V_k} CR_i \le B \qquad \forall n = 1:k \quad (2)$$

Equation (1) reflects the minimizing goal of the total number of location updates generated by the user moving between different cells. Equation (2) reflects that the total paging load cannot exceed the channel paging capacity B. This model sets the TA planning problem as a graph segmentation problem. However, in the classical graph segmentation algorithm, the signaling cost associated with paging in the objective function is not taken into account. Therefore, in order to deal with the deployment environment of massive SC and quickly find a more optimized TA planning solution, we further model the problem as a community detection problem in the complex network.

B. Modeling of the Community Detection problem based on complex network

Many systems in real world can be described by complex networks, which have become the research hotspot in various disciplines. The SC deployment in HCN is massively deployed at random. We can interpret the cell in TA planning as the problem of community detection in complex networks. At present, through the research of complex network, many scholars know that there is a kind of community structure between nodes in complex network. Community structure means that a certain number of nodes are closely connected to each other and form a close community, but the connections between communities are rather sparse in a complex network. Therefore, there is a close relationship between the community detection in complex networks and the TA planning. In this section, we further model the above problems as community detection problems in complex networks, then analyze and study the community detection problems in complex networks.

Divide the network diagram $G(V, E)$ in Fig. 1 into k sub-regions $(V_1, V_2, ..., V_k)$, corresponding to k communities $(C_1, C_2, ..., C_k)$ in the complex networks. Where $C_i(i \in k)$ denotes the vertex set contained in the community. The corresponding $E_{ij}(i, j \in k)$ denotes the number of connections between community *i* and the community *j* as shown in Fig. 2.

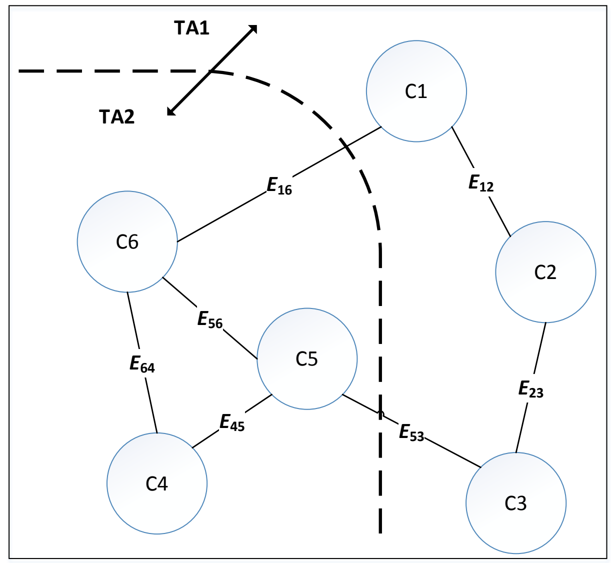

Figure 2. TA planning modeling based on community detection

Then the TA planning problem can be further modeled as:

$$Min \sum_{(i,j)\in(C_1,C_2,\dots,C_K)} E_{ij} \quad (3)$$

$$\text{s.t.} \sum_{i\in C_k} C_i \le B \quad \forall n = 1:k \quad (4)$$

Equation (3) means the minimized goal of the number of edges between the communities, and Equation (4) means that the total paging load occurring in the community cannot exceed the channel paging capacity B. This model further transforms the TA planning problem into a community detection problem. Then we will discuss the definition of modularity in community detection and evaluate the performance of TA planning algorithm by the modularity in community detection.

C. The definition of the modularity

In the community detection algorithm of complex network, it is almost impossible to determine the number of communities in advance, so there must be a method of measurement to calculate whether each result is the best result in the process of community detection. Here, we use modularity to measure whether a community partition is an optimal result. Good results are characterized inevitably by tight connections within communities and sparse connections between communities. At the same time, by further explaining the function of modularity in the TA planning scheme, the modularity is used to measure the performance of the TA planning scheme.

If the nodes set in the above network graph $G(V, E)$ is $N=\{1, 2, ..., n\}$, $A=(a_{ij})_{n\times n}$, $\forall i,j \in N$ is the adjacent matrix of the network. If there is an edge between node i and node j, then $a_{ij}=1$, $\forall i,j \in N$, otherwise $a_{ij}=0$, $\forall i,j \in N$. (5) is defined as following.

$$a_{ij} = \begin{cases} 1, & \text{existing edge between } i \text{ and } j \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

Assuming that k_i and k_j represent the two communities of vertex i and vertex j, the ratio of the edges number in the community and the total edges number in the network is defined:

$$\frac{\sum_{ij} a_{ij}\partial(k_i,k_j)}{\sum_{ij} a_{ij}} = \frac{1}{2m}\sum_{ij} a_{ij}\partial(k_i,k_j) \tag{6}$$

The function in (6) is defined as: If vertex i and vertex j are in the same community, that is, $k_i= k_j$ and $\partial(k_i, k_j) = 1$, otherwise is 0, where m represents the total edges number in the network.

Modularity value is defined as the ratio of the total edges number in the community to the total edges number in the network minus an expectation, which is the ratio of the total edges number in the community formed by the same community assignment to the total edges number in the network when the network is set as a random network. So the modularity Q is defined as the following:

$$Q = \frac{1}{2m}\sum_{ij}\left[a_{ij} - \frac{d_i d_j}{2m}\right]\partial(k_i,k_j) \tag{7}$$

In (7), d_i denotes the modularity of the vertex i, defined as the following (8):

$$d_i = \sum_j a_{ij} \tag{8}$$

Let e_{vw} denote the ratio of the sum edges in community v and community w to the total edges number, defined as:

$$e_{vw} = \frac{1}{2m}\sum_{ij} a_{ij}\partial(k_i,v)\partial(k_j,w) \tag{9}$$

Let b_v represent the ratio of the edges number associated with the points in the community v to the total edges number, defined as the following:

$$b_v = \frac{1}{2m}\sum_i d_i\partial(k_i,v) \tag{10}$$

To simplify the calculation of modularity Q, suppose that the network has been divided into r communities. There is a r-dimensional matrix, and the calculation of modularity Q can be given by the following:

$$\begin{aligned} Q &= \frac{1}{2m}\sum_{ij}\left[a_{ij} - \frac{d_i d_j}{2m}\right]\sum_v \partial(k_i,v)\partial(k_j,v) \\ &= \sum_v\left[\frac{1}{2m}\sum_{ij} a_{ij}\partial(k_i,v)\partial(k_j,v) - \frac{1}{2m}\sum_i d_i\partial(k_i,v)\ \frac{1}{2m}\sum_j d_j\partial(k_j,v)\right] \\ &= \sum_v (e_{vv} - b_v^2) \end{aligned} \tag{11}$$

In (11), e_{vv} represents the ratio of all edges in community v to all edges of the whole network, and b_v represents the ratio of the modularity of the nodes in the community v to the modularity of the whole network. It can be further interpreted as the difference between the connected edges number and the random expectation in a community network. When the actual connected edges number is higher than the random expectation, there is a tendency for the community nodes to be concentrated in several communities. Calculate the value of Q for each partition, and it is an ideal network partition with the largest Q value. The range of Q value is between 0-1. The larger the Q value is, the higher accuracy of the network partition's community structure is. In the actual network analysis, the highest Q value generally appears between 0.3 and 0.7.

Here, in order to measure the performance of the TA planning scheme with modularity Q of the community partition, we explain Equation (11): In the cellular network architecture, e_{vv} represents the ratio of the time of user cross-area movement occurred in the tracking area TA_v (The community v in a complex network corresponds to the v of TA in a cellular network, that is, TA_v) to the total time of users cross-area movement in the whole cellular network. b_v represents the ratio of the paging time in the tracking area TA_v to the total paging time in the whole cellular network. The larger the Q value is, the larger difference between the user cross-area movements and the paging time occurring in the TA is, which means that in this TA planning scheme, we divide more cells into the TA to ensure that the location update signaling is reduced. At the same time, the smaller system paging time in the tracking areas ensures that the system paging signaling reaches the minimum level, which indicates that the TA planning scheme is better at this time.

Next, we will introduce a community detection algorithm based on modularity - Newman fast algorithm, applying Newman fast algorithm to quickly give the community partition structure in the network and then give the corresponding TA planning scheme.

D. Newman Community Detection algorithm based on Modularity

The proposed Newman fast community detection algorithm based on modularity in this section is a kind of agglomerative algorithm based on greedy thought. The basic idea of the algorithm is to first set each vertex in the network as a separate community, and then select the community pairs that maximize the value of modularity Q to be merged. If all the vertices in the network belong to the same community, the merge process stops. The whole process is a bottom-up process, and finally this process get a tree map, in which the leaf nodes of the tree represent the vertices of the network and each layer of the tree corresponds to a specific partition of the network. The partition with the largest modularity is selected as the efficient partition of the network from all levels of the tree map.

Suppose the network have n nodes with m edges, the number of the community merged per step is r. Form an $r\times r$ matrix e, the matrix element e_{vw} of which represents the percentage of the edges number between the nodes in community v and the nodes in the community w to the total edges number of network.

The steps of the Newman fast community detection algorithm are as following:

1) Initialize the topology of the network $G=(V, E)$, which is n independent communities. The initialization matrix e_{vw} and b_v are given by the following in (12) and (13) respectively.

$$a_{vw} = \begin{cases} 1/2m, & \text{existing edge between } v \text{ and } w \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

$$b_v = \frac{d_i}{2m} \tag{13}$$

d_i in (13) denotes the modularity of node i, given by the above (8).

2) Merge the community pairs with the edge connected according to the direction of the maximum or minimum ΔQ, and calculate the modularity increment ΔQ after merging. The definition of ΔQ is given as the following formula:

$$\Delta Q = e_{vw} - e_{wv} - 2b_v b_w = 2(e_{vw} - b_{vw}) \tag{14}$$

3) Modify the community symmetry matrix e and the corresponding column of community v and community w after community pairs are merged.

4) Repeat step 2) and 3) to merge the community until the whole network is merged into one community.

5) Choose the partition with the largest modularity from all level partitions as the final partition structure of the network.

Applying the Newman fast community detection algorithm mentioned above, the community partition structure of the network can be quickly presented. The communities in the network will correspond to the tracking area (TA) in the HCN, and the corresponding TA planning scheme can be given.

IV. Experimental Analysis

The ultimate purpose of the TA planning is to find a balance between the location update signaling and the system paging signaling. In order to evaluate the performance of the TA planning, in this section, the performance of the TA planning scheme will be analyzed by the modularity introduced in the third section in case of different number of SC and different expectations of the SC Poisson distribution.

A. Experimental environment

1) Cellular deployment

Due to the randomness of the SC base stations deployment, many traditional base station deployment models are not suitable for HCN. In this paper, we will adopt the model of the SC base station that meets the Poisson point process. The Poisson point process $\beta_{A1}, ..., \beta_{An}$ can be defined as a subset of in complementary intersection regions $A_1, ..., A_n$ of random point processes β, and β_{A1}, ..., β_{An} are mutually independent. Then for any bounded region A, the point number $N\beta_A$ of β_A will follow the Poisson distribution with the parameter $\lambda\|A\|$, then there will be:

$$P(N\beta_{Ai} = k_i, 1 \le i \le n) = \prod_{i=1}^{n} \exp(-\lambda\|A_i\| \frac{\lambda\|A_i\|^{k_i}}{k_i!}) \tag{15}$$

In (15), λ is the expectation of the Poisson distribution point process, β represents the random point process, β_A represents a finite countable subset falling in region A during the random point process, and $N\beta_A$ represents the points number in the subset β_A.

According to (15), a schematic diagram of cellular base station distribution is obtained. As shown in Fig.3, the expectation of the SC Poisson distribution is λ=100, which distributed on a two-dimensional plane of 1000 × 1000 square meters with 102 actual small cellular. In this paper, the SC deployment model is used to conduct the experimental comparison simulation.

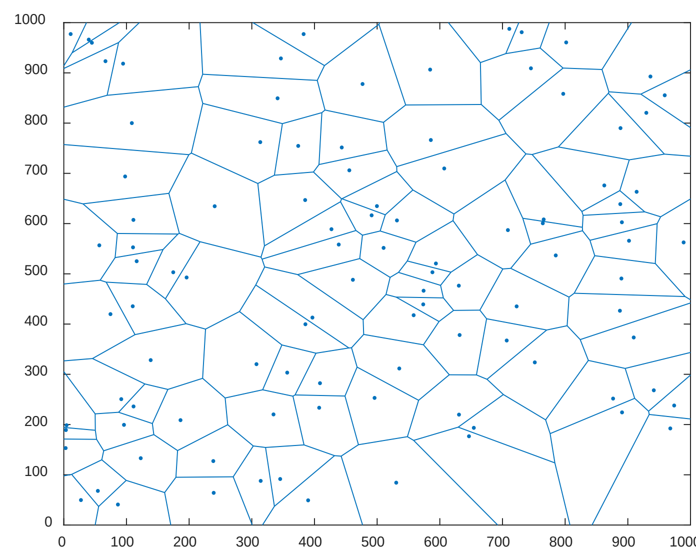

Figure 3. Schematic diagram of the cellular base station distribution, in which each point represents the location of the base station

2) Simulation parameters

The system simulation uses the above cell deployment model with Passion distribution, in which the parameters are set as Table 1.

Table 1. Simulation parameters and environment

Parameter name	value
Cellular deployment	Poisson point process
Scene size	1000×1000(square meter)
Simulation tools / Environment	MATLAB 2016a/Windows 10

B. *Performance analysis*

This paper improves on the basis of [7]. The TA planning scheme in [7] is to use the community detection algorithm based on cooperative game theory, and the community division is based on the revenue value generated by the cooperative game. However, in this paper, the community division by Newman algorithm is based on the modularity. Both the paper and the literature [7] apply the community detection algorithm to give a TA planning solution. Therefore, this paper compares the TA planning scheme based on collaborative game theory in [7] with the proposed scheme NCD-TAP by experiments. Analyze the performance of two TA planning schemes with different number of SC base stations and different expectation of SC Poisson distribution.

In this section, an SC base station model following Poisson point process is used to simulate. Here, different numbers of the SC base station distributed scenes are randomly generated. The modularity of each experiment and different scheme are all from the average of 10 experiments as shown in table 2.

According to the data analysis in Table 2, as the number of SC base stations in a scene gradually increases from 34 to 500, the modularity of the scheme in [7] will gradually decrease and gradually approach to about 0.0101, and at the same time, the modularity of the scheme in this paper will gradually decrease and gradually approach around 0.1250. It is worth noting that when the number of SC base stations in the scene is less than 50, the modularity of the scheme in [7] is greater than NCD-TAP. As the number of SC gradually increases from 50 to 500, the modularity of the proposed scheme will be much larger than the scheme in [7], as shown in Fig. 4. A great modularity indicates that in this TA planning scheme we divided more cells into TA to ensure that the location update signaling is reduced, and ensure that the system paging signaling reach a minimum level for the signaling overhead optimization. The proposed scheme in this paper is more suitable for the scene of large scale of SC base stations.

Here we also use the model of SC base station following Poisson point process to simulate and randomly generate the SC base station distribution scene with different expectation of SC Poisson distribution. The modularity of each experiment and different scheme are all from the average of 10 experiments as shown in table 3.

Table 2. Comparison of simulation results with different number of SC base stations

Number of base station	34	50	100	150	200	250	300	350	400	450	500
Value of Q in [7]	0.4737	0.3705	0.1418	0.0680	0.0436	0.0232	0.0118	0.0103	0.0102	0.0101	0.0101
Value of Q in NCD-TAP	0.3933	0.3340	0.2324	0.1897	0.1623	0.1490	0.1338	0.1300	0.1266	0.1260	0.1250

Table 3. Comparison of simulation results with different expectation of SC Poisson Distribution

Expectation of SC Poisson Distribution	100	200	300	400	500	600	700	800
Value of Q in [7]	0.09816	0.03570	0.02693	0.01374	0.01295	0.01277	0.01056	0.01057
Value of Q in NCD-TAP	0.23050	0.16125	0.12105	0.11560	0.11680	0.11230	0.11000	0.11020

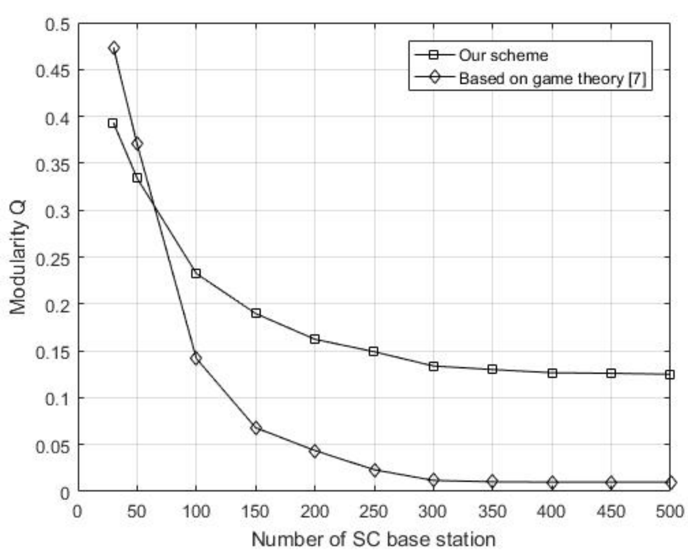

Figure 4. Comparison of the modularity Q values of two different SC schemes

According to the data analysis in Table 3, as the expectation of SC base stations gradually increases from 100 to 800, the modularity of the scheme in [7] will gradually decrease and gradually approach to about 0.0105. The modularity in NCD-TAP will gradually decrease and gradually approach around 0.1102. It is noteworthy that in the scene where the expectation of SC Poisson distribution is between 100 and 800, the modularity of NCD-TAP is always larger than that in [7], as shown in Fig. 5. In the same way, the greater the modularity is, the more optimal signaling overhead is realized in this scheme. The proposed scheme in this paper is more suitable for the scene of SC Poisson distribution with high expectation.

It can be seen from the analysis that the main reason why the modularity of the scheme in [7] is lower when the number of small cells and Poisson distribution of small cells is large. As the number of cells in the scene is increasing, the game defect, that is the prisoner’s dilemma phenomenon, will be more evident. By this stage, more and more small cells are divided into separate TAs, resulting in reducing the modularity of TA planning faster.

Comprehensive analysis shows that the proposed scheme is suitable for the scene where the number of SC and the expectation of SC Poisson distribution are larger. Therefore, this scheme in this paper can achieve a better balance between location update signaling and system update signaling in a massive cellular deployment environment.

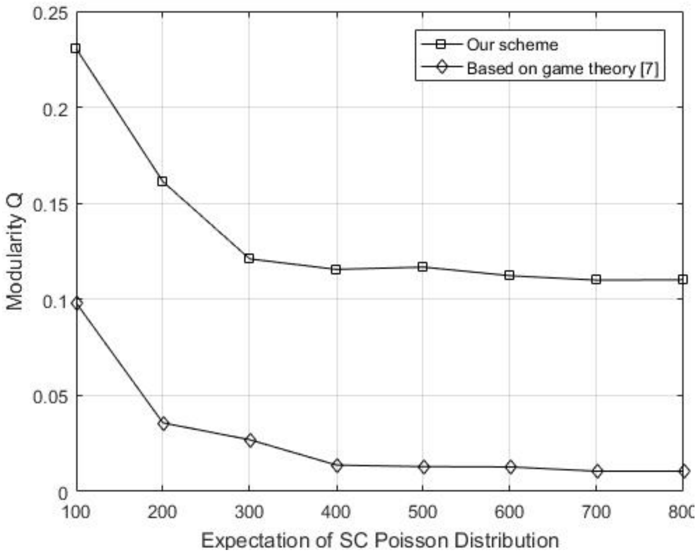

Figure 5. Comparison of modularity Q values of two schemes with different Poisson distribution expectations

V. Conclusion

In order to deal with the deployment environment of massive SC in HCN, and to solve the problems of uneven location updating signaling and ping-pong effect in the existing TA planning schemes, a TA planning scheme based on community detection is proposed in this paper. Firstly, the TA planning problem is modeled as a graph segmentation problem, the problem is further modeled as a community detection problem in a complex network and a TA planning scheme based on the Newman fast community detection algorithm is presented. Then, this paper proposes the modularity in community detection to evaluate the performance of TA planning scheme. Finally, through the simulation and comparison of the TA planning scheme based on cooperative game, this paper draws the conclusion that the proposed scheme NCD-TAP is suitable for HCN with large scale of SC and high expectation of Poisson distribution.

In the future work, on the one hand we will use the two-dimensional plane of the cellular base station that obeys the Poisson point distribution process to scatter user points, simulate user switching, paging data, and build a network map for TA planning. On the other hand, we will introduce more related TA planning schemes to analyze the performance of the TA planning scheme from the perspective of location update rate and signaling cost overhead.

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Shanshan Tu is an associate professor in Faculty of Information Technology, Beijing University of Technology, China. He worked in the Department of Electronic Engineering at Tsinghua University as a postdoctoral researcher from 2014 to 2016. He received his PhD degree from Computer Science Department at Beijing University of Post and Telecommunication in 2014. He visited University of Essex as joint doctoral training from 2013 to 2014. His research interests are in the areas of cloud computing and information hiding analysis technology.