International Journal of Computer Networks and Applications
Volume 2, Issue 1, January - February (2015)

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Overlapping Community Detection in Social Networks Using Parliamentary Optimization Algorithm

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Abstract – Parallel to growth of the Internet, social networks have become more attractive as a research topic in many different disciplines and many real systems can be denoted as a complex network. Identifying major clusters and community structures allow us to expose organizational principles in complex network such as web graphs and biological networks. It has been shown that communities are usually overlapping. Overlap is one of the characteristics of social networks, in which a person may belong to more than one social group. In recent years, overlapping community detection has attracted a lot of attention in the area of social networks applications. Many methods have been developed to solve overlapping community detection problem, using different tools and techniques. In this paper, one of the most recent social-based metaheuristic algorithm, Parliamentary Optimization Algorithm (POA), has been firstly proposed to discover overlapping communities in social networks.

Index Terms – Social Networks, Overlapping Community Detection, Parliamentary Optimization Algorithm.

1. INTRODUCTION

Networks are basic representation of various kinds of complex system, in society, biology, and other fields. Thanks to developments in computing and communications technology, the quantity of network data has increased. As the number and size of network datasets has increased, so too has the interest in computational techniques that help us to analyze the characteristic of networks.

Many complex systems, such as social [1] and biological networks [2], can be naturally represented as complex networks [3]. Nowadays, most of research focused on understanding the evolution and organization of such networks. To do so, networks are modeled as graphs, where nodes represent individual members and edges represent their relationships in systems. Particularly, community detection, as an effective way to understand the relationship between structure and function of complex networks.

Community is formed by individuals such that those within a group interact with each other more frequently than with those outside the group. Community detection divides a network into groups of nodes, where nodes are densely connected inside, while sparsely connected outside. However, it has been well understood that people in a real social network are naturally characterized by multiple community memberships. For example, a person usually has connections to several social groups like family, friends and colleges; a researcher may be active in several areas. In community detection, these objects should be divided into multiple groups, which is known as overlapping.

So far, lots of overlapping communities have been proposed, which can be roughly divided into two classes, node-based and link-based overlapping community detection algorithms. The node-based overlapping community detection algorithms, classify nodes of the network directly. The link-based algorithms cluster the edges of network, and map the final link communities to node communities by simply gather nodes incident to all edges within each link communities [4].

In this paper, we use social-based metaheuristic optimization algorithm to detect overlapping community in social networks. There are a lot of social-based meta-heuristic optimization algorithms recently proposed in the literature. Tabu search algorithm is the best known of these algorithms and used frequently the applications. There are many algorithms produced recently: Imperialist Competitive Algorithm, Parliamentary Optimization Algorithm, Teaching and Learning Based Optimization Algorithms, Social Emotional Optimization Algorithm, Brain Storm Optimization Algorithm, Group Leaders Optimization Algorithm, Hierarchical Social Metaheuristic, Social-Based Algorithm, Human Group Formation. Parliamentary Optimization Algorithm (POA) has been firstly proposed as a novel overlapping community detection method in this work.

The rest of the paper is organized as follows. Section 2 briefly surveys related work. In section 3, POA is described and in Section 4, the POA for overlapping community detection problem is explained. Experimental results are described in Section 5 and the paper is concluded in Section 6.

2. RELATED WORKS

Many algorithms have been developed to detect overlapping communities in complex networks, such as GaoCD [4], CONGA [5], CPM [6], GA-Net+ [7], etc.

GaoCD is a genetic algorithm developed for detecting overlapping community with link clustering. The algorithm first finds the link communities by optimizing objective function partition density D [8], and then map the link communities to node communities based on a novel genotype representation method. The number of the communities found by GaoCD can be automatically determined, without any prior information.

GA-Net+ [7], proposed by Pizzuti, first adopts genetic algorithm to detect overlapping communities. It proposes a method to transfer node graph to line graph, in which nodes present edges of the node graph, while edges present adjacent relationships of edges of node graph. The line graph is then used as the input of the genetic algorithm, and in each generation, the line graph is transferred to node graph to evaluate the fitness. After selection, the graph is transferred again for the next iteration of GA. The transfer between line graph and node graph costs much computation and decreases the effectiveness.

CPM is the most famous and widely used algorithm. However, CPM has a strict community definition and is not flexible enough for real network. When the network is too dense, CPM finds giant clique communities, however, when the network is too sparse, it finds no cliques at all. And thus, the coverage of CPM largely depends on the feature of the network, providing no global prospective for the whole network.

There are other algorithms for overlapping community detection, such that the SCP of Kumpula [9], Lancichinetti’s algorithm [10], etc. All of them need prior information, or have coverage problem, or suffer of efficiency.

3. PARLIAMENTARY OPTIMIZATION ALGORITHM

A parliamentary system, also known as the parliamentarianism is a system of government in which the power to make and execute the laws is held by the parliament. Members of the parliament are elected in general elections. People usually vote in favor of the parties rather than particular persons. Members of a parliament normally belong to political parties. They support their parties in parliamentary votes. Grouping members of a parliament into clusters, results in competitions among parties in trying to gain superiority over other parties. Almost in all democratic countries, political parties form the population of the parliaments [11].

In POA, optimization process is started by first creating a population of individuals. These individuals are supposed to be the members of the parliament. In the next step, population is divided into some political groups (parties) and a fixed number of members with highest fitness are selected as group candidates or leaders. After this step, intra-group competition begins. In the intra-group competition step, each regular member is biased toward all candidates in proportion to their fitnesses. This observation is modeled here as the weighted average of distance vectors from a regular member to candidates. At the end of intra-party competition, a few candidates with highest fitness are elected as final candidates of each group. They compete with candidates of other groups in the next stage. Both candidates and regular members of a group are important in determining the total power of a group [12].

Inter-group competition begins just after intra-group competitions ends. Political groups within the parliament perform competition with other groups to impose them their own candidate.

Powerful groups sometimes agree to join and merge into one to increase their wining chance. Inter-group competition begins just after intra-group competitions end. Political groups within the parliament compete with other groups to impose their own candidates to them [13]. Table 1 shows process steps of the POA.

3.1. Population initialization

A population of initial solutions with size N is being dispread over the d-dimensional problem space at random positions. Each individual of the population is coded as a d-dimensional continuous vector as in equation 1.

$$P = [p_1, \ p_2, \ldots, p_d], \ p_i \in \mathrm{IR} \quad (1)$$

Each individual could be either a regular member or a candidate of a given group. A fitness function f is used to calculate the power of an individual.

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Step 1. Create the initial population
Step 2. Partition population into M groups each with L individuals
- Step 2.1. Pick θ highly fitted individuals as candidates of each group

Step 3. Intra-group competition
- Step 3.1. Tendency regular members to candidates of each group
- Step 3.2. Reassign new candidates
- Step 3.3. Compute power of each group

Step 4. Inter-group competition
- Step 4.1. Pick λ most powerful groups and merge them with probability P_m
- Step 4.2. Remove γ weak groups with probability P_d

Step 5. If stopping condition is not met go to step 3
Step 6. Report the best candidate as the solution of the optimization problem

Table 1 Process of the POA

3.2. Population partitioning

In order to form initial groups, population is partitioned into M groups. Each group contains L individuals. N, M, and L are positive integers and are selected in such a way to satisfy the following equation.

$$N = M \times L \tag{2}$$

Top $\theta < L/3$ candidates with high fitness are then considered as candidates of each group. At this point all groups have the same number of members, however in the course of running the algorithm groups might earn different number of individuals because of merge and collapse mechanisms. Figure 1 shows the initial state of the population portioned into three groups, each with five candidates.

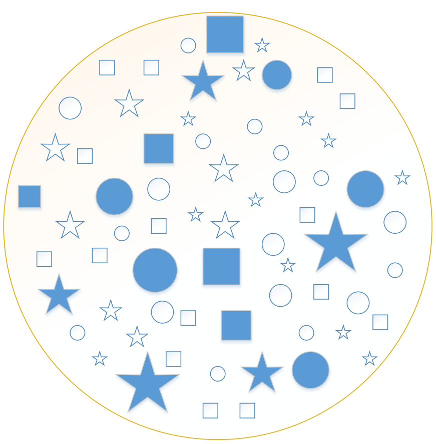

Figure 1 Population partitions at first iteration, blue symbols represent candidates

3.3. Intra-group competition

Regular members of a group get biased toward candidates after interactions take place between candidates and regular members. This biasness is assumed here to be linearly proportional to weighted average of vectors connecting a member to candidates. Each candidate is weighted to the extent of its fitness value as shown in equation 3.

$$p' = p_0 + \eta \left(\frac{\sum_{i=0}^{\theta} (p_i - p_0) \cdot f(p_i)}{\sum_{i=0}^{\theta} f(p_i)} \right) \tag{3}$$

In the above formula, η is a random number between 0.5 and 2 and allows the algorithm to search in a local search area around candidates. A regular member is allowed to change only if it takes a higher fitness value. After biasing, regular members might have higher fitness values than candidates. In such cases candidates are reassigned again. Figure 2 shows biasing mechanism. P_0 is a regular member and P_i is a candidate. P_0 is the new position of the regular member.

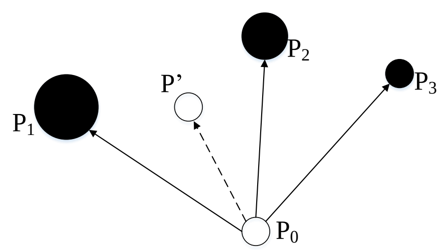

Figure 2 Biasing a member toward candidates

A regular member is allowed to change only if it takes a higher fitness value. After biasing, regular members might have higher fitness values than candidates. In such cases candidates are reassigned again.

Let $Q_i = \{Q_{i,1}, Q_{i,2}, \ldots, Q_{i,\theta}\}$ and $R_i = \{R_{i,\theta+1}, R_{i,\theta+2}, \ldots, R_{i,L}\}$ be the vectors of candidates and the remaining regular members of the i-th group respectively. Power of this group is calculated as in equation 4, in which m and n are candidate and regular member weighting constants.

$$Power^i = \frac{m.Avg(Q_i) + n.Avg(R_i)}{m+n}; m \geq n \tag{4}$$

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3.4. Inter-group competition

Stronger groups sometimes join and merge to one group in order to advance their power. To perform merging, a random number is generated and if it is smaller than P_m, λ most powerful groups are picked and merged into one. During the course of running the algorithm, weak groups are removed for saving computation power and reducing the function evaluations. Like merging, a random number is generated and if it is smaller than P_d, γ groups with minimum powers are eliminated. Figure 3 illustrates the inter-group cooperation between two sample groups. Candidates are reassigned after this operation.

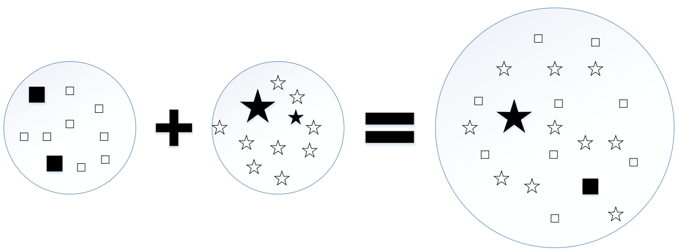

Figure 3 Merging two groups into one

3.5. Stopping condition

At the end of the algorithm, a group wins the competitions and its best member (candidate with the maximum fitness) is considered as the solution of the optimization problem. Two stopping conditions are possible: Algorithm terminates if either maximum number of iterations is reached or, during some successive iterations, no significant enhancement in fitness values is observed.

The whole optimization process is shown as flowchart in Figure 4.

4. OVERLAPPING COMMUNITY DETECTION IN NETWORKS WITH POA

As mentioned in the third section, POA is started by first creating a population of individuals. These individuals are supposed to be the members of the parliament. Individuals have constituted the initial population ($I_1, I_2, \ldots, I_m$), which are generated between 0 and 1 numbers randomly. In this work, number of communities ($C_1, C_2, \ldots, C_n$) found by proposed algorithm. Representation of the initial population is shown in Figure 5.

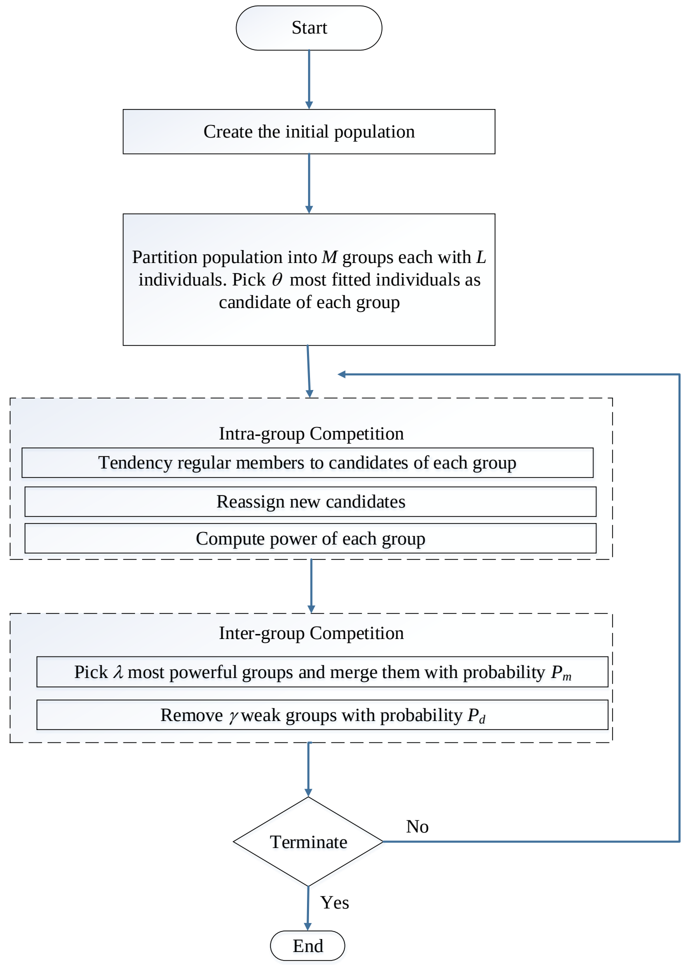

Figure 4 Flowchart of POA

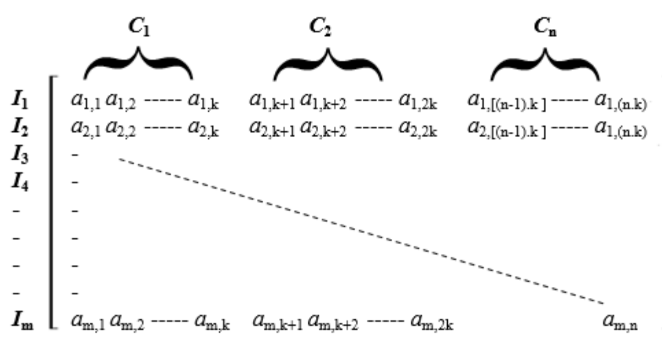

Figure 5 Representation of the initial population

In this matrix, k is the total number of nodes in the network. After this process, population is partitioned into M groups, each group contains L individuals. At this stage, a measurement is required to determine group of candidates. In Ref. [14], an extension of modularity EQ is proposed to evaluate the goodness of overlapped community decomposition. Modularity is a property of a network and a

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specific proposed division of that network into communities. The extended modularity is defined as

$$EQ = \frac{1}{2m} \sum_{i}^{0} \sum_{v \in Ci,\ w \in Ci} \frac{1}{Ov\ Ow} \left(Avw - \frac{kv\ kw}{2m} \right) \qquad (5)$$

Let O_v be the number of communities to which vertex v belongs, *Avw* are the elements of the adjacency matrix of network, *kv* is the degree of vertex v and m is the total number of edges in network. Strong community structure can be observed if *EQ* is close to 1. When the number of edges within a community gets close to random, *EQ* will tend to 0. Obviously, if all the nodes in a network belong to a single community, then *EQ* =0.

According to equation 5, candidates of groups determined and intra-group competition starts. Regular members of a group get biased toward candidates, candidates are determined again and power of each group is calculated as in equation 4. After intra-group competition, stronger groups join and merge to one group in order to amplify their power in inter-group competition. Algorithm terminates if during some successive iterations no significant enhancement in fitness observed. At the end of algorithm, a group wins the competitions and its best member in considered as the solution of the overlapping community detection problem.

5. EXPERIMENTAL RESULTS

In order to analyze the effectiveness of POA, experiments on artificial networks have been designed. The experiments on artificial networks evaluate the ability POA to detect the overlapping nodes. Figure 6 includes artificial network, which consist of 9 vertices and 13 edges. The implementation of the algorithms was carried out in MATLAB.

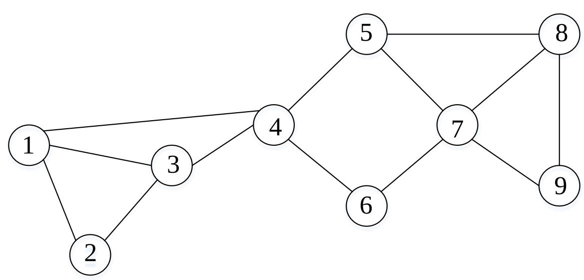

Figure 6 A typical kind of network

In the first step, initial population shown in Table 2 is generated. These values are generated randomly between 0 and 1 in MATLAB.

Produced first population is divided into 3 groups each of them consist of 10 individuals. In this case, the values of variables of equation 2 are listed in Table 3.

Variables	**Values**
N	30
M	3
L	10

Table 3 Values of variables of equation 2

The parameter values of intra-group competition step of POA used in equations 3 and 4 have been determined as shown in Table 4

Parameters	**Values**
η	0.68
m	0.58
n	0.23

Table 4 Parameter values of intra-group competition step

The fitness value is calculated for each group according to equation 5 and highest 3 individuals are selected as candidates of each group. Fitness values of the individuals of each group are shown in the Table 5.

Group 1		**Group 2**		**Group 3**	
Individuals	**Fitness Values**	**Individuals**	**Fitness Values**	**Individuals**	**Fitness Values**
I_1	1.96	I_1	**1.53**	I_1	1.05
I_2	1.50	I_2	0.80	I_2	0.21
I_3	1.38	I_3	0.86	I_3	0.67
I_4	2.00	I_4	0.65	I_4	0.97
I_5	**2.71**	I_5	**2.07**	I_5	**1.36**
I_6	**2.90**	I_6	0.86	I_6	**2.40**
I_7	**2.28**	I_7	0.26	I_7	0
I_8	1.50	I_8	0.42	I_8	1.11
I_9	0.61	I_9	2.07	I_9	1.25
I_{10}	0.61	I_{10}	**2.01**	I_{10}	**1.28**

Table 5 Fitness values of individuals

In the table values are written in bold accepted as candidates of each group. In intra-group competition process, according to the equation 3, other members of the group towards to determined candidates and then new candidates are identified. According to equation 4, the power of each group has calculated from the new candidates and these values are given in the Table 6.

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	Community 1									Community 2								
I_{1}	0.42	0.15	0.30	0.46	0.57	0.64	0.94	0.46	0.22	0.78	0.81	0.78	0.64	0.80	0.38	0.36	0.33	0.21
I_{2}	0.36	0.16	0.18	0.56	0.59	0.45	0.95	0.41	0.19	0.73	0.80	0.78	0.57	0.78	0.28	0.46	0.45	0.39
I_{3}	0.41	0.18	0.26	0.52	0.57	0.57	0.93	0.46	0.22	0.75	0.80	0.79	0.61	0.76	0.36	0.42	0.38	0.28
I_{4}	0.40	0.18	0.26	0.52	0.57	0.57	0.93	0.46	0.22	0.75	0.81	0.79	0.60	0.75	0.37	0.43	0.37	0.29
I_{5}	0,42	0,23	0,28	0,55	0,55	0,59	0,91	0,51	0,25	0,70	0,81	0,79	0,59	0,68	0,39	0,47	0,42	0,30
I_{6}	0,42	0,16	0,25	0,50	0,59	0,57	0,93	0,45	0,21	0,76	0,81	0,79	0,62	0,78	0,35	0,40	0,37	0,26
I_{7}	0,41	0,17	0,26	0,51	0,58	0,57	0,93	0,46	0,21	0,75	0,80	0,78	0,61	0,76	0,35	0,42	0,38	0,28
I_{8}	0,43	0,20	0,26	0,52	0,58	0,59	0,91	0,49	0,22	0,73	0,81	0,80	0,60	0,73	0,37	0,44	0,38	0,28
I_{9}	0,41	0,17	0,26	0,52	0,57	0,57	0,92	0,46	0,22	0,74	0,81	0,79	0,61	0,75	0,36	0,42	0,38	0,28
I_{10}	0,41	0,18	0,25	0,52	0,57	0,58	0,93	0,46	0,21	0,75	0,81	0,79	0,61	0,76	0,35	0,42	0,38	0,28
I_{11}	0,42	0,29	0,42	0,42	0,65	0,56	0,79	0,40	0,24	0,63	0,70	0,66	0,48	0,64	0,40	0,46	0,40	0,41
I_{12}	0,43	0,30	0,41	0,40	0,61	0,57	0,80	0,42	0,26	0,60	0,72	0,67	0,51	0,63	0,42	0,43	0,42	0,37
I_{13}	0,41	0,31	0,43	0,39	0,56	0,57	0,78	0,42	0,32	0,60	0,68	0,72	0,50	0,60	0,42	0,48	0,38	0,37
I_{14}	0,42	0,33	0,39	0,41	0,61	0,56	0,80	0,42	0,27	0,59	0,74	0,67	0,54	0,64	0,43	0,43	0,45	0,37
I_{15}	0,41	0,33	0,41	0,40	0,60	0,56	0,78	0,43	0,28	0,60	0,72	0,67	0,52	0,64	0,44	0,44	0,43	0,40
I_{16}	0,42	0,31	0,41	0,41	0,61	0,56	0,79	0,42	0,27	0,60	0,72	0,68	0,52	0,64	0,42	0,44	0,42	0,39
I_{17}	0,42	0,32	0,40	0,41	0,61	0,57	0,79	0,41	0,26	0,60	0,72	0,67	0,52	0,64	0,42	0,44	0,42	0,39
I_{18}	0,42	0,31	0,41	0,41	0,61	0,56	0,79	0,42	0,27	0,61	0,72	0,67	0,52	0,63	0,43	0,44	0,42	0,39
I_{19}	0,43	0,31	0,40	0,41	0,61	0,57	0,81	0,41	0,28	0,61	0,73	0,68	0,52	0,63	0,42	0,44	0,42	0,38
I_{20}	0,41	0,32	0,41	0,41	0,62	0,56	0,79	0,41	0,26	0,60	0,73	0,67	0,52	0,65	0,43	0,44	0,43	0,40
I_{21}	0,43	0,28	0,37	0,50	0,49	0,55	0,76	0,52	0,30	0,68	0,72	0,76	0,52	0,64	0,31	0,34	0,44	0,39
I_{22}	0,44	0,31	0,37	0,46	0,47	0,57	0,77	0,51	0,34	0,69	0,74	0,76	0,53	0,64	0,34	0,34	0,42	0,35
I_{23}	0,43	0,29	0,37	0,49	0,50	0,54	0,75	0,52	0,31	0,69	0,73	0,76	0,52	0,64	0,32	0,35	0,43	0,39
I_{24}	0,43	0,28	0,37	0,49	0,50	0,55	0,75	0,52	0,31	0,69	0,73	0,75	0,52	0,64	0,32	0,35	0,43	0,34
I_{25}	0,42	0,29	0,36	0,49	0,50	0,55	0,75	0,51	0,31	0,69	0,73	0,74	0,52	0,64	0,31	0,34	0,44	0,39
I_{26}	0,43	0,27	0,37	0,50	0,52	0,53	0,74	0,52	0,29	0,68	0,73	0,76	0,50	0,64	0,32	0,35	0,44	0,42
I_{27}	0,43	0,29	0,37	0,49	0,50	0,54	0,75	0,52	0,31	0,68	0,73	0,76	0,5	0,64	0,32	0,34	0,43	0,39
I_{28}	0,43	0,29	0,37	0,49	0,50	0,55	0,75	0,52	0,31	0,68	0,73	0,76	0,52	0,64	0,32	0,35	0,43	0,39
I_{29}	0,43	0,28	0,37	0,49	0,50	0,54	0,75	0,51	0,31	0,69	0,73	0,75	0,52	0,64	0,32	0,35	0,44	0,39
I_{30}	0,44	0,30	0,37	0,48	0,49	0,55	0,76	0,53	0,32	0,69	0,74	0,76	0,52	0,63	0,33	0,35	0,42	0,37

Table 2 Initial population

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Group number	Power of Group
1	2.26
2	1.57
3	1.41

Table 6 Power of groups

Inter-group competition begins after this step. In this step, a random value is generated and compared to this value the most powerful $\lambda=2$ groups are combined approximately P_m= 30 % or the weakest group is deleted P_d = 1%. If groups are not joined we return to the intra-group competition step. These steps continue until all groups combined and optimal element of the obtained group is considered as solving the problem. After merging all groups, fitness value of individuals are shown in Table 7. As mentioned at the end condition of the algorithm, the highest value in the table is considered as solution of overlapping community detection problem.

Individuals	Fitness Values	Individuals	Fitness Values	Individuals	Fitness Values
I_1	**4.63**	I_{11}	1.53	I_{21}	1.36
I_2	3.78	I_{12}	2.07	I_{22}	1.28
I_3	3.78	I_{13}	0.91	I_{23}	1.11
I_4	3.78	I_{14}	2.07	I_{24}	1.36
I_5	2.71	I_{15}	3.38	I_{25}	1.36
I_6	4.63	I_{16}	2.07	I_{26}	2.40
I_7	3.78	I_{17}	2.07	I_{27}	1.11
I_8	3.78	I_{18}	1.03	I_{28}	1.36
I_9	3.78	I_{19}	2.07	I_{29}	1.36
I_{10}	3.78	I_{20}	3.38	I_{30}	1.11

Table 7 Fitness values at the end of POA

According to Table 7, the first individual is solution. Figure 7 indicates the communities found by POA. It is clear that the network constitutes of two communities. Node 5 and node 6 are nodes with obvious overlapping node.

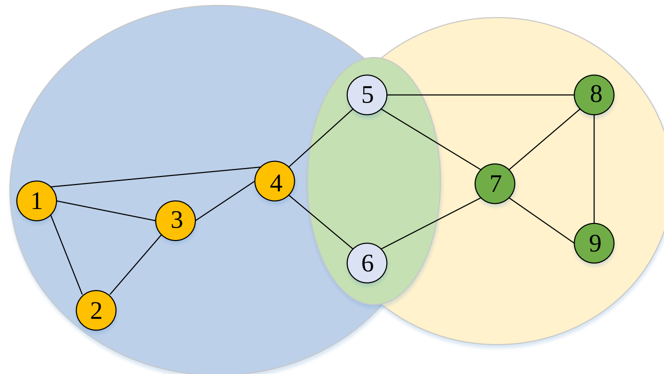

Figure 7 Communities found by POA

6. CONCLUSIONS

In this paper, a novel overlapping community detection algorithm, which tries to optimize network modularity using parliamentary optimization algorithm with fitness function has been proposed. To the best of our knowledge, it is the first time POA has been applied to overlapping community detection problems. Although POA is firstly proposed and not any modifications or additions have been performed to the algorithm, the effective experimental results obtained from the artificial network is promising. The designed POA can help to analyze the community structure and detect overlapping communities. The limitation of this work is that, only modularity measure has been used as the fitness function to find the overlapping community of a network. In our further work, POA will be generalized for multi objective purposes in large networks.

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