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A Michigan memetic algorithm for solving the community detection problem in complex network

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ABSTRACT

Community structure is an important feature in complex networks which has great significant for organization of networks. The community detection is the process of partitioning the network into some communities in such a way that there exist many connections in the communities and few connections between them. In this paper a Michigan memetic algorithm; called MLAMA-Net; is proposed for solving the community detection problem. The proposed algorithm is an evolutionary algorithm in which each chromosome represents a part of the solution and the whole population represents the solution. In the proposed algorithm, the population of chromosomes is a network of chromosomes which is isomorphic to the input network. Each node has a chromosome and a learning automaton (LA). The chromosome represents the community of corresponding node and saves the histories of exploration. The learning automaton represents a meme and saves the histories of the exploitation. The proposed algorithm is a distributed algorithm in which each chromosome locally evolves by evolutionary operators and improves by a local search. By interacting with both the evolutionary operators and local search, our algorithm effectively detects the community structure in complex networks and solves the resolution limit problem of modularity optimization. To show the superiority of our proposed algorithm over the some well-known algorithms, several computer experiments have been conducted. The obtained results show MLAMA-Net is effective and efficient at detecting the community structure in complex networks.

1. Introduction

Community structure in an important feature of complex networks which is used for understanding the function and organization of complex network. A community or a partition refers to a sub graph such that the nodes in sub graph are more densely connected internally than to the rest of graph. Community detection problem is a well-known problem in complex networks which is used in sociology, biology and computer science where systems are modeled by graphs. Newman and Girvan was defined modularity as an important measure function for evaluating the quality of community structure in complex networks [1]. Modularity is based on the idea that no community structure is expected to be found in a random network. On the basis of modularity concept, community detection can be modeled as a modularity optimization problem. Due to the wide spread of applications of community detection, the numerous optimization algorithms have been proposed to solve this problem in recent years.

Genetic algorithm (GA) is one of the famous methods for optimization problem. Genetic algorithms belong to the larger class of evolutionary algorithms (EAs) which generate solutions for optimization problem using techniques inspired by natural evolution. Genetic algorithms can be divided into two broad approaches, Michigan and Pittsburgh approaches. In pittsburg approach, one of the chromosomes in the population becomes the solution of the problem being solved whereas in Michigan approach the whole population represents the solution. For example in the community detection problem, in Michigan approach, each chromosome encodes a community for a node and the set of all chromosomes in the population represents the solution which is a partitioning for the network whereas in the pittsburgh approach each chromosome encodes a partitioning for the whole network.

Combining a genetic algorithm with a local search produces a type of evolutionary algorithm which is known as a memetic algorithm (MA) [2]. Memetic algorithm uses the local search to either accelerate the discovery of good solutions, for which evolution alone would take too long to discover, or to reach solutions that would otherwise be unreachable by evolution or a local search alone.

Learning automata are based on the general schemes of reinforcement learning algorithms. They select actions via a stochastic

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process and apply them on a random unknown environment. They can learn the best action by iteratively performing and receiving stochastic reinforcement signals from the unknown environment. These stochastic responses from the environment show the favorability of the selected actions, and the learning automata change their action selecting mechanism in favor of the most promising actions according to responses from the environment.

In the first part of this paper we present a new algorithm based on the Michigan memetic algorithm called MLAMA-Net, for detecting community structure in network. In the proposed algorithm, the population of chromosomes is a network of chromosomes which is isomorphic to the input network. The chromosome in each node of the network represents a part of the solution and the whole population represents the solution. When the algorithm terminates the chromosome in each node represents a community for its corresponding node and the whole population represents a partitioning for the network. Each node of network is also equipped with a learning automaton which is utilized to save the histories of local search. The proposed algorithm is a distributed algorithm in which each chromosome locally explores a community for its corresponding node by evolutionary operators and improves its community by a local search. MLAMA-Net introduces the priority concept to solve the resolution limit of modularity optimization in community detection problem.

In the second part of the paper, the proposed algorithm is compared with other well-known algorithms for the community detection problem on two groups of networks which are used in the literature: real world networks and synthetic networks. Computer simulations show that the proposed algorithm outperforms other algorithms in terms of quality of solution and accuracy of solution in both real world networks and synthetic networks.

The rest of the paper is organized as follows. The theory of learning automata is described in Section 2. In Section 3, an overview of related works on community detection problem is represented. The new proposed algorithm is described in Section 4. Section 5 is including of implementation considerations, simulation results, and comparison with other algorithms to highlight the contributions of the new algorithm. Finally, conclusions and future works are discussed in Section 6.

2. Theory of learning automata

A learning automaton [3] is an adaptive decision-making unit. It can be described as determination of an optimal action from a set of actions through repeated interactions with an unknown random environment. It selects an action based on a probability distribution at each instant and applies it on a random environment. The environment sends a reinforcement signal to the automaton after evaluating the input action. The learning automaton processes the response of environment and updates its action probability vector. By repeating this process, the automaton learns to choose the optimal action so that the average penalty obtained from the environment is minimized.

The environment is represented by a triple $<\underline{\alpha},\underline{\beta},\underline{c}>$ where $\underline{\alpha}=\{\alpha_1,\ldots,\alpha_r\}$ is the finite set of the inputs, $\underline{\beta}=\{\beta_1,\ldots,\beta_m\}$ is the set of outputs that can be taken by the reinforcement signal, and $\underline{c}=\{c_1,\ldots,c_r\}$ is the set of the penalty probabilities, where each element c_i of $\underline{c}$ is associated with one input action α_i. When the penalty probabilities are constant, the random environment is said a stationary random environment. It is called a non stationary environment, if they vary with time. Depending on the nature of the reinforcement signal, there are three types of environments: P-model, Q-model and S-model. The environments, in which the output can take only one of two values 0 or 1, are referred to as P-model environments. The reinforcement signal in Q-model environment selects a finite number of the values in the interval $[a,b]$. When the output of environments is a continuous random variable in the interval $[a,b]$, it is referred to as S-model. The relationship between the learning automaton and the random environment is shown in Fig. 1.

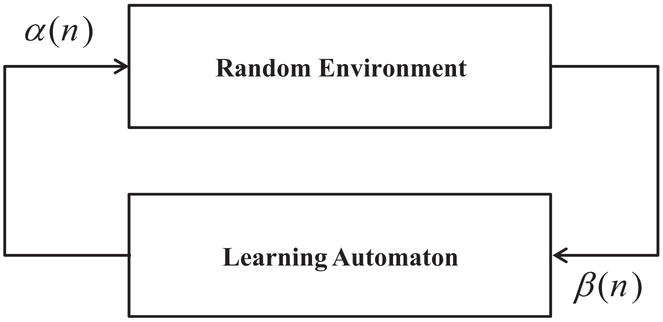


Fig. 1. The relationship between the learning automaton and random environment.

There are two main families of Learning automata [4]: fixed structure learning automata and variable structure learning automata. Variable structure learning automata are represented by a triple $<\underline{\beta},\underline{\alpha},T>$, where $\underline{\beta}$ is the set of inputs, $\underline{\alpha}$ is the set of output actions, and T is learning algorithm which is used to modify the action probability vector. Learning algorithm is the critical factor affecting the performance of variable structure learning automata. Suppose learning automaton selects action $\alpha_i(k)\in\underline{\alpha}$ according to action probability vector $\underline{p}(k)$ at instant k. The action probability vector $\underline{p}(k)$ is updated by the learning algorithm given in Eq. (1), if the selected action $\alpha_i(k)$ is rewarded by the random environment, and it is updated as given in Eq. (2), if the taken action is penalized. a and b denote the reward and penalty parameters and r is the number of actions that can be taken by learning automaton.

$$P_j(n+1)=\begin{cases}P_j(n)+a(1-P_j(n)) & j=i\\(1-a)P_j(n) & \forall j,j\neq i\end{cases}\tag{1}$$

$$P_j(n+1)=\begin{cases}(1-b)P_j(n) & j=i\\b/(1-r)+(1-b)P_j(n) & \forall j,j\neq i\end{cases}\tag{2}$$

If $a=b$, the recurrence Eqs. (1) and (2) are called linear reward-penalty (L_{R-P}) algorithm, if $a\gg b$ the given equations are called linear reward-ϵ penalty ($L_{R\epsilon P}$), and finally if $b=0$ they are called linear reward-Inaction (L_{R-I}). In the latter case, the action probability vector remains unchanged when the taken action is penalized by the environment.

Learning automata have a vast variety of applications in combinatorial optimization problems [5–10], computer networks [8,11–15], queuing theory [16,17], signal processing [18,19], information retrieval [20–22], adaptive control [23–25], neural networks engineering [26,27] and pattern recognition [28–30].

3. Related work

The community detection problem can be considered as a modularity optimization problem [1]. A network can be modeled by a graph $G=(V,E)$ where V is the set of $|V|=n$ nodes and $E=\{(i,j)|i,j\in V$ is the set of $|E|=m$ edges. The modularity can be written as

$$Q=\frac{1}{2m}\sum\nolimits_{i,j\in V}\left(A_{ij}-\frac{k_ik_j}{2m}\right)\delta(i,j)\tag{3}$$

where A_{ij} is the element of the adjacency matrix A, i.e., $A_{ij}=1$ if node v_i is connected to node v_j; otherwise, $A_{ij}=0$, m is the number of edges, $k_i = \sum_{j \in V} A_{ij}$ is the degree of node v_i and $\delta(.)$ is the delta function, i.e., $\delta(i,j) = 1$ if node v_i and node v_j are in the same community; otherwise, $\delta(i,j) = 0$. The term $\frac{k_i k_j}{2m}$ represents the expected number of edges between node v_i and node v_j in a random network with the same size and nodes degree distribution. The modularity with larger value shows the more significant community structure in given graph.

Resolution limit problem is the main problem in modularity optimization based algorithm that they may fail to find communities which are smaller than a certain size. Many approaches [31,32] have been proposed to solve the resolution limit problem by definition the other quality metrics. Most of these approaches need a tunable parameter to determine the resolution level of community structure. The formulation the community detection problem as a multi objective optimization problem is another approach to overcome the resolution limit problem [33,34]. The multi objective optimization based algorithms search the optimal solutions by optimizing multiple objective functions that evaluate the community structure from different views.

Due to the wide spread of applications of community detection, the wide variety algorithms have been reported for solving the community detection problem in the literature. A greedy algorithm, called FN, is proposed in [35] for community detection problem. The FN algorithm starts from a set of isolated nodes in which each node is a unique community and then iteratively connects a pair of communities with the maximum value of modularity at each step.

In [36] an algorithm, called CNM, was proposed for detecting community structure in network which works based on the optimization of modularity and uses a modern data structure to reduce the calculation complexity of modularity. CNM algorithm is faster than FN algorithm and allows us to extend community structure analysis to large networks.

A memetic algorithm, called Meme-Net, which is based on genetic algorithm and a hill climbing strategy as the local search was proposed in [37]. Meme-Net optimizes another quality function, modularity density, which includes a tunable parameter that allows one to explore the network at different resolutions.

A genetic algorithm [38], called GA-Net, was proposed to discover communities in social networks. GA-Net optimizes an efficient fitness function to identify densely connected communities of nodes with sparse connections between communities. GA-Net is efficient because the variation operators are modified to take into consideration only the actual correlations among the nodes.

In [33] a multi-objective evolutionary algorithm, called MOCD, was proposed for community detection problem. After analyzing and comparing a variety of objective functions that have been used for community detection, MOCD exploits the concept of correlation between objectives which characterizes the relationship between any two objective functions.

A multi-objective genetic algorithm to uncover community structure in complex network, called MOGA-Net, was proposed in [34]. MOGA-Net optimizes two objective functions able to identify densely connected communities of nodes having sparse inter connections. MOGA-Net generates a set of network divisions at different hierarchical levels in which solutions at deeper levels are contained in solutions having a lower number of communities. The number of modules is automatically determined by the objective functions.

In [39] a multi-objective evolutionary algorithm, called MOEAD-Net, was proposed for solving the community detection in networks. MOEAD-Net optimizes two conflicting objective functions decomposed from modularity density. The algorithm maximizes the density of internal degrees, and minimizes the density of external degrees simultaneously.

In [40] a hybrid community detection algorithm based on the modularity optimization and an improved genetic algorithm, called MIGA, was proposed. MIGA uses modularity as objective function and takes the simulated annealing method as the local search method.

An algorithm based on open cellular learning automata, called CLA-Net, was proposed for solving the community detection problem in [41]. In CLA-Net the whole network is modeled as irregular cellular learning automata (ICLA) in which the solution is constituted by current actions chosen by the learning automata in the network. CLA-Net effectively solves the resolution limit of modularity optimization by interacting with both the global and local environments.

4. The proposed algorithm for community detection problem

In this section, we propose a new evolutionary algorithm called MLAMA-Net for solving the community detection problem. The proposed algorithm is a hybrid algorithm based on the memetic algorithm and learning automata. In this algorithm the chromosomes which are represented on the basis of Michigan approach are associated to the nodes of network.

For this purpose an initial population isomorphic to input network is created. To construct initial population, each network node is equipped with a chromosome, and then a learning automaton is assigned to it. The chromosome represents the community of corresponding node and saves the histories of exploration and the learning automaton represents a meme and saves the histories of the exploitation. Each node v_i of network can be modeled by a duple $< CR^i, M^i(t) >$ where CR^i is a chromosome which represents the community of node v_i by an integer number and $M^i(t)$ is a meme which save the effect (history) of the local search on the chromosome CR^i at generation t. Initial chromosome CR^i is created randomly by selecting a random integer number from set $\underline{c} = \{c_1, c_2, \ldots, c_n\}$ as the set of all possible communities. At the beginning of each generation the evolutionary operators are applied on chromosome CR^i. First, mutation operator is applied on chromosome CR^i with rate r_m in which the value of chromosome CR^i is replaced by other value of set $\underline{c} = \{c_1, c_2, \ldots, c_n\}$. Then, crossover operator is performed on chromosome CR^i and one of its neighbors, which is selected randomly, with rate r_c in which the value of chromosome CR^i is exchanged with the value of selected chromosome.

Let GF be the fitness function which is used to evaluate the fitness of a chromosome based on its genotype and genotypes of its adjacent chromosomes. The fitness of chromosome CR^i at generation t; which is referred to as genetic fitness; is denoted by $GF^i(t)$. The genetic fitness of chromosome CR^i associated to node v_i of graph $G = (V, E)$ is calculated as follows:

$$GF^i(t) = \frac{1}{2m_l} \sum_{i,j \in N_i} \left(A_{ij} - \frac{k_i k_j}{2m_l} \right) \delta(i,j) \tag{4}$$

where $N_i = \{u | [u, v_i] \in E$ is the set of neighbors of node v_i, k_i is the degree of node v_i, A is a binary matrix where indicates the adjacency of chromosomes in which $A_{ij} = 1$, if chromosome CR^i is adjacent to chromosome CR^j; otherwise, $A_{ij} = 0$ and $m_l = \sum_{i,j \in N_i} A_{ij}$. The term $\delta(.)$ is the delta function, i.e., $\delta(i,j) = 1$ if node v_i and node v_j are in the same community; otherwise, $\delta(i,j) = 0$.

The effect (history) of the local search on chromosome CR^i at generation t is represented by meme $M^i(t)$ where is equipped with a learning automaton LA_i in which $\underline{a_i} = \{c_1, c_2, \ldots, c_n\}$ is the set of actions (communities) that can be taken by learning automaton LA_i. The effect of the local search on chromosome CR^i at generation t is represented by the action probability vector of learning automaton in the meme $M^i(t)$ as given by Eq. (5).

$$M^i(t) = \left[M_1^i(t), M_2^i(t), \ldots, M_n^i(t)\right] \tag{5}$$

where

$$1 \le i \le n \text{ and } \forall i, \sum_{k=1}^{n} M_k^i(t) = 1.$$

$M_k^i(t)$ denotes the probability that action k of leaning automaton in the meme $M^i(t)$ is selected in the exploitation process. In other words, $M_k^i(t)$ is the probability that community c_k is selected by local search for node v_i. $M_k^i(0)$ where $1 \le i, k \le n$ is initially set to $1/n$. Updating the action probability vector of learning automaton associated to meme $M^i(t)$ is performed on the basis of the result of applying the local search on the chromosome CR^i as described in next paragraph. Let MF be a function which is used to evaluate the effect (history) of local search on a chromosome. The effect of the local search on chromosome CR^i at generation t; which is referred to as memetic fitness; is denoted by $MF^i(t)$. The memetic fitness of chromosome CR^i is calculated as follows:

$$MF^i(t) = M_k^i(t), \tag{6}$$

where k is the action of learning automaton in the meme $M^i(t)$ which corresponds to the value of chromosome CR^i. Memetic fitness of a chromosome changes when the action probability vector of learning automaton in its corresponding meme is updated. Updating is performed on the basis of the result of applying the local search on a chromosome. It is worth noting that, local search changes only the action probability vector of the meme not value of the chromosome. That is, local search only changes the memetic fitness not the genetic fitness. Local search is applied on chromosome CR^i based on the genetic information (genotype and genetic fitness) and memetic information (action probability vector and memetic fitness) of chromosome CR^i and the genetic and memetic information of its adjacent chromosomes.

Let α_i be the community of node v_i which is represented by chromosome CR^i, $N_i = \{u | [u, v_i] \in E$ be the set of neighbors of node v_i, $N_i(c) = j \in N_i{:}\alpha_{\mathrm{j}} = c$ be the set of neighbors of node v_i with community c and $|N_i(c)|$ be the number of neighbors of node v_i with community c. At generation t, the action α_i of learning automaton associated to meme $M^i(t)$ is rewarded, if community of node v_i has the highest priority amongst its neighbors' communities. Otherwise, it will be penalized.

The priority of node v_i can be described as follows:

$$priority(v_i) = \begin{cases} 1 & if\ \left(|N_i(\alpha_i)| > |N_j(\alpha_j)|\right) \forall j \in N_i \\ 1 & if\ \left(|N_i(\alpha_i)| = |N_j(\alpha_j)|\right)\ and\ \left(MF^i(t) > MF^j(t)\right) \forall j \in N_i \\ 0 & otherwise \end{cases} \tag{7}$$

where $MF^i(t)$ and $MF^j(t)$ are the memetic fitness of chromosomes CR^i and CR^j at generation t, respectively. The priority concept can effectively overcome the resolution limit problem in the proposed algorithm. In the last step of proposed algorithm, learning automaton associated to meme $M^i(t)$ randomly chooses one of its actions and as a result a new chromosome is generated. If the genetic fitness of new chromosome be higher than genetic fitness of chromosome CR^i, the newly generated chromosome replaces the chromosome CR^i.

The community detection process continues (in parallel) for each node v_i, if the probability of an action of learning automaton associated to meme $M^i(t)$ exceeds a pre-specified threshold, e.g., π_i. The relationship between node v_i and its neighbors is shown in Fig. 2.

The proposed algorithm is a fully distributed algorithm in which each chromosome locally evolves based on its adjacent chromosomes and independent of the other chromosomes. The operation of the proposed algorithm can be described as follow. Initial chromosomes are created randomly and the probability of selecting an action for all learning automata is set to $1/n$. The proposed algorithm is progressed in a number of generations as long as the termination criteria are not satisfied.

Each generation is divided to three phases: exploration phase, exploitation phase and memetic effect phase. In exploration phase the mutation and the crossover operators are applied on chromosome CR^i with rates r_m and r_c respectively. In exploitation phase, local search is applied to chromosome CR^i, and then the action probability vector of the meme $M^i(t)$ (the history) is updated according to a learning algorithm. In memetic effect phase, chromosome CR^i is replaced with a new chromosome which is generated based on the action probability vector of learning automaton associated to meme $M^i(t)$, if genetic fitness of new chromosome is higher than genetic fitness of chromosome CR^i. Pseudo code for proposed algorithm demonstrated in Fig. 3.

5. Experimental results

In this section several experiments are described that study the efficiency of proposed algorithm. The results of proposed algorithm is compared with the results of the best-known community detection algorithms such as: CNM [36], Meme-Net [37], GA-Net [38], MOCD [33], MOGA-Net [34], MOEAD-Net [39], MIGA [40] and CLA-Net [41].

To show the performances of the different algorithms, we use two standard measures consist of Normalized Mutual Information (NMI) [42] and modularity [1]. Normalized Mutual Information (NMI) which is used for networks with known community structure evaluates the similarity between real community structure and community structure found by the algorithm. The NMI can be written as

$$\mathrm{NMI}(A, B) = \frac{-2 \sum\limits_{a \in A} \sum\limits_{b \in B} |a \cap b| \log\left(\frac{|a \cap b| n}{|a||b|}\right)}{\sum\limits_{a \in A} |a| \log\left(\frac{|a|}{n}\right) + \sum\limits_{b \in B} |b| \log\left(\frac{|b|}{n}\right)} \tag{8}$$

where a is a community in real community structure A and b is a community in obtained community structure B. The value of NMI is between $[0, 1]$ and the larger value means that the found community structure is more similar to real community structure.

Modularity (Eq. (3)) which is used for networks with unknown community structure evaluates the quality of community structure in complex networks. The modularity with larger value shows the more significant community structure in given network.

We compare the MLAMA-Net with other algorithms on two groups of networks which are used in the literature: real world networks and synthetic networks. The characteristics of the real world networks are given in Table 1. The modularity measure is used to evaluate the quality of the community structure obtained by different algorithms because the community structures of most these networks are unknown.

GN [43] and LFR [44] are two synthetic benchmark networks which are used to compare proposed algorithm with other algorithms. In GN benchmark, each network was generated with 128 nodes which are partitioned to 4 communities of 32 nodes each. The average degree of a node is equal to 16. Each node shares a fraction $1-\lambda$ of its edges with the other nodes in its community and a fraction λ with the other nodes of network; λ is the mixing parameter. The network with smaller value of λ has more significant community structure.

Fig. 4 demonstrates four samples of GN benchmark with different values for mixing parameter.

The GN benchmark networks do not reflect some important properties of real-world networks, like the power law distribution of node degrees and community sizes [41]. Therefore, the LFR

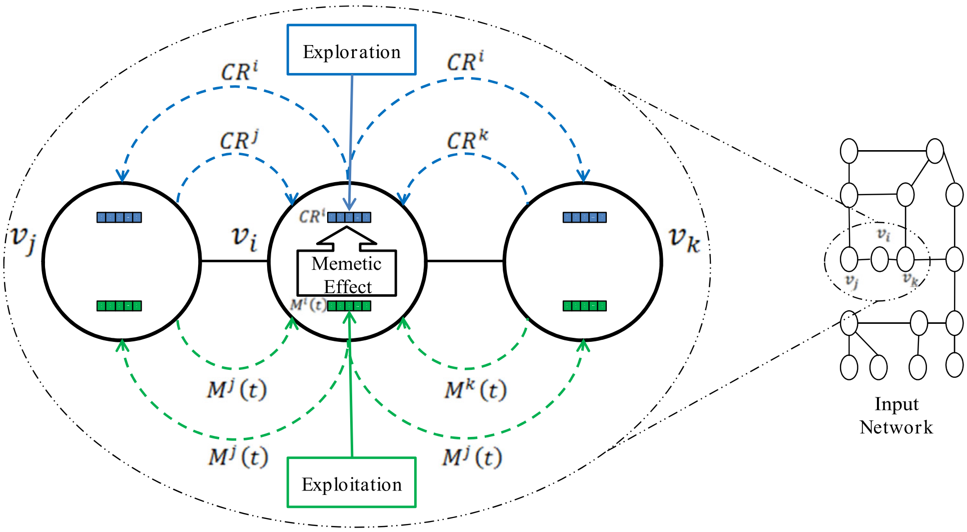
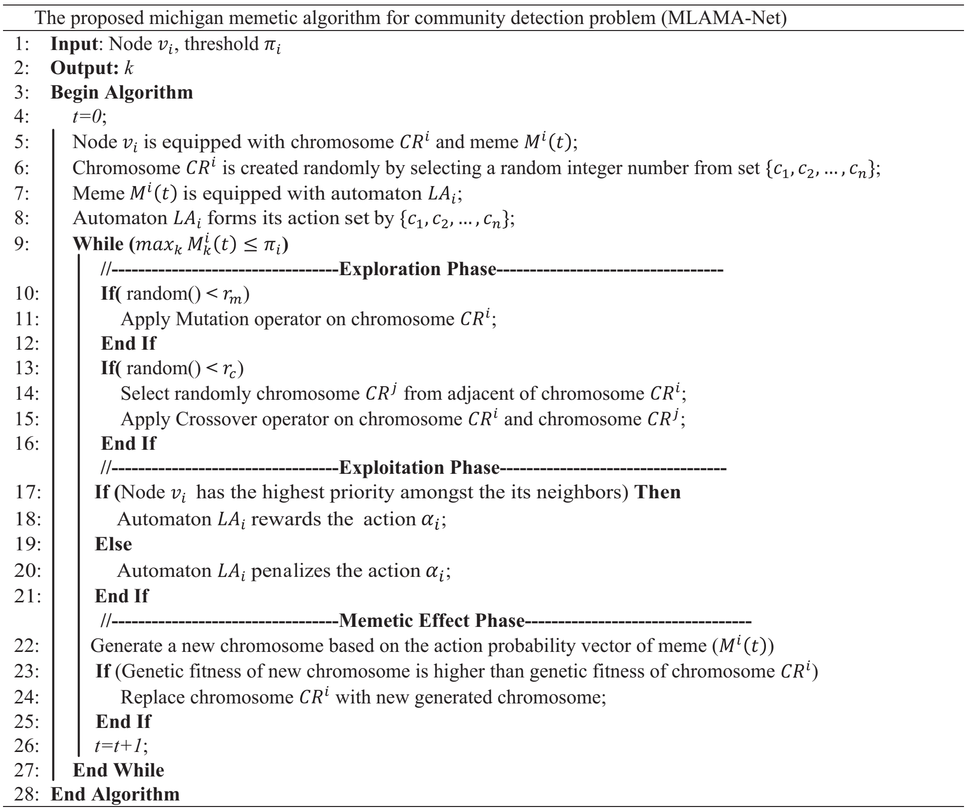


Fig. 2. The relationship between node v_i and its neighbors in MLAMA-Net algorithm.



The proposed michigan memetic algorithm for community detection problem (MLAMA-Net)

```
Input: Node $v_i$, threshold $\pi_i$
Output: $k$
Begin Algorithm
    $t=0$;
    Node $v_i$ is equipped with chromosome $CR^i$ and meme $M^i(t)$;
    Chromosome $CR^i$ is created randomly by selecting a random integer number from set $\{c_1, c_2, \dots, c_n\}$;
    Meme $M^i(t)$ is equipped with automaton $LA_i$;
    Automaton $LA_i$ forms its action set by $\{c_1, c_2, \dots, c_n\}$;
    While ($max_k\ M_k^i(t) \le \pi_i$)
        //----------------------------------Exploration Phase----------------------------------
        If( random() < $r_m$)
            Apply Mutation operator on chromosome $CR^i$;
        End If
        If( random() < $r_c$)
            Select randomly chromosome $CR^j$ from adjacent of chromosome $CR^i$;
            Apply Crossover operator on chromosome $CR^i$ and chromosome $CR^j$;
        End If
        //----------------------------------Exploitation Phase----------------------------------
        If (Node $v_i$ has the highest priority amongst the its neighbors) Then
            Automaton $LA_i$ rewards the action $\alpha_i$;
        Else
            Automaton $LA_i$ penalizes the action $\alpha_i$;
        End If
        //----------------------------------Memetic Effect Phase----------------------------------
        Generate a new chromosome based on the action probability vector of meme ($M^i(t)$)
        If (Genetic fitness of new chromosome is higher than genetic fitness of chromosome $CR^i$)
            Replace chromosome $CR^i$ with new generated chromosome;
        End If
        $t=t+1$;
    End While
End Algorithm
```

Fig. 3. Pseudo code for MLAMA-Net.

benchmark networks, which are more consistent with the properties of real-world networks were proposed in [44]. In LFR benchmark, the node degrees and the size of communities are taken from the power law distribution with exponent τ_1 and τ_2 respectively. Also, each node shares a fraction $1-\mu$ of its edges with the other nodes in its community and a fraction μ with the other nodes of network; μ is the mixing parameter. The network with smaller value of μ has more significant community structure. Fig. 5 demonstrates four samples of LFR benchmark with different values for mixing parameter.

The NMI measure is used to evaluate the similarity between real community structure and community structure obtained by different algorithms for networks in GN and LFR benchmark. For all experiments the mutation rate is 0.05, crossover rate is 0.5, the action probability vectors of learning automata are updated according to L_{R-I} learning algorithm with $a=0.5$ and algorithm is terminated (for all nodes) when the probability of an action of learning automaton is 0.95 or greater ($\pi_i = 0.95$).

5.1. Experiment 1

In this experiment we compared the results obtained from MLAMA-Net with the results of eight other algorithms, CNM algorithm [36], Meme-Net algorithm [37], GA-Net algorithm [38], MOCD algorithm [33], MOGA algorithm [34], MOEAD-Net algorithm [39], MIGA [40] and CLA-Net algorithm [41] for different real world networks described in Table 1, in terms of modularity measure. We use the modularity measure because the community structures of most real world networks are unknown.

Table 2 presents the results of the different algorithms for 6 different real world networks with respect to the average and maximum values of modularity measure, standard deviation and the p-values of the two-tailed t test. Each reported result was averaged over 100 runs. We performed a parametric test (t test) at the 95% significance level to provide statistical confidence. The t tests were performed after ensuring that the data followed a normal distribution (by using the Kolmogorov–Smirnov test). From the results described in Table 2 we report the following:

Table 1
The characteristics of real-world networks.

Network	Number of nodes	Number of edges	Description
Karate	34	78	Zachary's karate club
Dolphins	62	159	Lusseau's dolphins
Book	105	441	A network of Books about US politics
Football	115	616	American College football union
Net science	1589	2742	Coauthor ship network of scientists working on network theory
Power grid	4941	6594	The topology of the Power Grid of the United States

- The MLAMA-Net algorithm can find the community structure with largest modularity value on karate network, dolphins network, book network, football network and power grid network. Although, in net-science network, the modularity value obtained by CNM algorithm is largest value, the modularity value obtained by proposed algorithm is 0.0005 smaller than the largest value.
- The difference between the performance of the MLAMA-Net and the performance of the other algorithms is statistically significant (p-value < 0.05) in most cases.

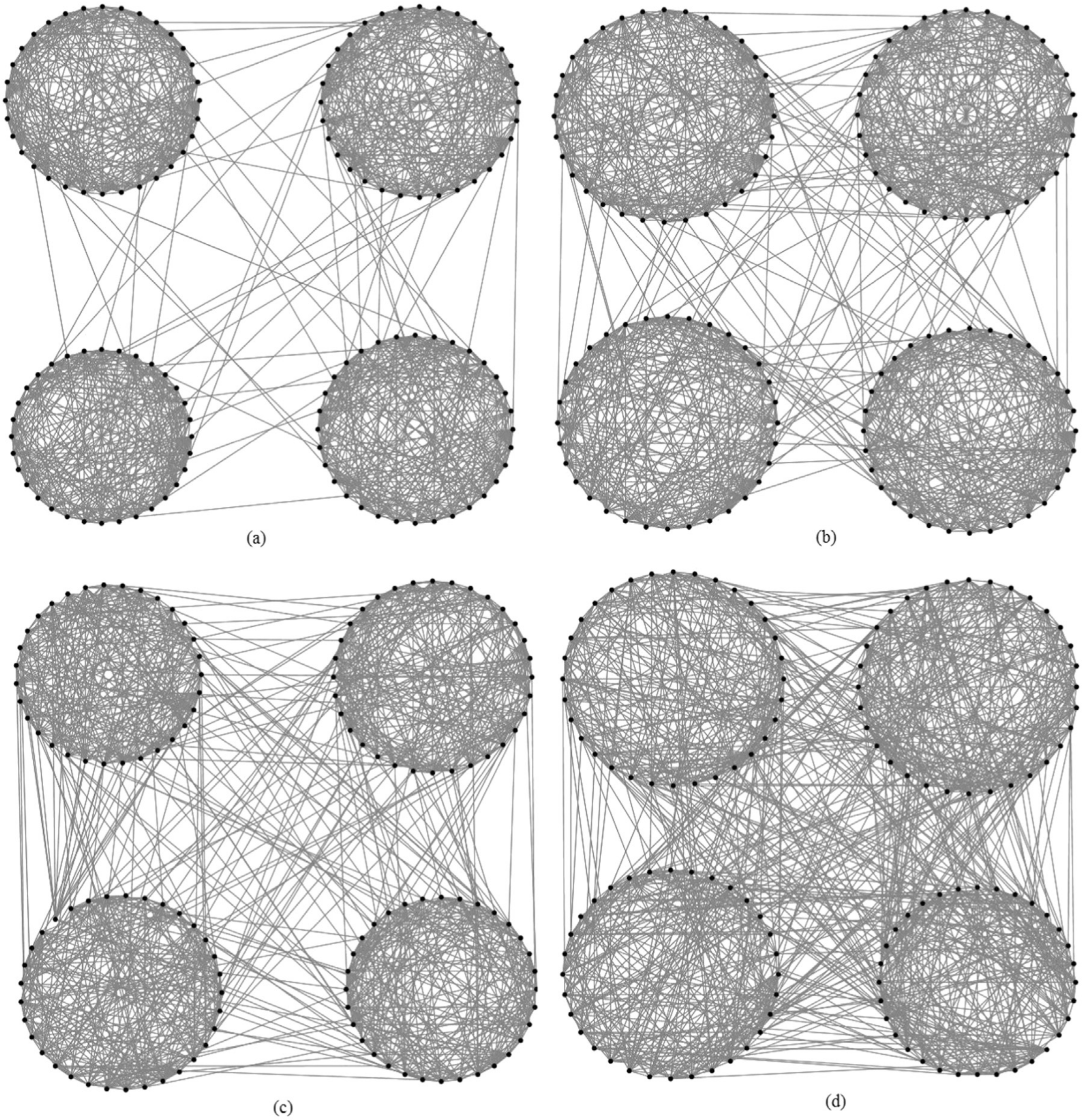


Fig. 4. Four samples of GN benchmark with 128 nodes and different mixing parameter values (a) $\lambda=0.05$, (b) $\lambda=0.10$, (c) $\lambda=0.15$ and (d) $\lambda=0.30$.

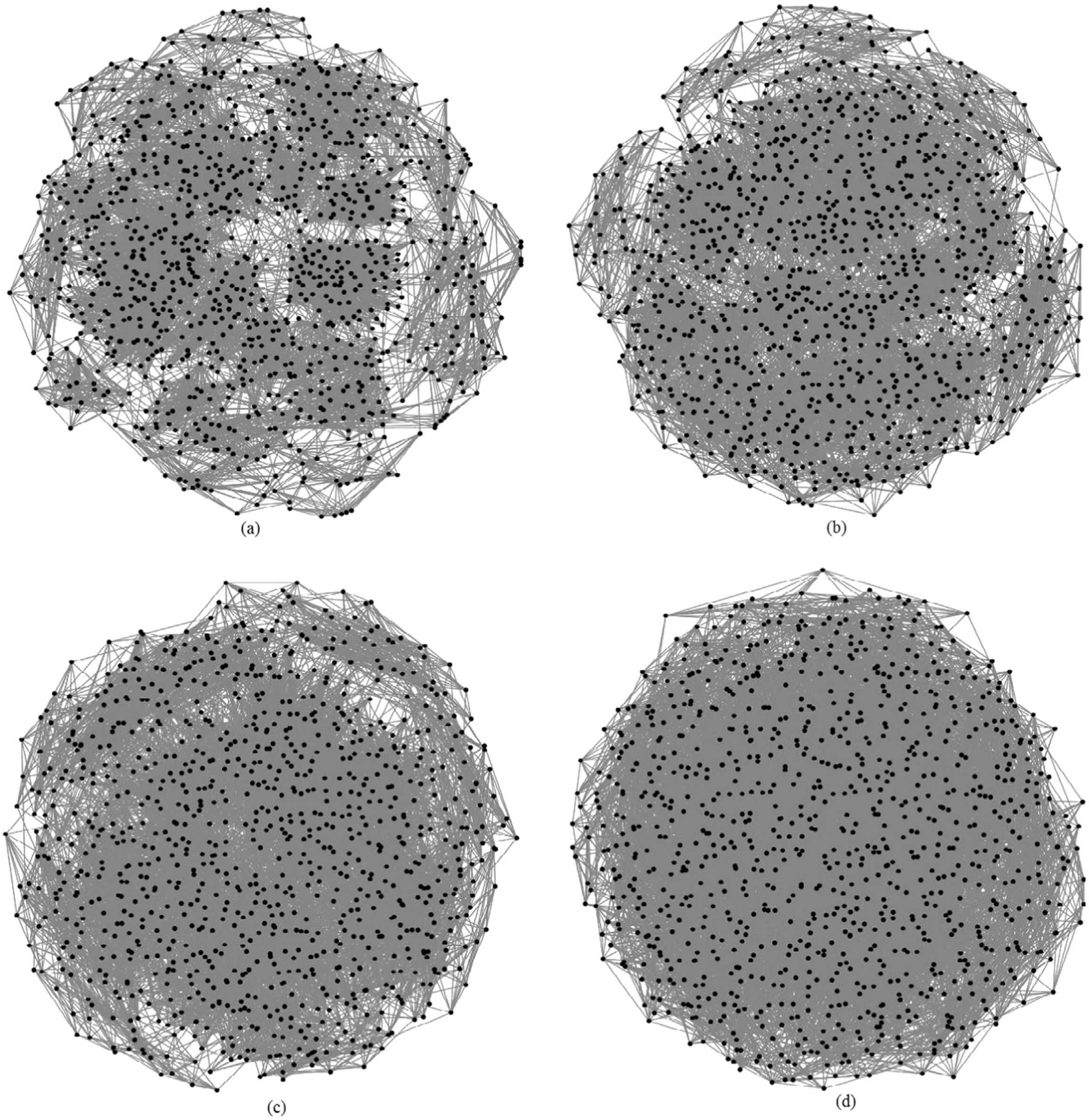


Fig. 5. Four samples of LFR benchmark with 1000 nodes and different mixing parameter values (a) $\mu = 0.05$, (b) $\mu = 0.10$, (c) $\mu = 0.15$ and (d) $\mu = 0.30$.

5.2. Experiment 2

This experiment's goal was to evaluate the accuracy of the community structures produced by different algorithms. For this purpose we use the GN benchmark network [43] with 128 nodes, which are partitioned to four communities with 32 nodes each. A critical mixing parameter λ is used to control the community structure in the network. The mixing parameter λ was varied from 0 to 0.5 by increments of 0.05. Since the communities in benchmark networks are already known, we use the Normalized Mutual Information (NMI) to evaluate the performances of different algorithms.

Fig. 6 shows the average NMI obtained by MLAMA-Net and other algorithms on GN benchmark networks with different mixing parameter. From the results shown in this figure we report the following:

- The MLAMA-Net algorithm outperforms other algorithms for all values of mixing parameter. The MLAMA-Net decomposes the problem of community detection into several sub problems (in MLAMA-Net algorithm each node of input network and its neighbors form a sub problem). The decomposition strategy has been proven to be highly effective at finding evenly distributed Pareto optimal solutions [45], so that it makes the MLAMA-Net outperforms the other algorithms when the community structure in the network is indistinct.
- For mixing parameter $\lambda < 0.3$, all algorithms, except GA-Net and MOGA-Net, can find the community structure corresponding to correct partitioning (NMI ≈ 1).
- The NMI of almost algorithms, except MLAMA-Net, beings to decrease for mixing parameter between [0.3, 0.4].
- The NMI of almost algorithms begins to decrease for mixing parameter $\lambda > 0.4$, because the community structure becomes indistinct.

5.3. Experiment 3

The GN benchmark networks [43] do not reflect some important properties of real world networks, like the power law distribution of node degrees and community sizes. Therefore, we

Table 2
Maximum modularity (Max.), average modularity (Avg.) and the result of statistical test for different algorithms on real world networks.

Network		MLAMA-Net	CLA-Net	CNM	MIGA	Meme-Net	GA-Net	MOCD	MOGA-Net	MOEAD-Net
Karate	Max.	**0.4198**	0.4188	0.3807	0.4188	0.4020	0.4059	0.4188	**0.4198**	**0.4198**
	Avg.	0.4136	0.4175	0.3807	0.3952	0.3857	0.4059	0.4188	0.4158	0.4198
	Std.	0.0102	0.0123	0.0234	0.0135	0.0224	0.0156	0.0123	0.0036	0.0012
	P value	–	**1.64E−02**	**6.70E−23**	**1.37E−18**	**1.37E−19**	**7.55E−05**	**1.56E−03**	**4.46E−02**	**2.75E−08**
Dolphins	Max.	**0.5277**	**0.5277**	0.4955	0.5210	0.5155	0.5014	0.5259	0.5258	0.5210
	Avg.	0.5222	0.5268	0.4938	0.4629	0.4838	0.4946	0.5210	0.5215	0.5189
	Std.	0.0032	0.0014	0.0124	0.0356	0.0632	0.0452	0.0141	0.0252	0.0153
	P value	–	**1.72E−23**	**3.46E−40**	**2.40E−30**	**2.38E−08**	**2.15E−08**	4.09E−01	7.83E−01	**3.73E−02**
Book	Max.	**0.5272**	0.5268	0.5181	0.5272	0.5181	0.5230	0.5230	0.5181	0.5268
	Avg.	0.5255	0.5254	0.5178	0.5269	0.5178	0.5230	0.5208	0.5027	0.5236
	Std.	0.0046	0.0048	0.0236	0.0147	0.0358	0.0145	0.0236	0.0014	0.0078
	P value	–	8.81E−01	**1.83E−03**	3.66E−01	**3.54E−02**	1.03E−01	**5.34E−02**	**7.11E−70**	**3.84E−02**
Football	Max.	**0.6058**	0.6046	0.5733	0.5911	0.5888	0.5940	0.5958	0.5280	0.6044
	Avg.	0.6050	0.6042	0.5706	0.5478	0.5512	0.5830	0.5785	0.5173	0.6032
	Std.	0.0023	0.0025	0.0125	0.0146	0.0236	0.0015	0.0021	0.0361	0.0024
	P value	–	**2.05E−02**	**1.51E−47**	**1.38E−61**	**5.21E−41**	**2.97E−92**	**2.20E−94**	**1.98E−43**	**4.30E−07**
Net science	Max.	0.9550	0.9346	**0.9555**	–	–	0.8581	0.8923	0.8916	0.9143
	Avg.	0.9544	0.9177	0.9554	–	–	0.8473	0.8886	0.8810	0.9060
	Std.	0.0004	0.0021	0.0014	–	–	0.0152	0.0147	0.0236	0.0025
	P value	–	**2.40E−124**	**5.80E−10**	–	–	**2.16E−86**	**1.72E−67**	**6.81E−53**	**5.88E−129**
Power grid	Max.	**0.9357**	0.7505	0.9345	–	–	0.6660	0.7065	0.7035	0.6880
	Avg.	0.9336	0.7350	0.9338	–	–	0.6571	0.7003	0.6949	0.6815
	Std.	0.0010	0.0025	0.0142	–	–	0.0236	0.0019	0.0025	0.0146
	P value	–	**5.89E−187**	8.89E−01	–	–	**5.79E−108**	**1.30E−203**	**7.31E−195**	**1.71E−124**

Best results are highlighted in bold.

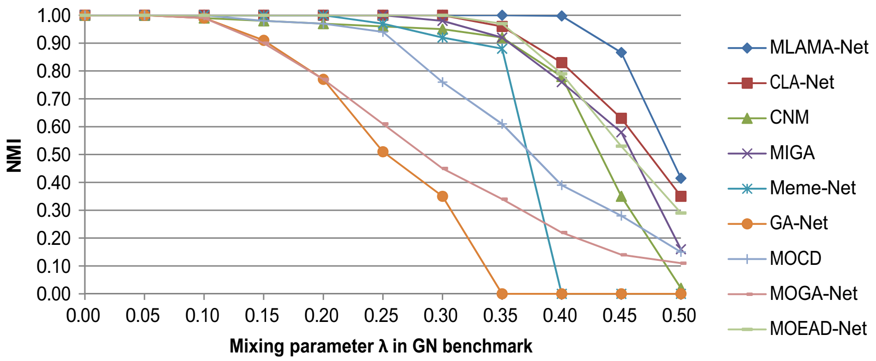


Fig. 6. The average NMI obtained by different algorithms on GN benchmark networks.

used the LFR benchmark networks [44], which are more consistent with the properties of real world networks, to evaluate the accuracy of the community structures produced by different algorithms. In this experiment the size of networks is set to 1000 and the node degrees and the size of communities are taken from the power law distribution with exponent $\tau_1 = 2$ and $\tau_2 = 1$ respectively. The degree of nodes is in the range from 0 to 50 with average value 20 and the community size is between [10, 50]. The mixing parameter μ was varied from 0 to 0.8 by increments of 0.05. Since the communities in benchmark networks are already known, we use the Normalized Mutual Information (NMI) to evaluate the performances of different algorithms.

Fig. 7 shows the average NMI obtained by MLAMA-Net and other algorithms on LFR benchmark networks with different mixing parameter values. From the results shown in this figure we report the following:

- For mixing parameter $\mu < 0.1$, all algorithms, except GA-Net and MOGA-Net, can find the community structure corresponding to correct partitioning (NMI ≈ 1).
- The NMI of almost algorithms, except MLAMA-Net, CLA-Net, Meme-Net and MIGA beings to decrease for mixing parameter between [0.1, 0.35].
- For mixing parameter between [0.35, 0.5], the NMI values of all algorithms, except MLAMA-Net, decrease.
- The MLAMA-Net algorithm outperforms the other algorithms for mixing parameter in range [0, 0.7]. This is due to the decomposition of the input network into a number of sub networks and using the priority concept in community detection process in the proposed algorithm.
- For mixing parameter $\mu > 0.7$, the MOEAD-Net algorithm perform better than proposed algorithm, but still MLAMA-Net outperforms the other algorithms.

5.4. Experiment 4

The goal of this experiment was to study the impact of the resolution limit problem on the community structure obtained by the MLAMA-Net algorithm. For this purpose, we use a sample network with 54 nodes. The sample network is partitioned to two communities C_1 with 50 nodes and C_2 with 4 nodes. The topologies of communities C_1 and C_2 are the same as the complete graph,

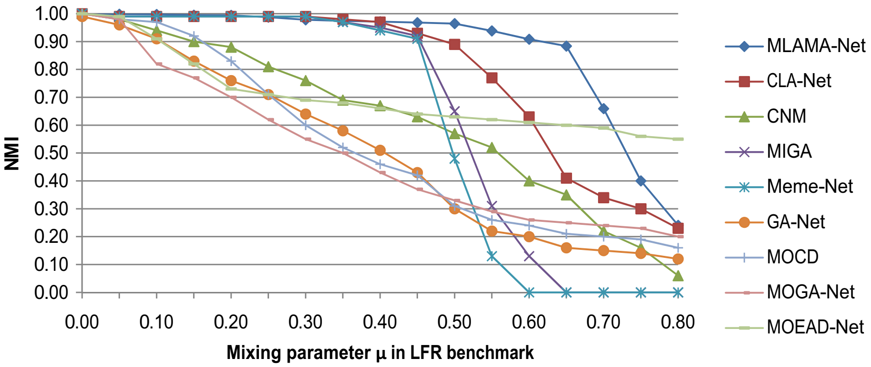


Fig. 7. The average NMI obtained by different algorithms on LFR benchmark networks.

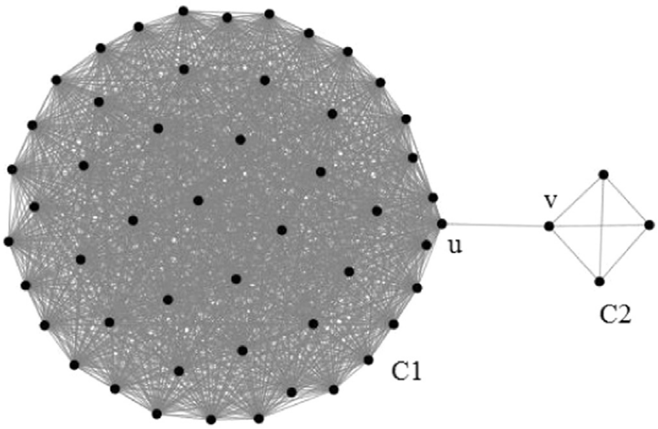


Fig. 8. The test network with two communities with different size for evaluation of resolution limit problem.

in which every pair of distinct nodes in a community is connected by an edge. Also, node u in community C_1 is connected to node v in community C_2.

Fig. 8 shows the described test network for evaluation of resolution test problem. The modularity of the community structure in the test network is 0.0097. However, according to basic modularity optimization, node u would be assigned to community C_2, because this community structure achieves a larger modularity value of 0.0101. This is due to the resolution limit of modularity optimization. We run the proposed MLAMA-Net algorithm on the test network 100 times. Since the other algorithms such as CNM and MIGA solely depend on the modularity optimization, they always incorrectly identify node u as a member of community C_2 [41]. The proposed algorithm can always find the correct communities in the test network, because it uses both the modularity and priority concept in community detection process.

5.5. Experiment 5

This experiment aimed to find the impact of learning automata and priority function on MLAMA-Net performance. For this purpose we compared the proposed algorithm with the proposed algorithm in which the learning automaton residing in each meme is replaced by a pure chance automaton (MLAMA-Net-PC) and the proposed algorithm in which the priority function is replaced by same priority for all nodes (MLAMA-Net-SP) for different networks, in terms of modularity and Normalized Mutual Information (NMI) measures. In pure chance automaton the actions are always chosen with equal probabilities.

Table 3
Maximum modularity (Max.), average modularity (Avg.) and the result of statistical tests for the MLAMA-Net, MLAMA-Net-PC and MLAMA-Net-SP algorithms on real world networks.

Network		MLAMA-Net	MLAMA-Net-PC	MLAMA-Net-SP
Karate	Max.	**0.4198**	0.4174	0.4030
	Avg.	0.4136	0.2658	0.2371
	Std.	0.0102	0.0948	0.1052
	P value	–	**2.99E − 28**	**1.46E − 30**
Dolphins	Max.	**0.5277**	0.5149	0.5201
	Avg.	0.5222	0.3326	0.3081
	Std.	0.0032	0.1263	0.1376
	P value	–	**2.99E − 27**	**2.49E − 28**
Book	Max.	**0.5272**	0.4815	0.4372
	Avg.	0.5255	0.2706	0.2621
	Std.	0.0046	0.0730	0.0746
	P value	–	**2.28E − 57**	**8.01E − 58**
Football	Max.	**0.6058**	0.6003	0.5963
	Avg.	0.6050	0.3896	0.3539
	Std.	0.0023	0.1815	0.1980
	P value	–	**9.99E − 21**	**1.86E − 22**
Net science	Max.	**0.9550**	0.2039	0.2022
	Avg.	0.9544	0.1787	0.1772
	Std.	0.0004	0.0105	0.0087
	P value	–	**5.16E − 187**	**3.02E − 195**
Power grid	Max.	**0.9357**	0.6660	0.6880
	Avg.	0.9336	0.3235	0.3631
	Std.	0.0010	0.1235	0.2312
	P value	–	**1.45E − 71**	**4.43E − 44**

Best results are highlighted in bold.

Table 3 presents the results of the MLAMA-Net algorithm, the MALAM-Net-PC algorithm and the MALAM-Net-SP algorithm for different real world networks with respect to the average and maximum values of modularity measure, standard deviation and the p-values of the two-tailed t test. Each reported result was averaged over 50 runs. We performed a parametric test (t test) at the 95% significance level to provide statistical confidence. The t tests were performed after ensuring that the data followed a normal distribution (by using the Kolmogorov–Smirnov test). From the results described in Table 3 we report the following:

- The MLAMA-Net algorithm can find the community structure with largest modularity value on all real word networks.
- The difference between the performance of the MLAMA-Net algorithm and the performance of the MLAMA-Net-PC is statistically significant (p-value < 0.05) in all cases.
- The difference between the performance of the MLAMA-Net algorithm and the performance of the MLAMA-Net-SP is statistically significant (p-value < 0.05) in all cases.

Fig. 9 shows the average NMI obtained by MLAMA-Net, MLAMA-Net-PC and MLAMA-Net-SP algorithms on GN benchmark networks with different mixing parameter. From the results shown in this figure we report the following:

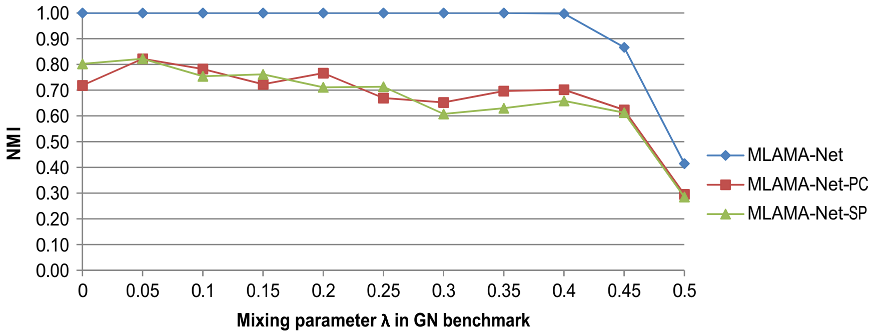


Fig. 9. The average NMI obtained by MLAMA-Net, MLAMA-Net-PC and MLAMA-Net-SP algorithms on GN benchmark networks.

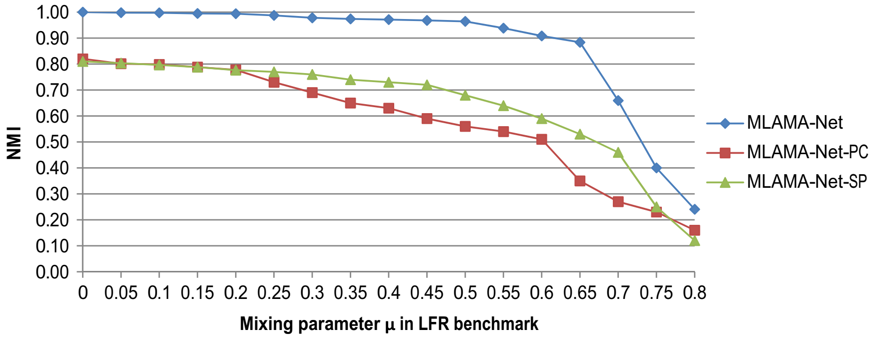


Fig. 10. The average NMI obtained by MLAMA-Net, MLAMA-Net-PC and MLAMA-Net-SP algorithms on LFR benchmark networks.

- The MLAMA-Net algorithm outperforms the MLAMA-Net-PC and MLAMA-Net-SP algorithms for all values of mixing parameter.

Fig. 10 shows the average NMI obtained by MLAMA-Net, MLAMA-Net-PC and MLAMA-Net-SP algorithms on LFR benchmark networks with different mixing parameter. From the results shown in this figure we report the following:

- The MLAMA-Net algorithm outperforms the MLAMA-Net-PC and MLAMA-Net-SP algorithms for all values of mixing parameter.

6. Conclusion

A new Michigan memetic algorithm called MLAMA-Net is proposed in this paper for solving the community detection in complex networks. The proposed algorithm is an evolutionary algorithm in which each chromosome represents a part of the solution and the whole population represents the solution. In the proposed algorithm each node of input network is equipped with a chromosome and a learning automaton. The chromosome represents the community of corresponding node and saves the histories of exploration. The learning automaton represents a meme and saves the histories of the exploitation. The proposed algorithm is a distributed algorithm in which each chromosome, without any prior information, locally evolves by evolutionary operators and improves by a local search. MLAMA-Net algorithm introduces the priority concept to solve the resolution limit of modularity optimization in community detection problem. To show the superiority of our proposed algorithm over the some well-known algorithms, several computer experiments have been conducted. The obtained results show MLAMA-Net is effective and efficient at detecting community structure in complex networks. MLAMA-Net is compared with other well-known algorithms for the community detection problem on both synthetic and real world networks. Our experimental results showed the superiority of the proposed algorithm in terms of quality of solution and accuracy of solution in both real world networks and synthetic networks.

References

[1] M.E. Newman, M. Girvan, Finding and evaluating community structure in networks, Phys. Rev. E 69 (2004) 026113.

[2] Y. Li, L. Jiao, P. Li, B. Wu, A hybrid memetic algorithm for global optimization, Neurocomputing 134 (2014) 132–139.

[3] K.S. Narendra, M.A.L. Thathachar, Learning Automata: an Introduction, Prentice-Hall, Inc, 1989.

[4] M.A.L. Thathachar, P.S. Sastry, Varieties of learning automata: an overview, IEEE Trans. Syst. Man Cybern. Part B: Cybern. 32 (2002) 711–722.

[5] M. Rezapoor Mirsaleh, M.R. Meybodi, A new memetic algorithm based on cellular learning automata for solving the vertex coloring problem, Memet. Comput. (2016) 1–12.

[6] B. Oommen, E. Hansen, The asymptotic optimality of discretized linear reward-inaction learning automata, IEEE Trans. Syst. Man Cybern. 14 (1984) 542–545.

[7] B. Johnoommen, Absorbing and ergodic discretized two-action learning automata, IEEE Trans. Syst. Man Cybern. 16 (1986) 282–293.

[8] J. Akbari Torkestani, M.R. Meybodi, Learning automata-based algorithms for finding minimum weakly connected dominating set in stochastic graphs, Int. J. Uncertain. Fuzziness Knowl.-Based Syst. 18 (2010) 721–758.

[9] J. Akbari Torkestani, An adaptive focused Web crawling algorithm based on learning automata, Appl. Intell. 37 (2012) 586–601.

[10] M. Rezapoor Mirsaleh, M.R. Meybodi, A learning automata-based memetic algorithm, Genet. Program. Evol. Mach. 16 (2015) 399–453.

[11] J. Akbari Torkestani, M.R. Meybodi, An efficient cluster-based CDMA/TDMA scheme for wireless mobile ad-hoc networks: a learning automata approach, J. Netw. Comput. Appl. 33 (2010) 477–490.

[12] J. Akbari Torkestani, M.R. Meybodi, Mobility-based multicast routing algorithm for wireless mobile Ad-hoc networks: a learning automata approach, Comput. Commun. 33 (2010) 721–735.

[13] J. Akbari Torkestani, M.R. Meybodi, An intelligent backbone formation algorithm for wireless ad hoc networks based on distributed learning automata, Comput. Netw. 54 (2010) 826–843.

[14] M. Jahanshahi, M. Dehghan, M. Meybodi, LAMR: learning automata based multicast routing protocol for multi-channel multi-radio wireless mesh networks, Appl. Intell. 38 (2013) 58–77.

[15] H. Mohamadi, S. Salleh, M.N. Razali, S. Marouf, A new learning automata-based approach for maximizing network lifetime in wireless sensor networks with adjustable sensing ranges, Neurocomputing 153 (2015) 11–19.

[16] M.R. Meybodi, Learning Automata and its Application to Priority Assignment in a Queueing System With Unknown Characteristics (Ph.D. thesis), Departement of Electrical Engineering and Computer Science, University of Oklahoma, Norman, Oklahoma, USA, 1983.

[17] M.L. Tsetlin, Automaton Theory and Modeling of Biological Systems, Academic Press, New York, 1973.

[18] A. Hashim, S. Amir, P. Mars, Application of learning automata to data compression, Adapt. Learn. Syst. (1986) 229–234.

[19] B. Manjunath, R. Chellappa, Stochastic learning networks for texture segmentation, in: Proceedings of the Twenty-Second Asilomar Conference on Signals, Systems and Computers, 1988, pp. 511–516.

[20] B.J. Oommen, E. Hansen, List organizing strategies using stochastic move-to-front and stochastic move-to-rear operations, SIAM J. Comput. 16 (1987) 705–716.

[21] B.J. Oommen, D.C.Y. Ma, Deterministic learning automata solutions to the equipartitioning problem, IEEE Trans. Comput. 37 (1988) 2–13.

[22] M. Mozafari, R. Alizadeh, A cellular learning automata model of investment behavior in the stock market, Neurocomputing 122 (2013) 470–479.

[23] G.P. Frost, Stochastic optimisation of vehicle suspension control systems via learning automata (Ph.D. thesis), Department of Aeronautical and Automotive Engineering, Loughborough University, Loughborough, 1998.

[24] M. Howell, G. Frost, T. Gordon, Q. Wu, Continuous action reinforcement learning applied to vehicle suspension control, Mechatronics 7 (1997) 263–276.

[25] C. Unsal, P. Kachroo, J.S. Bay, Multiple stochastic learning automata for vehicle path control in an automated highway system, IEEE Trans. Syst. Man Cybern. Part A: Syst. Hum. 29 (1999) 120–128.

[26] H. Beigy, M.R. Meybodi, A learning automata-based algorithm for determination of the number of hidden units for three-layer neural networks, Int. J. Syst. Sci. 40 (2009) 101–118.

[27] M.R. Meybodi, H. Beigy, Neural network engineering using learning automata: determining of desired size of three layer feed forward neural networks, J. Fac. Eng. 34 (2001) 1–26.

[28] B.J. Oommen, D.S. Croix, String taxonomy using learning automata, IEEE Trans. Syst. Man Cybern. Part B: Cybern. 27 (1997) 354–365.

[29] A.G. Barto, M.I. Jordan, Gradient following without back-propagation in layered networks, in: Proceedings of thr 1st Int. Conference Neural Nets, San Diego, 1987.

[30] M. Thathachar, V.V. Phansalkar, Learning the global maximum with parameterized learning automata, IEEE Trans. Neural Netw. 6 (1995) 398–406.

[31] A. Arenas, A. Fernandez, S. Gomez, Analysis of the structure of complex networks at different resolution levels, New J. Phys. 10 (2008) 053039.

[32] Z. Li, S. Zhang, R.-S. Wang, X.-S. Zhang, L. Chen, Quantitative function for community detection, Phys. Rev. E 77 (2008) 036109.

[33] C. Shi, Z. Yan, Y. Cai, B. Wu, Multi-objective community detection in complex networks, Appl. Soft Comput. 12 (2012) 850–859.

[34] C. Pizzuti, A multiobjective genetic algorithm to find communities in complex networks, IEEE Trans. Evol. Comput. 16 (2012) 418–430.

[35] M.E. Newman, Fast algorithm for detecting community structure in networks, Phys. Rev. E 69 (2004) 066133.

[36] A. Clauset, M.E. Newman, C. Moore, Finding community structure in very large networks, Phys. Rev. E 70 (2004) 066111.

[37] M. Gong, B. Fu, L. Jiao, H. Du, Memetic algorithm for community detection in networks, Phys. Rev. E 84 (2011) 056101.

[38] C. Pizzuti, GA-Net: a genetic algorithm for community detection in social networks, in: G. Rudolph, T. Jansen, N. Beume, S. Lucas, C. Poloni (Eds.), Parallel Problem Solving from Nature – PPSN X, 5199, Springer, Berlin Heidelberg, 2008, pp. 1081–1090.

[39] M. Gong, L. Ma, Q. Zhang, L. Jiao, Community detection in networks by using multiobjective evolutionary algorithm with decomposition, Phys. A: Stat. Mech. Appl. 391 (2012) 4050–4060.

[40] R. Shang, J. Bai, L. Jiao, C. Jin, Community detection based on modularity and an improved genetic algorithm, Phys. A: Stat. Mech. Appl. 392 (2013) 1215–1231.

[41] Y. Zhao, W. Jiang, S. Li, Y. Ma, G. Su, X. Lin, A cellular learning automata based algorithm for detecting community structure in complex networks, Neurocomputing 151 (2015) 1216–1226.

[42] L. Danon, A. Diaz-Guilera, J. Duch, A. Arenas, Comparing community structure identification, J. Stat. Mech.: Theory Exp. 2005 (2005) P09008.

[43] M. Girvan, M.E. Newman, Community structure in social and biological networks, Proc. Natl. Acad. Sci. USA 99 (2002) 7821–7826.

[44] A. Lancichinetti, S. Fortunato, F. Radicchi, Benchmark graphs for testing community detection algorithms, Phys. Rev. E 78 (2008) 046110.

[45] Q. Zhang, H. Li, MOEA/D: a multiobjective evolutionary algorithm based on decomposition, IEEE Trans. Evol. Comput. 11 (2007) 712–731.

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