IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received April 29, 2019, accepted June 1, 2019, date of publication June 7, 2019, date of current version July 22, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2921571

Multi-Layer Network Local Community Detection Based on Influence Relation

XIAOMING LI[1], GUANGQUAN XU[1,2], WENJUAN LIAN[3], HEQUN XIAN[4], LITAO JIAO[2], AND YU HUANG[5]

[1]College of Intelligence and Computing, Tianjin University, Tianjin 300300, China
[2]Qingdao Huanghai University, Qingdao 250000, China
[3]College of Computer Science and Engineering, Shandong University of Science and Technology, Qingdao 250000, China
[4]College of Computer Science and Technology, Qingdao University, Qingdao 250000, China
[5]National Engineering Research Center for Software Engineering, Peking University, Beijing 100871, China

Corresponding author: Guangquan Xu (losin@tju.edu.cn)

This work was supported in part by the State Key Development Program of China under Grant 2017YFE0111900, in part by the National Science Foundation of China under Grant 61572355 and Grant U1736115, in part by the Fundamental Research of Xinjiang Corps under Grant 2016AC015, in part by the Leading Scientific and Technological Personnel of Xinjiang Corps under Grant 2018AC006, and in part by the Major State Research Development Program of China under Grant 2016QY04W0804.

ABSTRACT In recent years, the discovery of local communities in multi-layer networks has become an active research field of complex systems. Such as communication, social networking, sensor network the rapid development of new technologies, the amount of data generated by increased, all want to obtain the network information difficulty is big, and the network, community, mutual influence between nodes, greatly enhance the complexity of network and make local found existing multilayer network method is unable to get more accurate test results. In this paper, based on the homogeneity drive of multi-layer network and the influence relation index of multi-layer path length measurement, a local community detection model based on the influence relation of the multi-layer network is proposed by combining the direct influence relation and indirect influence relation of the network (IMLC). Compared with six real multi-layer network data sets, the algorithm has better robustness in many most advanced multi-layer methods: GL, PMM, and ML-LCD.

INDEX TERMS Influence, local community detection, multi-layer network, sensor networks.

I. INTRODUCTION

With the development and progress of society, complex networks have become an indispensable part of people's lives. As people's very food and clothing are intimately entangled with various networks, research on complex networks has become a hot topic, and its applications in various fields have a huge impact on the world. However, there is an increasing awareness that the interaction of different networks makes research on single-layer networks too one-sided and lacking. Thus, there has been a push to combine all types of relationships with simple graph theory to achieve more complex real network transfer. To better align the topological relationship and the real state of a real-world system, an increasing number of researchers have been able to represent the complex relationships of the real world through multi-layer networks. The recognition club structure in a multi-layer network is a very influential paradigm [1]–[4]. Given the diversity and complexity of the networks in the real work, the single-layer network has not been able to describe their organization. Dickison *et al.* [5] proposes a multi-layer network model to analyse the intricate systems of the real world and define the relationship between multiple networks. He introduces a community detection algorithm based on multi-layer network polymerization, which is the main idea of using certain strategies to transform the original multi-layer network into a single-layer network; then, a single-layer algorithm is selected to implement the discovery operation. The main idea of this algorithm is for it the single-layer network learning algorithm to be applied to each layer and processed into the eigenmatrix of the node; subsequently, the traditional clustering algorithm can be applied to this matrix to obtain the community organization. However, because the internal relationships of the multi-layer networks are complex and multi-layered, each node has a different influence. How to use the influence of the nodes in a multi-layer network and the

The associate editor coordinating the review of this manuscript and approving it for publication was Zheli Liu.

2169-3536 © 2019 IEEE. Translations and content mining are permitted for academic research only.
Personal use is also permitted, but republication/redistribution requires IEEE permission.
See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

implementation of the multi-layer networks local club detection has become a new research topic [6], [7]. At present, the influence of individuals or groups is measured individually, and the influence and influence mechanism of the individuals and groups is also measured; the influence of the groups has a certain advantage given the scale of the network, and the research and modelling of the nodes can further help people understand the structure of the community in a social network. Thus, research on the influence of the network nodes has very important theoretical value and applied value of the examination of a network.

Local community detection focuses on the study of the subgraph structure. Starting from the selected node, it detects the community structure containing the node according to a certain classification algorithm and does not need to predict the global information of the entire network in advance. In a multi-layer network, the selection of the seed nodes determines the robustness of the algorithm results. If the seed nodes are at the core of the multi-layer network, robust results will be achieved. The importance of nodes in multilayer networks is usually measured by the centrality. The centrality is an important measure of nodes, edges or some other subgraphs in a network. The diversity of multilayer complex network topologies determines that the seed node measurement itself is a type of very difficult problem. So identifying a method to measure the central network node using a more accurate measurement algorithm is still currently challenging. Selecting nodes of higher influence can thus further improve the existing local community detection algorithm's robustness [8].

The structure of this paper is this : in the second section, the basic theory and influential theory of multi-layer network community detection are reviewed. The third section outlines the local community detection method and a model founded on the influence of a multilayer network. In section 4, based on real multi-layer network data, a single-layer regional community detection algorithm and multi-layer network local community detection algorithm test comparison and performance evaluation are realized. In section 5, this paper is summarized, and feasible suggestions are given for future research.

II. RELATED WORKS

With the multi-layer network model becoming increasingly widespread in the various fields of science, the topic of the "multi-layer image" has become of great interest. Relevant researchers have developed various types of applicable algorithms according to their own ideas. Generally, existing algorithms for community detection tend to be divided into two categories: multi-layer network clustering and single-layer algorithm expansion.

In the multi-layer network layer clustering algorithm, by clustering the layers in a multi-layer network into a single-layer network, the community detection algorithm of the existing single-layer network is utilized to realize community detection in the multi-layer network. This approach has two clustering schemes. The first method is that the multi-layer network is converted into a weighted graph $G = \langle V; E; W \rangle$, where W is the weight matrix, according to the weight of each layer of the multilayer network in a single network, which is then applied to the single-layer network for detecting community structure [9]. FIGURE 1 illustrates the process of layer aggregation. The second method is to use the single-layer community detection algorithm on the multi-layer network to detect the community structure of each layer prior to combining all the community structures obtained through the set clustering method [10]. FIGURE 2 illustrates the process of multi-layer community structure combination.

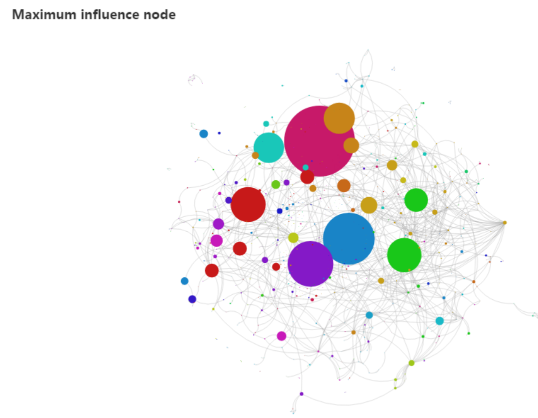


FIGURE 1. Single-layer network influences maximum node.

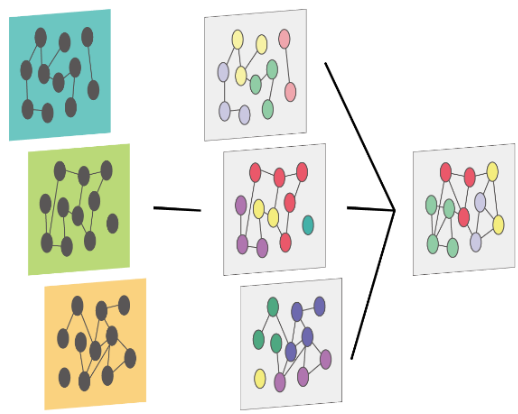


FIGURE 2. The combination process of the multi-layer network community structure.

The scale of social networks is becoming increasingly large, and the amount of information included in them is also increasing. Since the method based on local information does not need to analyse the global structure of networks from a local perspective, it has attracted extensive attention from researchers in recent years [11]. Bagrow and Bollt [12] put forward a method starting from the source node and adding a continuous shell each time a node joins. Lancichinetti *et al.* [13] put forward a fitness function F index to measure the corporate internal and external connection density difference. The algorithm's advantage lies in its simple calculation and high feasibility; however, its initial node is chosen randomly, it has a certain instability, and the algorithm of the fitness parameters must also be known ahead of time. Chen *et al.* [14] proposed a local community centre node detection based on local degrees of the new method. In the method, the local communities are not found from a given starting node but from a local centre node that is associated with a given starting node. Tabarzad and Hamzeh [15] proposed a heuristic method to detect communities by investigating the local information. Comparing the proposed method with the most advanced method, as determined by testing association and member evaluation, the proposed method is better than the advanced method and provides more accurate results. Chen *et al.* [16] proposed a half local centre degree measurement method in the centre of the low correlation degree and achieved a balance between the other time-consuming measurements. The literature [17], [18] proposed a multiple agent based on a distributed environment angle of view of a mining algorithm based on the indigenous community. Because the choice of the initial node makes some existing algorithms produce calculation results that are not robust, a reasonable node search strategy must be formulated to improve the local community findings. To solve this problem, many scholars have begun to maximize the influence of the node as the initial node [19], [20] and use the influence to find community structure.

The node influence describes the ability of a node to influence other nodes; the node influence is affected by its location and activity performance. To maximize the impact is to find a small number of seed nodes in the social network so that the influence can spread rapidly through the seed nodes in a short time throughout the social network. Leskovec *et al.* [21] proposed the CELF algorithm, which makes use of the characteristics of submodular functions in the influence propagation model to improve the efficiency of the greedy algorithm by several hundred times. Chen *et al.* [22] further proposed a degree reduction optimization algorithm based on the degree of the nodes. The experimental results of the algorithm were similar to those of the greedy algorithm, but the efficiency was significantly improved. Jung *et al.* [23] proposed the IRIE model. First, the influence of all nodes was sorted by the global influence ranking algorithm. Compared with the greedy algorithm, the efficiency and speed of this model are improved greatly. Goyal *et al.* [24] proposed the CD model to solve the problem of influence maximization and directly estimated the influence probability among users through the historical data of users. Compared with other algorithms, the Monte Carlo algorithm avoids a large amount of time consumption in learning the probability of influence between users. Li *et al.* [25] improved the network marketing by considering the location of shared users and by proposing and studying the issue of influence maximization in location-aware social networks, thus ultimately improving the issue of influence maximization based on geography and social influence.

The qualitative definition of the community structure has some limitations for the detection of the community structure. Therefore, scholars in different fields have put forward evaluation criteria for community detection and introduced three typical evaluation indexes, namely, standard mutual information, module degree measurement and local module measurement.

Standardized mutual information (NMI): For networks with known community structures, NMI can evaluate the performance of community detection methods. NMI is an important measure of community discovery, which compares the accuracy of communities divided by algorithms and the generated orthodox communities in a single-layer network. The measurement value is typically between 0 and 1; the higher the value is, the more accurate the detection result of the algorithm is. When the value is 1, the same consequence as the tag community can be obtained. There is no division method of NMI in the multi-layer network. To match the accuracy of the algorithm, this paper calculates the value of the NMI for each layer and then divides by the average number of layers to provide the multi-layer NMI value between the measurement algorithm and the generated data set [26].

Local modularity: To realize the community division of complex networks, certain evaluation indexes are needed to evaluate the results of the network division by algorithms. For the detection results of local communities, this measure is usually only used to consider community boundary nodes and to measure the definition of the community boundary, which is defined as the number of edges connected between community boundary nodes and nodes inside the community and the proportion of the edges connected with other nodes outside the community [27].

III. LOCAL MODULE DEGREES OF MULTI-LAYER NETWORK

A. MULTI-LAYER NETWORKS

Many real-world complex systems consist of a set of basic units connected by different types of relationships. All of these systems can be used to better describe the relationship network, and there are more of systems in a network with more relations. Every type of relationship provides links among the same set of nodes for different types of interactions to better describe the network with more relationships. In 2014, Boccaletti provided a mathematical definition of a multi-layer network [28]: a layer of a multilayer network $\mathrm{G}_{\mathcal{L}} = (y, \ell)$ is a set of different network layers ℓ, and for each edge between the layers $\mathcal{L}$ of a collection, $\mathrm{y} = \{\mathrm{G}_\alpha; \alpha \in \{1, \cdots \mathcal{L}\}\}, \mathrm{G}_\alpha = (\mathrm{X}_\alpha, \mathrm{E}_\alpha)$. For each network layer or layer in a multilayer network, $\ell = \left\{\mathrm{E}_{\alpha\beta} \in \mathrm{X}_\alpha \times \mathrm{X}_\beta; \alpha, \beta \in \{1, \cdots, \mathcal{L}\}, \alpha \neq \beta\right\}$ and $\mathrm{y} = \{\mathrm{G}_\alpha; \alpha \in \{1, \cdots \mathcal{L}\}\}, \mathrm{G}_\alpha = (\mathrm{X}_\alpha, \mathrm{E}_\alpha)$, where a network layer or layer that is a multilayer network, $\ell = \left\{\mathrm{E}_{\alpha\beta} \in \mathrm{X}_\alpha \times \mathrm{X}_\beta; \alpha, \beta \in \{1, \cdots, \mathcal{L}\}, \alpha \neq \beta\right\}$ is the set of connecting edges between the nodes of different network layers G_α and G_β. The constituent elements in E_α are called cross layers, and $\mathrm{E}_{\alpha\beta}$ is the interlayer between the nodes of the edge.

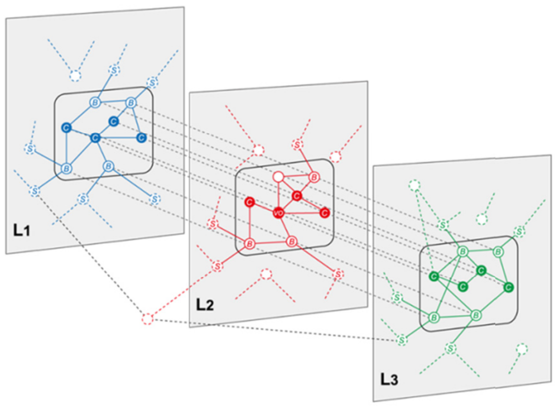


FIGURE 3. Schematic diagram of multi-layer network community detection.

TABLE 1. Multi-layer network symbols.

Symbols for a multilayer network	
Symbol	Description
$G_{\mathcal{L}}$	Multilayer graph G with $\mathcal{L}$ layers
$V_{\mathcal{L}}$	$\mathcal{L}$-layer node set
$\mathcal{V}$	Node set
$\mathcal{L}$	The set of layers
B	A collection of local community boundary nodes
S	The set of all points that have an edge with B
V0	Seed node

This paper defines a multilayer network as follows: for a layer of a multilayer network, $G_{\mathcal{L}} = (V_{\mathcal{L}}, E_{\mathcal{L}}, \mathcal{V}, \mathcal{L})$ with different network layer sets $\mathcal{L}$, node sets V, and $V_{\mathcal{L}} \subseteq \mathcal{V} \times \mathcal{L}$ for each layer of the multilayer network node that contains or is equivalent to the node and the product of the layer. The set of edges $E_{\mathcal{L}} \subseteq V_{\mathcal{L}} \times V_{\mathcal{L}}$ is a collection of unique sides. FIGURE 3 shows a detection schematic diagram of the local communities in a multi-layer network, and Table 1 lists the symbols of the multi-layer network applied in this paper.

B. LOCAL COMMUNITY SEED NODES

In the multi-layer network, local community detection is realized. Greedy local expansion is carried out through the local detection algorithm from the initial node, and the local community structure is finally obtained in the multi-layer network. However, the location of the initial node determines the accuracy of the local community algorithm. If the initial node is located at the core of the community (or the node has a high influence value), the local community detection algorithm is more robust than if it is located at the boundary (or has a low influence strength).Therefore, it is significant to find seed nodes in a multi-layer network for local community detection. In social networks, the centrality measurement results of a node can directly reflect its importance in the network. In the network, there are many metrics that can be used to quantify this situation, such as the degree centrality, median centrality and graph centrality. The intermediate centrality index and tight centrality index based on global information have a high algorithm complexity, and the global structure of the community is often difficult to obtain in the local network, which is unsuitable. Although the node degree index considers the connection of the neighbour information from a local perspective, it cannot be sorted according to the order size for a multi-layer network. Therefore, in this paper measures the importance of nodes using a new quantity:

Consider a multilayer network with $\mathcal{L}$ layers and N layer nodes $G_{\mathcal{L}} = (y, \ell)$, where node $i \in X\,(i = 1, \cdots, N)$ has vectors for the connections or degrees given as

$$k_i = \left(k_i^{[1]}, \cdots, k_i^{[\mathcal{L}]}\right) \tag{1}$$

Among them, $k_i^{[G_\alpha]}$ is node i in layer G_α in degrees, and the calculation expression for $k_i^{[G_\alpha]} = G_{\alpha_{ij}}^{[G_\alpha]}$. The importance of a node i is defined as

$$o_i = \sum_{G_\alpha=1}^{\mathcal{L}} k_i^{[G_\alpha]} \tag{2}$$

In this paper, a semi-local centrality index is proposed according to the importance of the multi-layer network nodes. Starting from the nearest neighbour and sub-neighbour information of the source node, this index can effectively identify the importance degree of the node under local information. Its definition is as follows:

$$\delta(u) = \sum\nolimits_{\omega\in\Gamma(U)} N(o_i) \tag{3}$$

$$C(v) = \sum\nolimits_{u\in\Gamma(v)} \delta(u) \tag{4}$$

The types $\Gamma(U)$) and $\Gamma(v)$ are sets of nodes U and v, respectively, from the nearest-neighbour nodes; $N(o_i)$ is the sum of the repetitions of the nearest-neighbour nodes of node i in the multi-layer network; and $C(v)$ is the largest node, which is the seed node.

C. INDIRECT INFLUENCES OF MULTI-LAYER NETWORK NODES

At the present stage, due to the rapid promotion of various social software, such as communication technology, scientific research projects and Weibo social networking, relevant researchers are paying increasing attention to this field. In addition, hidden factors such as friends, attributes and similarity of interests should be taken into consideration. Based on this consideration, this part of the content of the unified choice of the indicator influence is used to measure the pertinent hidden factors. In a multi-layer network, the similarity influence between layers, the similarity and structure influence between nodes of the same layer, the influence measurement between nodes of different layers and the weight index of each influence relationship are set. This section further integrates the influence values in the local detection of a multi-layer network through the selection of influential relations and obtains a relatively efficient multi-layer community detection algorithm that fully combines the structure and similar factors to improve the accuracy of the detection of the local communities of a multi-layer network.

$$Inf(u, v) = \omega_1 SInf(u, v) + \omega_2 DInf(u, v) \tag{5}$$

In the formula, SInf (u, v) and DInf (u, v) respectively represent the direct and indirect influences of node u on node v. The weight of each component of the influence sums to $\omega_1 + \omega_2 = 1$.

1) INDIRECT INFLUENCE OF MULTI-LAYER NETWORK NODES

The correlation theory of informatics holds that the length of a propagation path is negatively correlated with the accuracy and completeness of the results. In a whole transmission link, the more intermediate nodes there are, the worse the effect on the transmission. For the path selection of the impact, in this paper calculates the intensity of the indirect influence relationship between nodes through the shortest path of the multi-layer network.

The path length relates to the number of edges in a path. There are at least two different types of edges in multilayer networks, in-layer edges E_α and inter-layer edges $E_{\alpha\beta}$. In this paper uses two nodes in the multilayer network, (u) and (v), to create a geodesic line to define the connection between the two nodes of a shortest path. Given a multilayer network u = (y, l), its set of edges is

$$E(u) = \{E_1, \cdots, E_M\} \cup l \tag{6}$$

uA path of length is defined q-1 as a non-empty staggered sequence of nodes and edges:

$$\left\{x_1^{a_1}, l_1, x_2^{a_2}, l_2, \cdots, l_{q-1}, x_q^{a_q}\right\} \tag{7}$$

Among them, $\alpha_1, \alpha_2, \cdots, \alpha_q \in \{1, \cdots, M\}$. Thus, for all r < q, there is a subset that belongs to ε, and there is E(u)

$$l_r = \left(x_r^{\alpha_r}, x_{r+1}^{\alpha_{r+1}}\right) \in \varepsilon \tag{8}$$

If the edge is $l_1, \cdots, l_{q-1}$ weighted, the length of the path is defined as the sum of the reciprocal weights. If the starting point and the ending point are the same $x_1^{\alpha_1} = x_q^{\alpha_q}$, then the path is closed.

The path $\varepsilon = \left\{x_1^{\alpha_1}, x_2^{\alpha_2}, \cdots, x_q^{\alpha_q}\right\}$ that mediates between two nodes $x_1^{\alpha_1}$ and $x_q^{\alpha_q}$ in a multilayer network is u described as a path in which the nodes do not repeat. A ring is defined as a closed path whose starting point and ending point are at the same node. If a path between any two nodes in the multi-layer network can be found, then the network is connected; otherwise, it is not connected. However, different types of network connectivity may occur if the edges in different network layers are considered [29].

The path length refers to the number of edges in a path. There are at least two different types of edges in multilayer networks: inside edges and outside edges. The definition of a path then depends on equating the two different types of edges. The following definition of the path length is tantamount to treating the two types of edges equally. In a multilayer network, the geodesic path between two nodes u and v is described as the shortest path connecting the two nodes. The distance d_m between these two nodes is the length of any geodesic path between them. The maximum distance D(u) between any two nodes in a multilayer network is referred to as the diameter of the multilayer network.

If for any two different network layers γ and δ there are two different network layers α and β that satisfy $X_t' \subseteq X_\alpha, E_\gamma' \subseteq E_\alpha$ and $X_{v\beta}' \subseteq X_{\alpha\beta}$. Then, $N = \left(y', t'\right)$ is $u = (y, t)$ a sub-network of the multi-layer network, and the u connected branch is a maximally connected subgraph of it. If two paths connecting the same pair of nodes in a multilayer network have only the same starting and ending points, the two paths are said to be node-independent.

The path length between two points u and v in a multi-layer network u is defined as:

$$L(u) = \frac{1}{N(N-1)} \sum_{u,v \in X_u, u \neq v} d_{uv} \tag{9}$$

where the definition of $|X_u| = N_0$ provides a way to calculate the other structural attributes of the network, such as the network efficiency of a single-layer network, defined as:

$$e(u) = \frac{1}{N(N-1)} \sum_{u,v \in X_u, u \neq v} \frac{1}{d_{uv}} \tag{10}$$

If the path length of a multilayer network is defined, the definition is not the same if the mid-layer edge connection and the inter-layer edge connection are considered to be different. Suppose that $u = (y, t)$ is a multi-layer network, and one path is denoted as

$$\Im = \left\{x_1^{a_1}, l_1, x_2^{a_2}, l_2, \cdots, l_q, x_{q-1}^{a_{q-1}}\right\} \tag{11}$$

Its length is defined as:

$$l(\Im) = q + \beta \sum_{j=2}^{q} \Delta(j) \tag{12}$$

where β is any given non-negative parameter, and

$$\Delta(j) = \begin{cases} 1, & \text{IF } l_i \in l \\ 0, & Other \end{cases} \tag{13}$$

In such a multi-layer network, the distance between nodes i and j is the shortest length of all of the paths between them. In a multilayer network $G_{\mathcal{L}}$ between two nodes u and v, the path length is defined as:

$$L(G_{\mathcal{L}}) = \frac{1}{N(N-1)} \sum_{u,v \in X_u, u \neq v} d_{uv} \tag{14}$$

where $\left|X_{G_{\mathcal{L}}}\right| = N_0$ also provides a way to calculate the influence properties of two nodes in the multi-layer network, that is, to find the shortest path between two nodes in the multi-layer network. It is defined as:

$$SInf(u, v) = Min(\frac{1}{N(N-1)} \sum_{u,v \in X_u, u \neq v} d_{uv}) \tag{15}$$

D. DIRECT RESPONSE OF MULTI-LAYER NETWORK NODES

It is found that social network and communication network have typical homogeneity. In other words, there is a trend of correlation between related nodes with similar characteristics [30]. In the field of communication science, this tendency of correlation is called the reciprocal influence relationship. Within the scope of the multi-layer related system, the influence measurement links involved should not only fully combine the similar social influence generated by the structure itself but also focus on the influence generated by the attributes of the nodes and the similarity between layers. This paper focuses on the direct impact relations.

$$LC^{\text{int}}(C) = \frac{1}{|C|} \sum_{u,v \in C} \sum_{\substack{L_\alpha, L_\alpha \in \mathcal{L} \\ \wedge u \in V_\alpha, v \in V_\beta}} \frac{|N_\alpha(u) \cap N_\beta(v)|}{\sqrt{|N_\alpha(u)|\,|N_\beta(v)|}}$$

$$LC^{ext}(C) = \frac{1}{|B|} \sum_{u,v \in B} \sum_{\substack{L_\alpha, L_\alpha \in \mathcal{L} \\ \wedge u \in V_\alpha, v \in V_\beta}} \frac{|N_\alpha(u) \cap N_\beta(v)|}{\sqrt{|N_\alpha(u)|\,|N_\beta(v)|}} \tag{16}$$

where $N_\alpha(u) = \{v \in V \,|(u, v) \in E_\alpha\}$ represents the neighbour set of node u in a layer. The similarity influence between nodes u and v in the multi-layer network is calculated as follows:

$$DInf_{\alpha,\beta}(u, v) = {LC^{ext}(C)}/{LC^{ext}(C)} \tag{17}$$

If $DInf_{\alpha,\beta}(u, v) > 1$, it indicates that nodes u and v in the network layer α and β have similar influences, that is, the influence relationship in the local communities is greater than that in the communities to be tested. If $DInf_{\alpha,\beta}(u, v) < 1$, it indicates that the influence of nodes u and v in the network layers α and β in the local communities is less than that of the communities to be tested.

E. MULTI-LAYER NETWORK LOCAL COMMUNITY DETECTION IS BASED ON INFLUENCE EXPANSION

In conclusion, based on the direct influence and indirect influence measurement, in this paper proposes a multi-layer network local community detection algorithm, as shown in Table 2. The first three behaviours in Table 2 calculate the seed nodes of the multi-layer network. The fifth and ninth behaviours judge the merging process of the seed nodes through the impact measurement, and the final algorithm obtains the local communities through the influence measurement. Table 2 reports the pseudo code of the universal scheme of the attribute multilayer local detection method proposed in this paper.

In this section, IMLC, a multi-layer network local community detection algorithm based on influence relations is introduced, which can support multi-layer graphs with

TABLE 2. Local community detection algorithm of a multi-layer network based on influence measurement.

Algorithm 1: Multi-layer network local community detection algorithm (IMLC) based on influence measurement
1: $G_{\mathcal{L}} = (V_{\mathcal{L}}, E_{\mathcal{L}}, , V, \mathcal{L})$
2: S= V
3: $B = \{u \in C \,|\, \exists\, ((u, L_i), (v, L_j)) \in E_{\mathcal{L}} \cap v \epsilon S\}$
4: v_0 ; // Use formula (4) to get the seed node
5: $S = S - \{v_0\}$; $C = \{v_0\}$
6: for node $v_j \in S$ and $\{v \in V \backslash C \,|\, \exists ((u, L_i), (v, L_j)) \in E_{\mathcal{L}} \cap u \epsilon C\}$ do
7: if $\mathrm{Inf}(u_B, v_j) > \mathrm{Inf}(v_S, v_j)$ then// Formula (5) is used to judge the influence of two sets on node v_j
8: $C = C \cup \{u_B\}$// Compare node v_B in the boundary set to the local club c
9: $B = B \cup \{v_j\} \backslash \{u_B\}$// Node v_j is merged into the boundary set B of the local community, and the $\{u_B\}$node is removed from the boundary set
10: $S = S \backslash \{v_j\}$// Remove wait detection nodes to set S
11: Else
12: End if
13: j! j+1
14: End for
15: Return C
16: end

two or more layers. The algorithm first sorts the nodes according to formula (4), calculates the regional seed node V_0 of the multi-layer network, and initializes it as the local community C. B is the boundary set of the local community where node V_0 is located. Second, considering the magnitude of the influence, the nodes in the layer with a high influence with V_0 are bound to join the neighbourhood as the adjacent nodes of V_0. In addition, the influence relationship between different layers of nodes is considered in the expansion of local communities. The higher the impact between nodes and their neighbours, the more likely they are divided into the same local community set. For node Vi in set S to be detected, assume $\mathrm{Inf}\,(V_B, V_i) > \mathrm{Inf}\,(V_S, V_i)$, and insert node Vi into community C; otherwise, compare the next node of S directly connected to the boundary set B. By means of the continuous iteration of all nodes, the detection of the local community C with V_0 as the seed node is finally realized. The pseudo-code of the general scheme based on the multi-layer local detection (IMLC) method is as follows:

IV. EXPERIMENTAL RESULTS

The performance of IMLC is evaluated through extensive experimentation on single- and multi-level real-world networks. The experiments are performed on a computer with Windows 7, 3.10 GHz and 32.00 GB RAM.

A. DATA SET

To judge the rationality of the algorithm, this paper uses 6 real multi-layer network data sets to verify the rationality of the performance of the IMLC model.

ObamaInIsrael2013 [31]: The multi-layer Internet data set of President Obama's visit to Israel in 2013 obtained from Twitter was divided into three layers, corresponding to retweets, mentions and replies. Users can forward other users' tweets, implying that a user supports information shared by another user and forwards it to his followers. Users can reply to other users' tweets, which represents the exchange between users in response to the information included in the user's tweets. A user can mention another user in a tweet, which indicates a willingness to share a message with the user mentioned above.

Airline data set [32]: The data set takes different airlines operating in Europe as attributes, with each layer corresponding to a different airline. Thirty-seven different layers are used to form the multi-layer network.

Employee data set of Aarhus University [33]: The data set collects data from the employees of the Department of Computer Science of AUCS. The study involved 61 workers (142 relationships in total), including professors, postdoctoral researchers, doctoral students and managers. The data set includes five types of relationships: current work relationships, repetitive leisure activities, regular lunches together, shared posts, and Facebook friendships. The coauthor network is the smallest and least connected of all the layers, with the largest number of edges in the work network and the lunch network and the highest average degree of vertexes in the Facebook network.

MIT media lab data set [34]: The multilayer figure contains the MIT Media Lab's collection of human-computer interaction data and experimental data, which included 94 people. These people's data correspond to the nodes in the multilayer network layer for interaction in two ways, including the friends layer, which refers to friendship, and the SMS layer, which is based on message exchange and refers to the Bluetooth device scanning equipment layer. The dataset provides three layers with 17782 and 113 edges.

DBLP data set [35]: In the DBLP data set, each node corresponds to a single author, and the layer represents the top 50 computer science conferences. If two authors co-authored at least two papers at a particular meeting, they were linked in a single layer.

Wireless Sensor Network data set: Thermal power plants, which are mostly used to generate electricity, utilize equipment such as coal millers, coal feeders, fans, and sensors, and good equipment maintenance is crucial to the generation of stable power supplies. Traditional planned preventive maintenance (PPM) models are adopted in most of thermal power plants. Thousands of wireless sensors, e.g., temperature sensors, pressure sensors, humidity sensors, and speed sensors, are installed to monitor the state of the equipment in real time. Data can be acquired continuously from these sensors, and monitoring the sensor data helps monitor the status of the equipment. Schematic diagram of wireless sensor network in a thermal power plant is shown in FIGURE 4:

Table 3 displays the main characteristics of the experimental data sets in this paper. The node relationships in all data sets are considered to be symmetric # Nodes refers to the number of nodes in the data set, # Edges refers to the number of edges in the data set, #Layers refers to the number of layers in the data set, Density refers to the degree of data

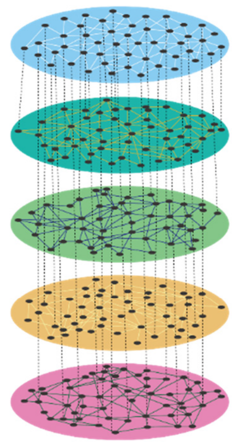


FIGURE 4. Wireless sensor networks for thermal power plants.

set, Adeg refers to the average degree of nodes considering multiple edges, and Alayer refers to the average number of layers in the nodes. The number of DBLP layers in the data set is the highest, reaching 50. Wireless Sensor Network holds the largest number of nodes and edges.

B. COMPARISONS OF ALGORITHMS AND EVALUATION INDEXES

1) COMPARISON OF ALGORITHMS

To evaluate the performance of IMLC, in this paper uses three community detection methods to compare with the IMLC implementation.

Community detection algorithm LART [36]: This is used to detect communities with some or all layers overlapping in a multi-layer network. The algorithm is based on a random walk on a multi-layer network, and the transition probability of the random walk is dependent on the local topological similarity between any given node and each layer to realize the detection of a multi-layer community. The advantage of this algorithm is that it only needs to define a parameter t, which determines the length of the random walk. The value of t can change within some boundaries. As long as the random walk time is short enough, the local community structure can be studied.

PMM [37]: This algorithm extracts structural features from each dimension of the network through modular analysis and integrates them to detect the community structure. For noisy networks, the optimal community processing results can be obtained by using the main modular maximization (PMM) method.

Community detection algorithm GL [38]: This algorithm obtains the combination of a single network by connecting each node in one network slice to the link coupling of itself in another network slice. This framework allows people to study community structures in a very general environment that includes networks that evolve over time, has multiple types of links (multiple complexities) and involves multiple scales of networks.

TABLE 3. Characteristics of multi-layer network data sets.

Dataset	# Nodes	# Edges	#Layers	Density	Adeg	Aleyas
ObamaInIsrael2013	2281259	4061960	3	6.23e-5	3.36	1.05
Airlines	417	3588	37	0.023	17.20	4.88
CS-AARHUS	61	620	5	0.122	20.32	3.67
MIT Media Lab	88	355	3	0.047	8.12	2.46
DBLP	83901	159302	50	8.9e–4	3.80	1.35
Wireless Sensor Network	1632	56356	5	3.25e-5	3.16	1.12

ML-LCD [29]: This algorithm is based on the function optimization of the internal and external connectivity of the local community of the multi-layer network. When the local community is found through a given seed node, the extensive analysis of 7 real multi-layer networks shows the significance and ability of the method in detecting the local community of the multi-layer network

2) EVALUATION INDICATORS

To realize community division in a complex network, some evaluation indexes are needed to evaluate the result of the network division. Due to the existence of large-scale unknown societies in the data set of the experiments in this paper, in this paper quantifies or evaluates the classification level of societies through the module degree. The larger the value is, the better the society structure is, thus allowing the influence of the value of impact on the algorithm to be better verified.

C. WEIGHT OF MULTI-LAYER NETWORK INFLUENCE

The accuracy of the community detection is determined by the influence of the above algorithms. This section describes the measurement of the direct influence and indirect influence relationships. First, repeat the IMLC algorithm through the multi-layer network medium maximum node and start to generate a local community; then, sort by degree, find the degree of the largest node that is not in this local community, and generate a second community. Eventually, all will be covered. Finally, the nodes that are not listed in any community will be added to the local community adjacent to the node according to the IMLC algorithm. Then, run this process 50 times to obtain the average modularity result.

To obtain a better influence weight ratio, different detection and comparison effects are obtained in according to different values of omega in formula (1). By comparing the influence of the two data sets on IMLC when the influence increases, the direct influence parameter, ω_1, is taken as the reference parameter, and the two parameters ω_1 and ω_2 are taken as fixed parameters to realize the comparison. The Adeg higher CS-AARHUS and Adeg sparse Wireless Sensor Network data sets are run 50 times to achieve the comparison of the results and to determine the influence of the two parts of the weight, as shown in FIGURE 5.

It can be found that when the influence weight is ω_1 and ω_2; when $\omega_2 > 0.5$, a large degree of modularity is obtained, and when ω_2 is 0.6, a suitable detection effect can be obtained. In the data set of CS-AARHUS, the highest module degree can be achieved in 50 runs when $\omega_2 = 0.3$, but the average effect is better when $\omega_2 = 0.4$. In the dataset of the Wireless Sensor Network, because the dataset was sparse, the maximum modularity effect was obtained when $\omega_2 = 0.3$, and the average effect was also better when $\omega_2 = 0.4$. Therefore, in this paper, the influence weight between the middle layer and other layers is detected in the multilayer network: $\omega_1 = 0.4$, $\omega_2 = 0.6$.

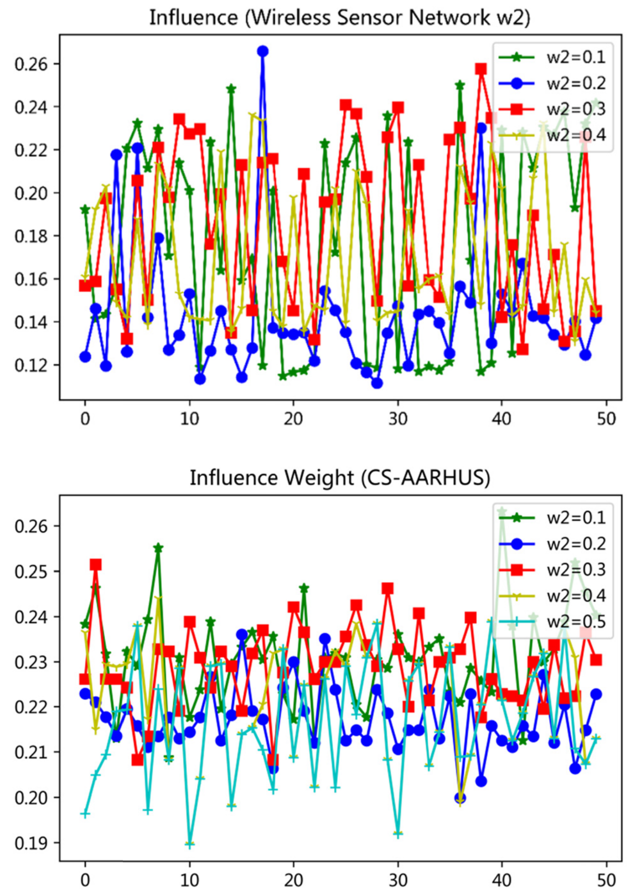


FIGURE 5. Results of influence weights.

D. MODULE DEGREE ANALYSIS

Figure 6 is the multi-layer network modularity obtained after 50 runs of different data sets. In order to view the graph more accurately, we use the module degree of the maximum algorithm to represent the outermost circle graph in this graph. Therefore, the legend displayed each time is very different.

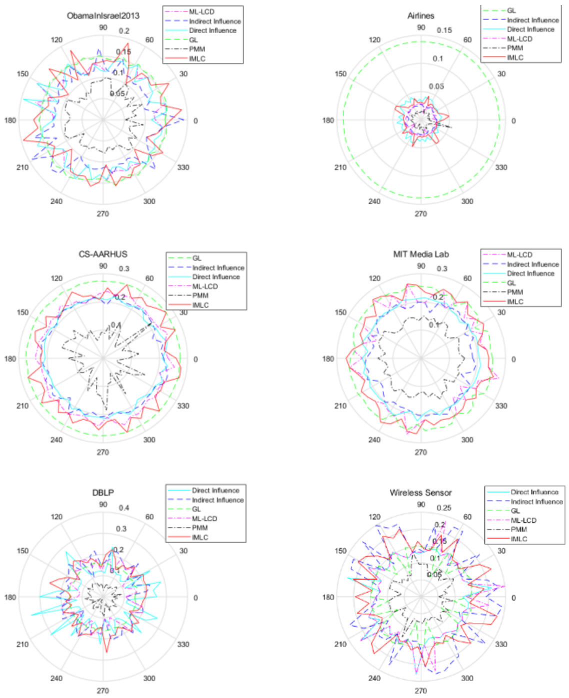


FIGURE 6. Results of 50 runs of different algorithms on 6 data sets.

In this paper, the global network module degree index used in the different data sets was run 50 times, and the module degree was obtained each time for comparative analysis. By comparing the degree of modularity of multiple algorithms running in different data sets and by combining this data with the change of the modularity of the evaluation algorithm in multiple runs, the effect of the evaluation algorithm in detecting a community in a multi-layer network is evaluated. FIGURE 6 shows the effect of each algorithm running 50 times in different data sets.

The detection method set out in the present paper has been tested and verified with the most advanced global community detection method. Owing to the LART algorithm and large Wireless Sensor Network, there is a memory overflow; thus, the result of program running cannot be obtained. Therefore, in this paper only shows the overheat diagrams of the GL, PMM, ML-LCD, and IMLC algorithms in the figure. As shown in FIGURE6, only the direct influence relationship or the influence relationship of indirect nodes are considered, and the detection result is far lower than that of the comprehensive influence relationship algorithm. The IMLC algorithm proposed in this paper can achieve better modularization results in the dataset with obvious influence, especially in the Wireless Sensor Network dataset, and the algorithm in this paper has achieved a better detection effect. The Wireless Sensor Network data set is generally the most suitable for good friendly relations and has a relatively high impact. However, in the airline data set, the testing results obtained were far lower than those of the GL algorithm. This was because the airlines had too many layers and the data was relatively sparse data sets. The data set of every route was different, and there were fewer similarities between layers. The IMLC algorithm considers that relations do not provide an advantage, so in the process of multilayer local community detection, a better result cannot be obtained. However, the algorithm in this paper considers the influence relationship between layers. Compared with the ML-LCD algorithm, the algorithm presented in this paper can obtain relatively reliable results.

In the ObamaInIsrael2013 data set, the data sets have higher Adeg and lower Aleyas; the algorithm presented in this paper has a shorter operation time and produces similar results as the GL algorithm. The algorithms only consider the indirect influence on a module, which produces average values that are higher than the direct influence algorithm results but with decreased algorithm stability. The GL algorithm is almost smooth running as a result; the algorithm IMLC produces better results than GL, but the overall stability is lower than that of the GL algorithm. The ML-LCD algorithm produces roughly the same result as the IMLC algorithm. For the data set CS-AARHUS, the module degree obtained by the algorithm in this paper is lower than that of the GL algorithm or PMM algorithm, but it is better than the algorithm that only considers the direct influence value and the algorithm that only considers the indirect influence value; further, the algorithm presented in this paper is better than that of the ML-LCD algorithm because the influence relation of the layers is considered. In the CS-AARHUS algorithm, after the fusion of multiple influence values, the IMLC algorithm can obtain results similar to the GL algorithm and better than the PMM algorithm in partial operation consequences. For the DBLP data set, the algorithm put forth in this paper produces operation times for obtaining the module values that are similar to the GL algorithm, but these values are greater than those of the PMM algorithm and ML - LCD algorithm. More notable is the influence of the direct influence value in contrast to only considering the influence of the interlayer, as most of the technology and biological networks have different distribution networks. According to the characteristics of the multi-layer network DuDu association, a better detection result is obtained for similar but not connected nodes when considering the influence of the inside layer. In the MIT Media Lab data set, the algorithm IMLC set out in the present paper can achieve a better detection effect than the GL algorithm or PMM algorithm, and it is also higher than algorithms that only consider either the direct influence value or the indirect influence value. According to the analysis in Table 2, the data sets of the MIT Media Lab all have low Adeg. It can be seen that for data sets with sparse nodes, the algorithm integrating multi-influence relations can produce better results. For data sets DBLP and Airlines, the IMLC algorithm has more robust results than the ML-LCD algorithm due to the higher number of layers. In the algorithm that only considers the indirect influence, it can also generate better results and achieve the optimal detection effect after running for a long time. However, compared with the IMLC algorithm integrating multiple impact values, the stability is worse than that of the algorithm integrating multiple influence relations.

The data set of ObamaInIsrael2013 is unique. Because it is large, to ensure the operation of PMM algorithm and GL algorithm, in this paper intercepted the data of the first fifth of the data set, that is, the first 456252 nodes, as the experimental data set. However, through a comprehensive comparison with several data sets, the GL algorithm generated average results that were better than those obtained by other community detection algorithms. To better compare with the other optimal algorithms, the proposed method does not use local module degrees, but the algorithm obtains the global community structure by comparing global module many times after the operation. Therefore, the results in the four data sets are not optimal relative to the GL algorithm but are better than PMM algorithm and ML-LCD algorithm.

E. COMPUTATIONAL EFFICIENCY

To test the time complexity of different algorithms, this paper uses different algorithms for different sizes of 6 real networks to realize the analysis. Because the node number of a smaller data set cannot correct the algorithm running time efficiency, in the Wireless Sensor Network in the existing test data sets, all configurations can be run, and the Wireless Sensor Network data total average running time for running a total of 50 times is 26216 seconds. Thus, in this section, the IMLC algorithm to detect the data set has better run time compared to the time on the Wireless Sensor Network. FIGURE7 shows the final test results. It can be found that the running time of the four algorithms is proportional to the network size. However, the running time of the IMLC on datasets with a relatively large number of nodes is relatively less than those of the GL and PMM algorithms, which enables it to process multi-layer large-scale sparse networks very efficiently.

It can be determined from FIGURE7 that the running time of IMLC algorithm is basically running in a lower period, but more time is spent running on average. Compared with the GL algorithm, the PMM algorithm has a better running time. In particular, there are more times when the running time is less than the average running time, but there are also times when the running time is close to the maximum. For the GL algorithm, the running time is greater than the average running time, and the running time of several times is the maximum running time. Compared with the IMLC algorithm and PMM algorithm, the ML-LCD algorithm achieves a higher average time complexity. Although ML-LCD is larger than the GL algorithm in terms of the partial running time, the average running time is lower than that of GL. In particular, in a large-scale data set such as Wireless Sensor Network, due to the insufficient memory in the configuration of the test equipment, the GL algorithm and PMM algorithm experience memory overflows and cannot run normally. Therefore, this paper intercepts the data of the first fifth of the data set, namely, the first 456252 nodes, as the test data set. It can be observed that IMLC adopts the local community detection method, which can adapt to the larger data set and produce better operational efficiency.

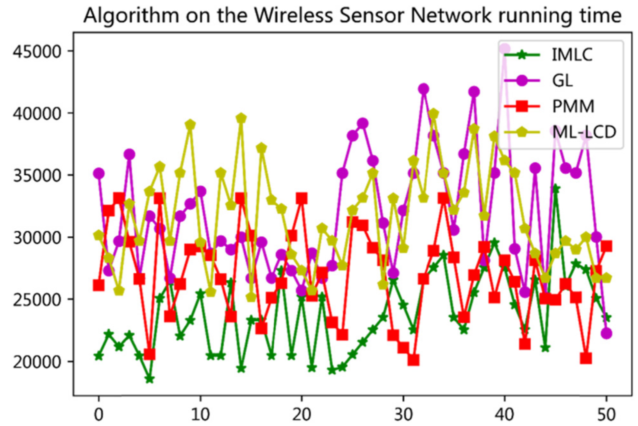


FIGURE 7. Time results of 50 runs are based on the Wireless Sensor Network dataset.

V. CONCLUSION

In this paper, founded on the nature of network layer, node layer and influence relationship, this paper proposes a local community detection model of multi-layer network which integrates the influence relationship between layers and within layers. Based on the homogeneous drive of multi-layer network and the influence relative index of multi-layer path length measurement, the local core nodes of the multi-layer network are calculated based on multi-layer tensor. Finally, through a large number of experiments in six real multi-layer network data sets to evaluate the impact of the influence weight and multi-layer influence relationship on community detection robustness, the accuracy and stability of the algorithm are verified by multi-layer data. In multi-layer data sparse network connection and large data sets, the method of this paper can identify the same or higher quality data sets and have better time efficiency and. In the sensor network, we will consider the changes of local community structure in the multi-layer network by adding sensor nodes dynamically.

REFERENCES

[1] M. Kivelä, A. Arenas, M. Barthelemy, J. P. Gleeson, Y. Moreno, and M. A. Porter, "Multilayer networks," *J. Complex Netw.*, vol. 2, no. 3, pp. 203–271, 2014.

[2] C. W. Loe and H. J. Jensen, "Comparison of communities detection algorithms for multiplex," *Phys. A, Stat. Mech. Appl.*, vol. 431, pp. 29–45, Aug. 2015.

[3] X. Zeng, G. Xu, X. Zheng, Y. Xiang, and W. Zhou, "E-AUA: An efficient anonymous user authentication protocol for mobile IoT," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 1506–1519, Apr. 2018. doi: 10.1109/JIOT.2018.2847447.

[4] D. Cai, Z. Shao, X. He, X. Yan, and J. Han, "Community mining from multi-relational networks," *Knowledge Discovery in Databases: PKDD* (Lecture Notes in Computer Science). Berlin, Germany: Springer, 2005, pp. 445–452.

[5] M. E. Dickison, M. Magnani, and L. Rossi, *Multilayer Social Networks*. Cambridge, U.K.: Cambridge Univ. Press, 2016.

[6] G. D'Agostino and A. Scala, *Networks of Networks: The Last Frontier of Complexity*. Berlin, Germany: Springer, 2014.

[7] J. Pei, D. Jiang, and A. Zhang, "On mining cross-graph quasi-cliques," in *Proc. 11th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, Chicago, IL, USA, 2005, pp. 228–238.

[8] X. Li, G. Xu, and M. Tang, "Community detection for multi-layer social network based on local random walk," *J. Vis. Commun. Image Represent.*, vol. 57, pp. 91–98, Nov. 2018.

[9] D. Suthers, J. Fusco, P. Schank, K.-H. Chu, and M. Schlager, "Discovery of community structures in a heterogeneous professional online network," in *Proc. 46th Hawaii Int. Conf. Syst. Sci.*, Maui, HI, USA, 2013, pp. 3262–3271.

[10] M. Berlingerio, F. Pinelli, and F. Calabrese, "*ABACUS*: Frequent pattern mining-based community discovery in multidimensional networks," *Data Mining Knowl. Discovery*, vol. 27, no. 3, pp. 294–320, Nov. 2013.

[11] A. Clauset, M. E. J. Newman, and C. Moore, "Finding community structure in very large networks," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 70, no. 6, Dec. 2004, Art. no. 066111.

[12] J. P. Bagrow and E. M. Bollt, "Local method for detecting communities," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 72, no. 4, Oct. 2005, Art. no. 046108.

[13] A. Lancichinetti, S. Fortunato, and J. Kertész, "Detecting the overlapping and hierarchical community structure in complex networks," *New J. Phys.*, vol. 11, no. 3, Mar. 2009, Art. no. 033015.

[14] Q. Chen, T.-T. Wu, and M. Fang, "Detecting local community structures in complex networks based on local degree central nodes," *Phys. A, Stat. Mech. Appl.*, vol. 392, no. 3, pp. 529–537, Feb. 2013.

[15] M. A. Tabarzad and A. Hamzeh, "A heuristic local community detection method (HLCD)," *Appl. Intell.*, vol. 46, no. 1, pp. 62–78, Jan. 2017.

[16] D. Chen, L. Lü, M.-S. Shang, Y.-C. Zhang, and T. Zhou, "Identifying influential nodes in complex networks," *Phys. A, Statist. Mech. Appl.*, vol. 391, pp. 1777–1787, Feb. 2012.

[17] P. Wang and J. Liu, "A multi-agent genetic algorithm for local community detection by extending the tightest nodes," in *Proc. IEEE Congr. Evol. Comput.*, Vancouver, BC, Canada, Jul. 2016, pp. 3215–3221.

[18] Z. Bu, Z. Wu, J. Cao, and Y. Jiang, "Local community mining on distributed and dynamic networks from a multiagent perspective," *IEEE Trans. Cybern.*, vol. 46, no. 4, pp. 986–999, Apr. 2016.

[19] Y. Zhao, Y. Wang, and M. Wu, "Overlapping community detection based on node influence propagation in heterogeneous social networks," (in Chinese), *J. Chin. Comput. Syst.*, vol. 36, pp. 2190–2196, 2015.

[20] J. Li, X. Wang, K. Deng, X. Yang, T. Sellis, and J. X. Yu, "Most influential community search over large social networks," in *Proc. IEEE 33rd Int. Conf. Data Eng. (ICDE)*, San Diego, CA, USA, Apr. 2017, pp. 871–882.

[21] J. Leskovec, A. Krause, C. Guestrin, C. Faloutsos, J. VanBriesen, and N. Glance, "Cost-effective outbreak detection in networks," in *Proc. 13th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, San Jose, CA, USA, 2007, pp. 420–429.

[22] W. Chen, Y. Wang, and S. Yang, "Efficient influence maximization in social networks," in *Proc. 15th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, Paris, France, 2009, pp. 199–208.

[23] K. Jung, W. Heo, and W. Chen, "IRIE: Scalable and robust influence maximization in social networks," in *Proc. IEEE 12th Int. Conf. Data Mining*, Brussels, Belgium, Dec. 2012, pp. 918–923.

[24] A. Goyal, F. Bonchi, and L. V. S. Lakshmanan, "A data-based approach to social influence maximization," *Proc. VLDB Endowment*, vol. 5, no. 1, pp. 73–84, Sep. 2011.

[25] J. Li, T. Sellis, J. S. Culpepper, Z. He, C. Liu, and J. Wang, "Geo-social influence spanning maximization," *IEEE Trans. Knowl. Data Eng.*, vol. 29, no. 8, pp. 1653–1666, Aug. 2017.

[26] M. De Domenico, A. Lancichinetti, A. Arenas, and M. Rosvall, "Identifying modular flows on multilayer networks reveals highly overlapping organization in interconnected systems," *Phys. Rev. X*, vol. 5, no. 1, Mar. 2015, Art. no. 011027.

[27] A. Clauset, "Finding local community structure in networks," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 72, no. 2, Aug. 2005, Art. no. 026132.

[28] S. Boccaletti, G. Bianconi, R. Criado, C. I. Del Genio, J. Gómez-Gardenes, M. Romance, I. Sendina-Nadal, Z. Wang, and M. Zanin, "The structure and dynamics of multilayer networks," *Phys. Rep.*, vol. 544, no. 1, pp. 1–122, Nov. 2014.

[29] R. Interdonato, A. Tagarelli, D. Ienco, A. Sallaberry, and P. Poncelet, "Local community detection in multilayer networks," *Data Mining Knowl. Discovery*, vol. 31, no. 5, pp. 1444–1479, Sep. 2017.

[30] Y. Li, K. He, D. Bindel, and J. E. Hopcroft, "Uncovering the small community structure in large networks: A local spectral approach," in *Proc. 24th Int. Conf. World Wide Web*, Florence, Italy, 2015, pp. 658–668.

[31] E. Omodei, M. De Domenico, and A. Arenas, "Characterizing interactions in online social networks during exceptional events," *Front. Phys.*, vol. 3, Aug. 2015, Art. no. 59.

[32] A. Cardillo, J. Gómez-Gardeñes, M. Zanin, M. Romance, D. Papo, F. del Pozo, and S. Boccaletti, "Emergence of network features from multiplexity," *Sci. Rep.*, vol. 3, Feb. 2013, Art. no. 1344.

[33] M. Magnani, B. Micenkova, and L. Rossi, "Combinatorial analysis of multiple networks," Mar. 2013, *arXiv:1303.4986*. [Online]. Available: https://arxiv.org/abs/1303.4986

[34] R. Bourqui, D. Ienco, A. Sallaberry, and P. Poncelet, "Multilayer graph edge bundling," in *Proc. IEEE Pacific Vis. Symp.*, Taipei, Taiwan, Apr. 2016, pp. 184–188.

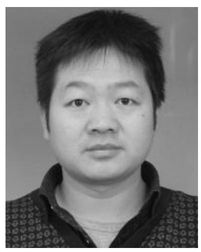
[35] B. Boden, S. Günnemann, H. Hoffmann, and T. Seidl, "Mining coherent subgraphs in multi-layer graphs with edge labels," in *Proc. 18th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, Beijing, China, 2012, pp. 1258–1266.

[36] Z. Kuncheva and G. Montana, "Community detection in multiplex networks using locally adaptive random walks," in *Proc. IEEE/ACM Int. Conf. Adv. Soc. Netw. Anal. Mining*, Paris, France, Aug. 2015, pp. 1308–1315.

[37] L. Tang, X. Wang, and H. Liu, "Uncoverning groups via heterogeneous interaction analysis," in *Proc. 9th IEEE Int. Conf. Data Mining*, Miami, FL, USA, Dec. 2009, pp. 503–512.

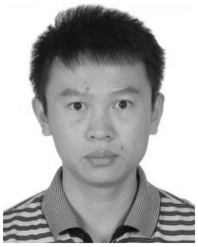
[38] P. J. Mucha, T. Richardson, K. Macon, M. A. Porter, and J.-P. Onnela, "Community structure in time-dependent, multiscale, and multiplex networks," *Science*, vol. 328, no. 5980, pp. 876–878, May 2010.

XIAOMING LI received the master's degree from Xinjiang University, in 2008. He is currently pursuing the Ph.D. degree with the School of Computer Science and Technology, Tianjin University, China. He is also a Deputy Researcher of the Network Information Center, Twelve Divisions of the Corps. His research interests include human behavior dynamics, multi-layer network local community detection, and data mining.



GUANGQUAN XU received the Ph.D. degree from Tianjin University, China, in 2008. He is currently a Full Professor with the Tianjin Key Laboratory of Advanced Networking (TANK), College of Intelligence and Computing, Tianjin University. He is also the Director of the Network Security Joint Lab and the Network Attack and Defense Joint Lab. He has published more than 70 papers in reputable international journals and conferences, including IEEE IoT J, FGCS, IEEE Access, PUC, JPDC, and the IEEE Multimedia. His research interests include cyber security and trust management. He served as a TPC Member for IEEE UIC 2018, SPNCE2019, IEEE UIC2015, IEEE ICECCS 2014. He is a member of the CCF. He also served as a Reviewer for journals such as IEEE Access, ACM TIST, JPDC, IEEE TITS, *Soft Computing*, FGCS, and *Computational Intelligence*.

WENJUAN LIAN received the master's and Ph.D. degrees from the Shandong University of Science and Technology, in 2002 and 2011, respectively, where she is currently an Associate Professor with the College of Computer Science and Engineering. She has published more than 20 papers in core journals and international conferences, finished more than 10 national and provincial projects, published three books. Her research interests include deep learning and cyber security.



HEQUN XIAN received the Ph.D. degree from the Institute of Software, Chinese Academy of Sciences, in 2009. He was a Visiting Scholar with the College of Information Science and Technology, Pennsylvania State University. His research interests include cryptography, cloud computing security, and network security.

LITAO JIAO received the M.B.A. degree from the Shandong University of Science and Technology, in 2016. He is currently an Associate Professor with Qingdao Huanghai University, China. He received the Prize of Provincial Educational Achievement in 2018, participated in five major provincial and municipal research projects, and published more than ten papers. His research interests include HR management and information security.

YU HUANG is currently with the National Engineering Research Center for Software Engineering, Peking University, Beijing, China.