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Community-Oriented Multimedia Content Maximization Mechanism in Social Internet of Things

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ABSTRACT Social Internet of thing (SIoT) is an emerging area that introduces sociology theories into IoT networks, in order to support the spread behaviour of multimedia contents. With the explosive growth of data in the internet, traditional solutions are no longer suitable for large-scale SIoT networks. To address this challenge, this work target to optimize the information propagation in SIoT networks. First, we establish a novel model to divide SIoT network into communities on the basis of network social attributes. Second, we propose an information dissemination control mechanism based on variation trends of content popularity, in order to maximize the spread performance of information. Third, we check the relations between performance indicators and network attributes via a computer simulation. Simulation results show the feasibility of the proposed mechanism. Simulations results also reveal that the proposed mechanism make better balance compared with existing solutions in terms of efficiency and complexity.

INDEX TERMS Social Internet of Thing, multimedia, content popularity, community.

I. INTRODUCTION

Manufacture progress of intelligent devices promotes the development of internet of things (IoT), enabling the integration of large vast devices in a platform to support abundant functions from industry, public, domestic, personal requirements [1]. Under this background, IoT-based multimedia applications are emerging and rapidly promoted in the cloud network [2] including various scopes of videos, voices and texts. Current ongoing issues of IoT-based multimedia are like video traffic optimization, network virtualization, network secure, etc.

Social internet of things (SIoT) is a typical class of IoT which brings thoughts of sociology into communication networks [3]. Social relationships are established between things and objects autonomously with respect to humans. Benefit from the deep implantation of social softwares into sensor networks, SIoT is becoming more intelligent and ubiquitous in daily life of individuals. Emerging technologies support SIoT to propagate various classes of contents, including video, photo, text, etc. Accordingly, multimedia applications grow rapidly in large population of SIoT platforms.

Different with traditional IoT, one open research issue of SIoT is to maximize the information spread based on social relations. In a SIoT network, nodes with distinct social properties present different capability of spreading information. Take the Sina Weibo as an example, if every user is regarded a node, internet celebrities with vast fans can spreading news via friendship in a more rapid manner. Hence, to spread the information efficiently, it's important to excavate proper potential internet celebrities, which is named leaders. To excavate leaders from a SIoT networks, there is some preliminary basic work to be done, and one important work is the divide network into communities. Communities are basic unit of SIoT, in which nodes are classified and clustered in a tight group. The leaders can adequately influence the communities with their limit influence.

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Existing works normally employ greedy or their extended algorithms to excavate leaders, however such series of methods sacrifice time efficiency which is difficult to apply in growing scale of networks. Also, some typical properties such as content popularity variation is not fully considered in the modelling of these algorithms. To motivate these work, we fully consider the realistic scale and properties of current SIoT networks. The contributions of this paper are listed as follows:

- We construct a novel model of community division to prepare excavate leaders of SIoT networks. The proposed model contains fracturing and assemble modules of communities, and quantify the spreading effect of nodes using labels. The proposed model consider to achieve balance between the community division workload and leader excavation preparations.
- We propose a mechanism for leader excavation process based on content popularity, namely Content Popularity aware Information Dissemination Maximization Mechanism (CPIDM). The proposed mechanism utilizes sub-module theory to compute the edge influence of communities, further optimize the excavation of leader set.
- We validate the performance of proposed mechanism of using a computer simulation. Three existing algorithms has been compared with our mechanism. The performance indicator of SIoT has been checked with some major parameters of the networks. The results indicate the feasibility and efficiency of the proposed mechanisms.

The remainder of this paper is organized as follows. In Section II, we introduced related work of this paper. In Section III, we present the system model and state the unsolved problem. In Section IV, we establish a novel model to divide SIOT network into multiple communities. In Section V, we propose an effective mechanism to excavate leader set and maximize the spreading effect of multimedia information. In section VI, the numerical results are obtained to verify our proposed model and mechanism. Finally, we conclude the paper in Section VII.

II. RELATED WORK

To motivate with this work, we have checked plenty of papers from plenty of areas which addressed multimedia applications. Reference [4] proposed an information transfer mechanism based on the similarity property of local vehicle media. Reference [5] studied two signal transmission mechanisms in mobile molecular communication networks based on a multimedia view. Reference [6] discussed the collaboration issue of socially aware energy-efficient mobile edge in video distribution application. Reference [7] introduced the principal concepts of multimedia cloud computing and presented a novel framework. Reference [8] established a chain model of molecular communication based three types of biomedia formations. In [9], an user centric video transmission mechanism is developed for D2D communication networks. Also in [10], a social attribute aware incentive mechanism have been proposed for D2D communication networks. These two works improve the reliability performance of multimedia applications in D2D networks. Moreover, [11] has proposed the dynamic privacy protection of trust relationships aware data for mobile crowd-sensing frameworks.

The internet of thing has attracted a lot of attentions in the recent years, the investigations locate in many aspects of IoT. For instance, [12] resented vision and motivations for cloud IoT applications, and highlighted the challenge and future trends of cloud IoT networks. Reference [13] proposed a blockchain method to build IoT system, which has been proved effective for controlling and configure of IoT devices. Reference [14] focused on latency critical IoT applications and analyzes their requirements, and discussed new business opportunities through IoT connectivity enabled by future networks. Reference [15] studied the safety issue of IoT network and their risking challenges from Mirai botnet. Reference [16] proposed an IoT gateway system based on Zigbee and GPRS protocols according to the typical IoT application scenarios and requirements.

Social network has been introduced from sociology class to study the relations of internet. Some fundamental works focuses on this area. Reference [17] reported on the development of social network analysis, tracing its origins in classical sociology and its formulation in social scientific and mathematical work. Further, the integration of social network and IoT is an emerging subject, named Social Internet of Things (SIoT), providing a feasible tool to investigate the social property of IoT networks. Reference [3] introduced a paradigm of social network of intelligent objects based on the notion of social relationships among objects. Reference [18] proposed and analyzed the design notion of adaptive trust management for social IoT systems. Reference [19] proposed the integration of social networking concepts into the Internet of Things, and analyzed possible strategies for the benefit of overall network navigability. Reference [21] proposed a trustworthy crowdsourcing model in SIoT, in which social cloud provides compute and storage functions, and works as a service provider to bridge end users and sensing entities.

III. PROBLEM STATEMENT OF SOCIAL WEB OF THING

Social Web of Thing (SWT) is a combination of IoT and social networks, of which the structure is listed in Figure 1. SWT can be classified into multiple sub-networks based on different properties. In return, these sub-networks gather to be a complex one on both forms of physical (IoT) and logic networks (Social Networks). IoT network and social network are logically mapped. For example, one user of social network can have multiple things of IoT network. In return, one thing of IoT network can be shared by multiple users of social network.

Here, let $G = (V, E, W)$ denote the network. The users are expressed by the nodes of the network, which belong to set of V. The relations between the nodes are expressed by the edges of the network, which belong to set of E. The types

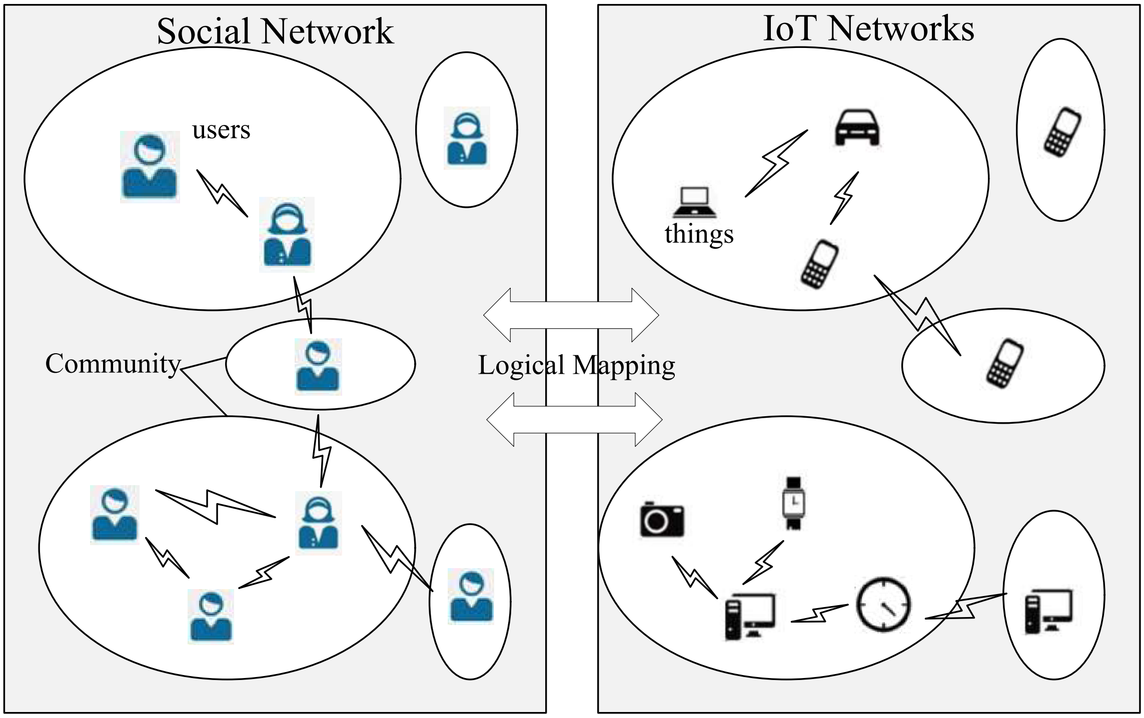

FIGURE 1. Proposed network structure of Social Internet of Thing.

and levels of the relations are expressed by the weights of the edges, which belong to set of W.

The nodes of the networks can be classified into three types based on their statuses: 1) infected nodes; 2) uninfected nodes; 3) immune nodes. Infected nodes are defined as the ones who have received information, and willing to delivery information. Uninfected nodes are defined as the ones who have not received information. Immune nodes are defined as the ones who have received information, and not willing to delivery information.

The infected nodes may converse the statues of uninfected nodes, and in return, uninfected nodes cannot converse the infected nodes. Also, there is no possibility of conversion between uninfected nodes and immune nodes.

We define the spreading ability as the percentage of infected nodes in the total number of nodes. Assume that there is a group of nodes in the network which lead the spreading process of the information, which is named as leader nodes $(K, K < N)$. In a spreading process, the target is to find the optimal group S of leader nodes to maximize the number of infected nodes,

$$S = \arg \max_{S \subseteq V, |S|=K} \Gamma(S) \tag{1}$$

where $\Gamma(S)$ denotes the desired number of the infected nodes when the spreading process has finished.

$\Gamma(S)$ is the target function, which own an important property: Submodule property. Namely, given a set S and its subset T, $T \subseteq s$, if any node besides S join S and T, we derive,

$$\Gamma(S \cup \{v\}) - \Gamma(S) \le \Gamma(T \cup \{v\}) - \Gamma(T) \tag{2}$$

Submodule property is explained as follows. With the increase of leader nodes, there exists marginal effects to enlarge the spreading effect via adding new one into the group of leader nodes. Submodule property holds because the superposition of the spreading effect for two leader nodes.

IV. DIVISION MODEL OF COMMUNITIES

Communities are basic units of Social web of thing. To investigate the property of Social web of thing, it's important to study the division of the communities. However, the division of the community is complex and diversiform due to the wide scopes of user interest. For an ideal division model, nodes of a community interact with each other, and nodes of different communities have no interactions.

In this work, we propose a novel model to divide communities. The proposed model has two modules. The first module is named as community fracturing, and the second module is named as community assembly. In the following, we will introduce the following two modules in detail.

A. COMMUNITY FRACTURING

Community fracturing obtains the elementary divided communities using labels method. The detailed process contains three steps:

Step 1: In the beginning, we allocate an unique community label for each node. For any node $u \in V$, the label is denoted by L_u.

Step 2: We calculate and obtain the neighbour set based on the following process:

Assume a group of nodes $\{u\}$ are infectious ones, and their infectious set is initialized as $A_0 = \{u\}$. After t round of iterations, any node of the $t-1$ round of infectious set A_{t-1} has a possibility to infect the uninfected nodes, expressed by,

$$\lambda_{u_iu_j} = \frac{w_{u_iu_j}}{d_{u_i}} \tag{3}$$

where $w_{u_iu_j}$ denotes the weights between different nodes. d_{u_i} denotes the degree of node u_i. For an uninfectious neighbouring node u_j, it joins A_t once u_j is infected.

Step 3: During each round, update the labels of the infected nodes $\{u\}$. Given a group of node $\{u\} \in V$, their neighbouring set is expressed as $NS = v1, \ldots, vn$. Accordingly, the community set of NS is denoted by $NS.C = \{NS.C_1, \ldots NS.C_s\}$. Here s is the number of the community that neighbouring nodes belong to. $NS.C_i$ is the neighbouring set whose label is i and are infected by nodes $\{u\}$. As a result of t round of iterations, the label of node u_i is,

$$L^t_{u_i} = \arg\max_{1\le i\le s}\left\{1 - \prod_{v_j\in NS.C_i^{t-1}}\left(1-\lambda_{u_iv_j}\right)\right\}, \quad \forall u_i \in V \tag{4}$$

where $\lambda_{u_iv_j}$ is the probability that node u_i infect v_j.

B. COMMUNITY ASSEMBLY

The target of community assembly is to regulate the number of communities. The motivation is that proper number of communities is beneficial to balance the spreading ability of community and networks, and guarantee the rationality of leader set division. In addition, too many round of iterations increase the complexity of the computation, which is unable to be applied in actual social network.

Assume that the network is divided into H elementary communities after the process of community fracturing module. To assemble the communities in a proper way, we introduce a new indicator C_{ij} to express the closeness degree between two different community C_i and C_j. C_{ij} is determined by average edge weights of the network $G = (V, E, W)$, which is given by,

$$C_{ij} = \frac{\sum_{u\in C_i, v\in C_j} w_{uv}}{|C_i| + |C_j|} - \frac{\sum_{u\in C_i, v\in\{V-C_i\}} w_{uv}}{|V|} \tag{5}$$

where $|C_i|$ denotes the node number of C_i. $V - C_i$ denotes the surplus communities of the network besides C_i. We assemble the communities based on the calculation of C_{ij}: if $C_{ij} > 0$, we assemble C_i and C_j; otherwise, we do not.

V. MAXIMUM INFORMATION SPREADING MECHANISM

In this section, we propose a mechanism, named Content Popularity aware Information Dissemination Maximization Mechanism (CPIDM), in order to to maximum the information spreading in the network. The proposed mechanism contains two folds. The first fold is analysis of the popularity to predict the spreading effect. The second fold is leader excavation.

A. POPULARITY ANALYSIS

The variation trend of content popularity is denoted by $I(t)$. It has been reported to approximately follow the Gaussian Distribution [20],

$$I(t) = \frac{1}{t\cdot\sqrt{2\pi}\sigma}\exp\left\{-\frac{(\ln t-\mu)^2}{2\sigma^2}\right\}, \quad t > 0 \tag{6}$$

where σ and μ determine the peak and time-to-peak of the popularity. The nodes tend to receive information of which μ is small. If μ approaches 0, $I(t)$ is approximated as Heavy-tailed distribution. Large μ impacts the spreading efficiency of information. Moreover, increase σ can significantly increase the probability $p(t)$ of infecting uninfected nodes and enlarge the area of information propagation.

Most of the users are easy to be attracted by some types of hot events. Hence their mapping nodes are easier to be infected by those types of hot events information. However, popularity decrease with time, as a result decrease the infecting probability $p(t)$. $p(t)$ presents the interest degree of nodes to the content. For a same node and same piece of information, if $|p(t_1) - p(t_1)|$ is smaller, the node is easier to receive that information and get infected. There is an exponent relation between $p(t)$ and $I(t)$. Accordingly, $p(t)$ can be expressed as,

$$p(t) = t^{-\mu/\sigma}\cdot I(t) \tag{7}$$

We apply both direct and indirect indicators to quantify the spreading effect. The direct spreading effect means the effect of nodes to their neighbours, given by,

$$\Gamma_{DI}(\{v\}) = \sum_{u=1}^{d(v)} w_{uv}/\bar{w} \tag{8}$$

where $d(v)$ is the degree of node v. w_{uv} is the weight between nodes u and v. $\bar{w}$ is the average weight of the network edges.

The indirect spreading effect means the effect of nodes to non-neighbours, given by,

$$\Gamma_{II}(\{v\}) = \sum_{u=1}^{d(v)}\sum_{w=1}^{d(u)} w_{uw}/\bar{w_{vu}} \tag{9}$$

Note that over 2 transmission hops of the information have little effect so we just consider 2 hop nodes for indirect spreading effect. In above equation, node u is 1-hop neighbour of node v, and node w is 2-hop neighbour of node v.

The major goal of popularity analysis is to check the percentage of infected nodes under different infection probability $p(t)$. In general, when $p(t)$ is small, the infecting effect of nodes to their 2-hop neighbours is weak. In this case, the percentage of direct spreading effect is much higher than indirect one; When $p(t)$ is large, it's easy to infer the adverse conclusion. The expression of spreading effect is given by,

$$\Gamma(\{v\}) = (1 - p(t))\cdot e^{\Gamma_{DI}(\{v\})} + p(t)\cdot\Gamma_{II}(\{v\}) \tag{10}$$

B. LEADER EXCAVATION

As we mentioned in above sections, the excavation of leader nodes is very important, since it determines the spreading efficiency in the communication process. One common excavation method is greedy algorithm, i.e., select the nodes whose has highest popularity in each round. However, greedy algorithm is low efficiency, since it consider all nodes in each round to calculate the spreading effect. As a result, the complexity increase with rapid growth.

In order to increase the efficiency of the algorithm, this work utilize the sub-module property of $\Gamma(\cdot)$. With the increase of leader nodes set, new increased leader nodes bring decreased spreading effect gains. By this way, we excavate the leader nodes step by step.

Assume that we get M community after the process of popularity analysis. We apply Eq. (10) to calculate the spreading effect of each node. Based on the calculation, we select the node of every community which has the largest spreading effect. Those nodes are sort and added into the spare leader node set S^*. Also, the leader node set is initialize as $S = \{\emptyset\}$.

It's possible that there is overlap of spreading effect between new leader nodes and existing leader nodes, so the existing leader nodes may not present their optimized spreading effect. Thereby, we calculate the edge spreading effect $\Delta\Gamma(\{v\})$, expressed by,

$$\Delta\Gamma(\{v\}) = \Gamma(S \cup \{v\}) - \Gamma(S) \tag{11}$$

The sizes of M and K are not known in advance. We discuss two cases, i.e., $K \leq M$ and $K > M$. If $K \leq M$, we just need to select K nodes in the spare leader node set S^*, based on the independence of communities. If $K > M$, some communities has at least 2 leader nodes. In this case, we need to use Eq. (11) to obtain the nodes which has the significant edge spreading effect.

To illustrate above steps, let $v_k (k = 1, 2, \cdots, K)$ denote the leader nodes set in the k^{th} round. The leader excavation process is described as follows. In the first round, we select node $u \in S^*$ which is sort in the first place, into the leader node set v_1, then the node u is removed from the set S^*. Under condition of $K > M$, we further calculate the edge spreading effect $\Delta\Gamma(\{v\})$ of remaining nodes, select the node whose $\Delta\Gamma(\{v\})$ is largest and add the node into S^*. Then, use Eq. (11) to calculate the edge spreading effect $\Delta\Gamma(\{u\})$ of the first sorted node u. If $\Delta\Gamma(\{u\})$ is not smaller than the spreading effect of second sorted nodes u', i.e., $\Delta\Gamma(\{u\}) \geq \Gamma(\{u'\})$, then such node is selected as v_2; otherwise, we have to calculate edge spreading effect of third sorted nodes u'', and select the node with largest edge spreading effect as v_2. We repeat the above steps, until K leader nodes are selected.

We find that it's not necessary to calculate the edge spreading effect of each node in every round of leader excavation. Based on the sub-module property of $\Gamma(\cdot)$, the leader nodes just to meet the above-mentioned simplified conditions. The proposed mechanism decrease the computation complexity and guarantee the highest spreading effect of leader nodes, and not harm the accuracy of leader excavation.

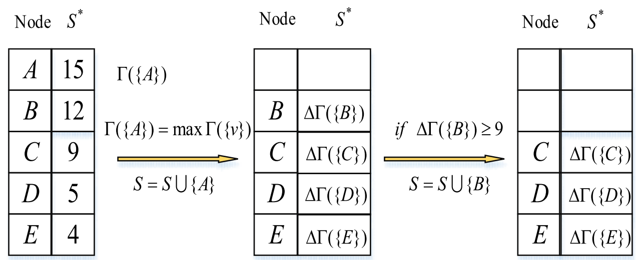

FIGURE 2. An diagram example of leader selection process.

TABLE 1. Simulation configure.

Parameter	Value or Range
Total node number	500-3000
Time-to-peak of popularity	40-80(min)
Average infect probability	0.01-0.2
Leader set scale	5-50
Maximum neighbour	22
Average neighbour	12
Simulation Time	32000(s)

One simple example of leader excavation is shown in Figure 2. Image we need to select 3 leaders from 5 communities, which meet $K \leq M$. Based on the independence of communities, to maximize the spread of information, we obtain the 5 nodes (A,B,C,D,E) whose spreading effect is highest, and then select 3 from them. After the sorting process, assume node A of the spare set S^* has highest spreading effect $\Gamma(\{A\}) = 15$, then add node A into leader node set S in the first round. In the second round, we first calculate the edge spreading effect $\Delta\Gamma(\{B\})$, if it is not smaller than 9, then add B into set S. Otherwise continue to calculate the edge spreading effect of remaining nodes C,D,E, sort those calculated values, and select leader node based on the sorting. Then repeat above steps until meet $|S| = K$.

VI. PERFORMANCE EVALUATION

In this section, we first introduce the configuration of simulation, then we present and analyze the numerical results of this work.

A. SIMULATION DESIGN

We use MATLAB simulator in this work to check the performance of the proposed mechanism. In order to make a comparison, another three existing algorithms are introduced in the simulation, which are respectively MixGreedy [22], SA [23] and Random [24] algorithms. We compare the four algorithm from different areas and analyze their advantages and disadvantages. Major parameters of the simulation are listed in Table.

B. NUMERICAL RESULTS

Figure 3 depicts the propagation scope of information and the corresponding number of infected nodes with different numbers of opinion leaders. As can be seen from the results in Figure 3, the number of opinion leaders increases, the spreading effects of the four algorithms are increasing.

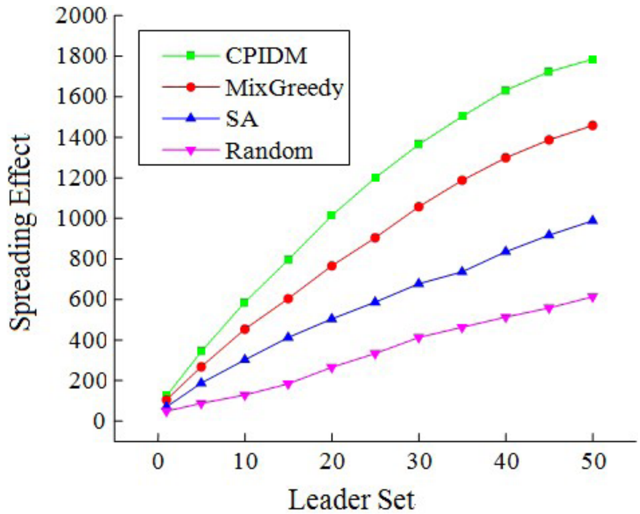

FIGURE 3. The spreading effect of 4 algorithm with different number of leader set.

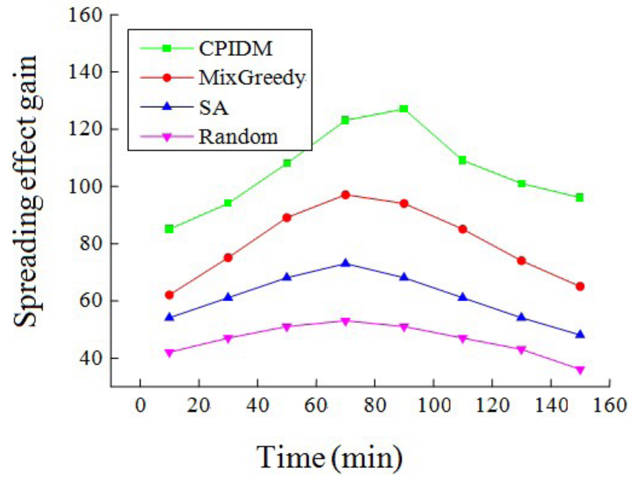

FIGURE 4. Increasing spreading effect gain with time for 4 algorithm. $\mu = 80$, number of nodes is 300, number of leaders is 30.

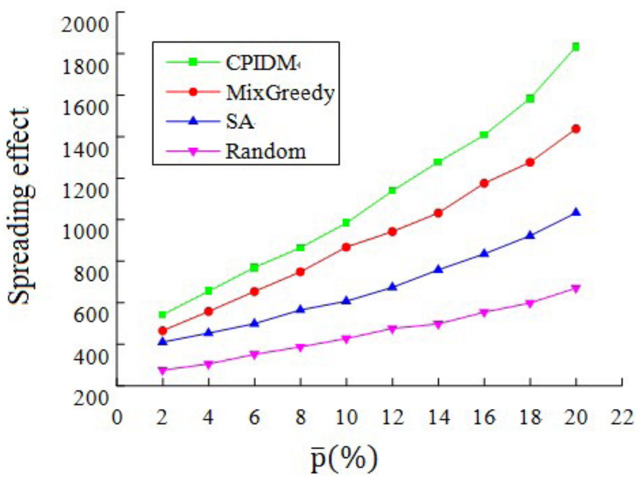

FIGURE 5. Spreading effect with average infecting probability for 4 algorithm. Number of nodes is 3000, number of leaders is 50.

The reason is that more leaders selected, more significant spreading effect of information presents in the network. In addition, compared with SA and Random algorithm, the change trends of CPIDM and MixGreedy are larger, because both of the two algorithms are improved based on greedy algorithms, and the influence gain of nodes which are added to leader set is relatively low. The results show that CPIDM algorithm has the highest ability of information dissemination, which is about 18 percent improvement compared to MixGreedy Algorithm.

Figure 4 shows how spreading effect varies with time. It can be easily seen that the spreading effects of the 4 algorithm first increase before before 70 min. Among of the algorithms, the upward trend of CPIDM and MixGreedy are more significant. After about 90 minutes,spreading effect begin to decrease. The reason is that the content popularity of the information $I(t)$ first increases with time and then decrease, that restrain infection ability of information. Specially, spreading effect of CPIDM in this figure basically conforms to the change trend illustrated in Eq. (6). Differently, after 90 minutes, there is no rapid decrease of spreading effect of the leader nodes set, because although the content content popularity significant declines, while there are a lot of previous infections, the information still maintains a high capability of spreading effect.

Figure 5 shows the information propagation with the increase of the average infection probability $\bar{p}$ of leaders. As we can see in the figure, when the probability of infection $\bar{p}$ increases, the impact diffusion ability of three algorithms has significantly improved except Random algorithm. The reason is that the probability of infection $\bar{p}$ has a great impact on the evaluation of spreading effect, as illustrated in in Eq. (10). Namely, when the probability of infection $\bar{p}$ is large, the indirect spreading effect of leaders accounts for a larger proportion, which can affect nodes with greater distances. When the probability of infection $\bar{p}$ is low, they basically spread the information to neighbors. In addition, the information spreading effect of CPIDM is about 16 percent higher than MixGreedy on average, which can reach a maximum of 24 percent. We conclude that the efficiency of CPIDM is relatively high.

Figure 6 shows that the average infection probability $\bar{p}$ of leaders increases, we need more time to reaches 30 percent of ratio of infected nodes to total nodes. It should be noted that the unit of the ordinate in Fig. 6 is exponential increased. Also, it can be seen from the results that when the probability of infection is larger, the time required for information propagation decreases approximately exponentially. In addition, nodes are affected by multiple opinion leaders, decrease the requirement of time. Comparing the 4 algorithms, it is found that Random has the lowest impact efficiency because the leaders are randomly chosen. To achieve the same spreading effect, it takes more time to spread information. The performance difference between CPIDM and MixGreedy is large when the infection efficiency is low, and the difference is small when the infection efficiency is high. The reason

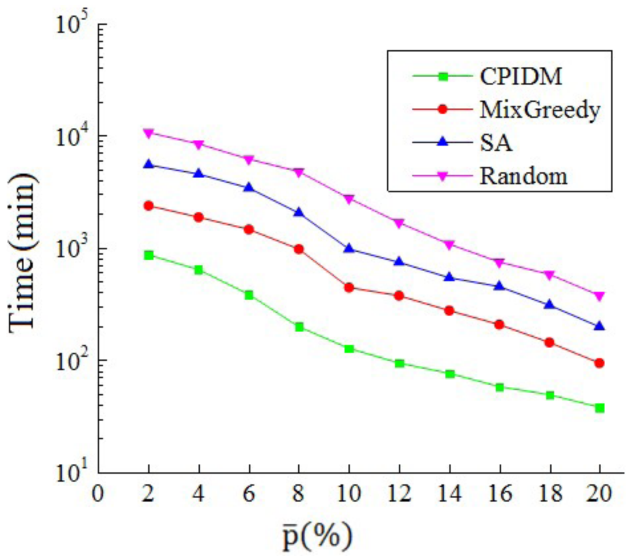

FIGURE 6. Required time with infection probability for 4 algorithm. Number of nodes is 3000, number of leaders is 50.

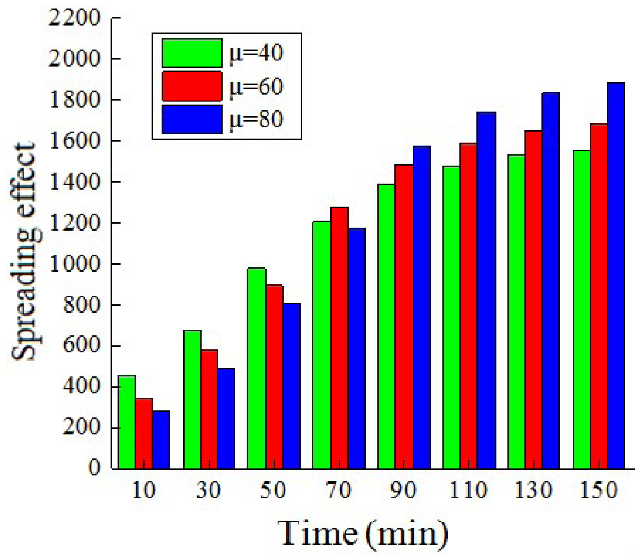

FIGURE 7. Spread effect of CPIDM under different time-to-peak of popularity.

is that both of the algorithms are based on GA extensions, and they target for local optimization. In addition, the reason why CPIDM works better is that in the community division, the network is divided into multiple communities with the same radius, which decreases time of the intra-community information propagation, as a result shortens the total time of information propagation.

Figure 7 shows the influence of CPIDM over time on the spreading effect when μ is 40min, 60min, and 80min, respectively. Based on the results, it can be found that the impact diffusion ability is higher before 50min if $\mu = 40$. The performance is better when the time reaches 70min if $\mu = 70$. The performance is more prominent after 90min if $\mu = 80$. The reason is that the information spreading effect is affected by the information activity $I(t)$. The information propagate rapidly in the beginning, and slowly after reaching the active peak of the information, as a result the infected nodes increase slowly. It is easy to infer that increase μ may not bring a better performance, because popularity of information has a life cycle. Namely, it is possible that the propagation of information has ended even time has not reached the time-to-peak yet.

Figure 8 shows the required time of the 4 algorithms in community division and leader excavation, with the network scale grows. It can be seen from the results that Random algorithm takes the least time, because it does not need to calculate the spreading effect of the nodes, it just randomly selects leaders from the communities; MixGreedy takes the highest time, because it accounts for all of nodes in the leader excavation process. In addition, CPIDM is higher than SA, as it just needs to calculate the spreading effect of limited nodes in the leader excavation process, which significantly reduces the calculation time. Moveover, it can be seen that with the growth of the network scale, MixGreedy and SA obviously increase the calculating time, thereby they are not proper

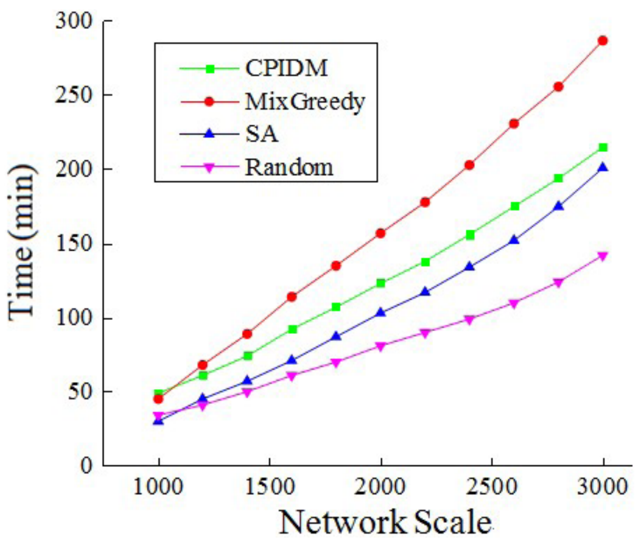

FIGURE 8. Required computation time with different scale of network for 4 algorithm.

for large-scale networks. However, our proposed CPIDM has good scalability and strong adaptability to applied in large-scale networks.

VII. CONCLUSION

This work studied the spread of multimedia information in social internet of things networks. We established a model of community division using the social attribute labels. With the divided communities, we proposed a mechanism to maximize the spreading effect of information. We checked the performance of proposed mechanism with different parameters of networks. We compared the performance of proposed mechanism with 3 existing algorithms. The results indicate the high performance of our mechanism. In the future, we will study the QoS controlling issue of SIoT network applications. We will also study the secure issues to face the threat to SIoT.

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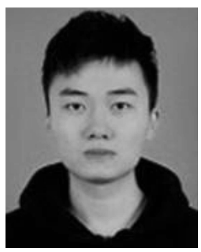

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