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D2D Relay Communication Scheme Incorporating Multi-Dimensional Information in Multimedia Transmission

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ABSTRACT The rapid development of mobile multimedia services integrated with online and offline social networks has made the mutual transmission of smart devices more frequent. Device to Device relay communication (D2D relay communication) can extend the transmission range of shared multimedia services, further reducing the burden on the base stations. However, when multimedia services are transmitted by D2D relay communication, the selfishness of the relay nodes affects the quality of the transmission. In order to solve this problem, the integration of social factors has become a common research topic. However, social factors generally come from multi-dimensional information. The more kinds of information, the more hidden information, and the measurement of social relations will become extremely difficult. Hence, this paper focuses on the measurement of social relationships based on multi-dimensional information and then combines physical domains to choose relay nodes. Firstly, the transmission performance of D2D relay communication is analyzed in the physical domain. Then, in order to better integrate multi-dimensional information, we construct a hypernet architecture based on spatiotemporal-user-location-category and quantify the edge weights. Three categories of weighted super-edge structures are defined to capture a variety of hidden social relationships, and the social relationship strength of any two users is measured. Finally, a relay selection algorithm that maximizes the social rate is proposed, which combines social relationships of multi-dimensional information and quality of physical transmission. The simulation results show that the Based on Maximum Social Rate for Relay Selection Algorithm (MSRRS) proposed in this paper has a significant improvement in transmission quality and transmission stability for multimedia application compared with the traditional relay selection algorithm.

INDEX TERMS D2D, relay communication, social awareness, hypernet, multimedia transmission.

I. INTRODUCTION

With the rapid development of Mobile Internet and multimedia services, the transmission and sharing of multimedia content between users are gradually becoming popular. In addition, the rise of new applications such as VR/AR and the Internet of Things (IOT) will lead to the gradual growth in the number of smartphones and smart wearables. Undoubtedly, these multimedia services and a large number of emerging smart devices will bring huge traffic burden to the communication network [1]–[3]. According to the latest Cisco Visualization network index[4], the number of mobile devices per capita is expected to reach 1.5 units by 2021, and mobile data traffic will increase by about 7 times from 2016-2021, with mobile multimedia accounting for the largest proportion. However, the available spectrum resources are limited. How to meet people's growing demand for communication services with limited resources is an urgent problem to be solved [5].

D2D communication is a technology for communication of adjacent terminals [6], [7]. After the establishment of the D2D communication link between two adjacent terminals, data communication among devices will no longer need the core network's support or intermediate equipment [8], [9].

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This communication way directly enables to provide users with higher rate and lower latency in data communication services. In addition, thanks to the characteristics of short-distance communication, D2D users can communicate at lower transmit power, and the energy efficiency of terminal devices can be improved. These characteristics make D2D communication an effective technology to relieve base station's pressure, improve resource utilization and data transmission rate [10]–[13].

It is well known that the quality of D2D communication is easily affected by the distance between the two parties and the wireless channel environment [14]. Especially with the rise of interactive mobile multimedia and AR/VR mobile multimedia networks, device's communication tends to high mobility and flexibility. In order to reduce the communication delay for such multimedia applications and to ensure the transmission quality, D2D relay communication has become one of the important research fields, and has been widely concerned and studied by the industry in recent years [15], [16]. Similar to the traditional relay communication technology, D2D relay communication is mainly used to extend the communication range and improve the communication quality of devices. However, D2D relay communication has more flexibility than traditional one. Relay node plays an extremely important role in D2D Relay communication, so its selection has always been one of the research hotspots [17]–[19].

In order to explore the characteristics of relay nodes, integrating online social network in physical factors is gradually popular in relay selection mechanism. Many researchers believe that, the interpersonal relationship will reflect the transmission stability of relay devices, because the devices are carried by people that are prone to homogeneity [20]–[22]. In addition, mobile multimedia applications have gradually combined with geographic location to add the fun and effective, so the comprehensive impact of discussion of location and social relationships is gradually being studied [23]. Despite the combination of the two, users' social factors are multi-dimensional, which should include spatiotemporal network, online social network, location information, category and other information. However, the more types of information, the more hidden information, and the measurement of social relationships becomes extremely difficult. Therefore, the main purpose of this paper is to design a new relay selection strategy that considers multi-dimensional information. This strategy solves the multi-dimensional information is difficult to integrate and to measure. By this scheme, D2D relay transmission rate and link stability are effectively improved. The main contributions of this paper are as follows:

- In order to explore the social relationships between users as much as possible, this paper divided the social networks into four layers super-networks model of "spatiotemporal-user-location-category". Through this model, time factors can be integrated into the networks by node form to reduce the inaccuracy measurement of social relationships caused by the lack of time dimension;
- For the data sparsity problem caused by spatiotemporal information, this paper constructed a variety of weighted super-edge structures. These structures can effectively reflect the implicit relation among nodes, so as to further mine the social relationships between users;
- A social rate metric is proposed to integrate the user's social relationships and transmission rates in relay selection. Based on the social rate values, a relay selection algorithm based on maximum social rate is proposed. Compared with the traditional algorithms, the selected relay nodes have better performance in relay transmission stability and transmission rate.

The organization of this paper is as follows: Section II summarizes the related work. Section III is the system model of D2D relay communication given in this paper. Section IV and Section V are mainly the construction of the system super-networks architecture and the quantification of the edge weights. In Section VI, the social perception method of integrating multidimensional information is introduced. The relay selection algorithm for maximizing social rate is described in detail in Section VII. The Section VIII is simulation verification. The last part is the summary of this article.

II. RELATED WORK

D2D relay communication can improve spectrum efficiency, and can extend coverage. It has important application value in the field of public security. Inspired by the great earthquake and tsunami in Japan, researchers in [24] turn their attention to the D2D multi-hop relay communication without infrastructure, put forward the concept of D2D multi-hop communication network system which is suitable for many different wireless technologies, and expound the related open problems in the system. A D2D assisted communication framework is proposed in [25]. By this framework, relay transmission technology is introduced into the traditional underlay/overlay D2D communication. Besides, the authors designed the corresponding adaptive mode selection and resource allocation scheme to ensure the communication performance between ordinary cellular users and D2D users.

The selection of relay nodes plays a very important role in D2D relay communication network. If the selected relay node is not suitable, it will greatly reduce the success rate of D2D relay communication, and then reduce the transmission performance and the operation efficiency of cellular network [26]. In [27], a distributed relay selection method is proposed to coordinate the same frequency interference between D2D relay communication equipment and cellular communication equipment. A joint method of two-level relay selection and resource allocation is proposed in [28], which can select the optimal relay node and transmission power. This method by maximizing the total throughput of two links under the premise can ensure the service quality of D2D link and cellular link. For the scene of multiple D2D relay communication devices to reuse the same cellular device's uplink channel, an *Iterative Hungarian Method to Joint Relay Selection and Resource Allocation* is proposed in [29], which reduces the complexity of three-dimensional matching problems that include power allocation, relay selection, and subchannel allocation, and optimizes throughput performance.

With the increasing popularity of smart devices and the rapid development of social networks, mobile social networks are affecting every aspect of human life. Since the devices in the D2D relay communication are carried by human, they are indirectly endowed with relevant human attributes[30]. To further improve the performance of D2D relay communication, researchers begin to incorporate social attributes into the studies of D2D relay communication [31]. In order to promote effective cooperation among devices, authors in [32] proposes a theoretical framework of joint game theory, and designes a D2D relay communication strategy based on social relationship, which significantly improves transmission performance compared to the non-assisted communication scheme. With consideration of the influence of energy loss and trust relationship among users on the quality of D2D relay communication, a new relay selection mechanism is proposed in [33], in which the social attributes among users and physical attributes such as channel quality and energy consumption are fully considered, so as to ensure that users can actively participate in collaborative communication and to realize the improvement of transmission performance and energy efficiency. Considering the security, reliability and detection cost of D2D relay communication, a relay selection algorithm based on social relation and user mobile location is proposed. This algorithm can determine and narrow the set of candidate nodes, thus ensuring the security and reliability of relay nodes while reducing the detection cost of relay nodes [34].

User's mobility will affect the stability of D2D relay transmission link, and social trust between users will affect the security and reliability of transmission link. Although the above researches have designed the D2D relay communication scheme by integrating the physical domain and the social domain, improving the transmission performance, most of them only consider the online social network and the user's short-term location information, and fail to integrate the spatiotemporal relationship information among users. In fact, the user's mobility is closely related to the spatiotemporal relationship of users. In response to the above problems, some researchers have gradually incorporated spatiotemporal information into the social domain and applied it to the relay node selection of D2D relay communication [23]. However, the researchers do not realize that the more comprehensive the types of information in the social domain, the more difficult it is to integrate different types of information, and the more hidden connections between the various factors. It is worth noting that when considering the spatiotemporal information and failing to mine the hidden internal relations in the information, it is easy to cause the data sparsity. We have already done some work on the sparsity problem caused by time and

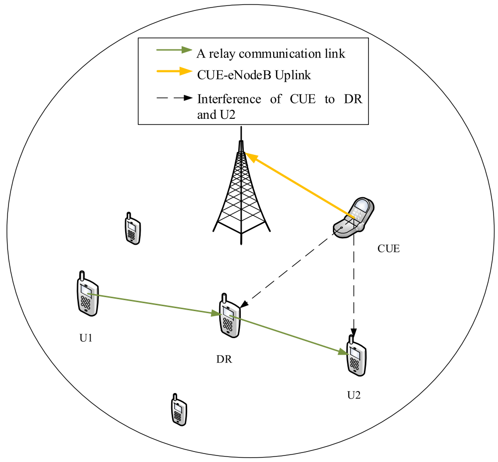

FIGURE 1. The D2D relay communication scene in the cell.

space, and applied it to the link prediction of social networks. However, considering the unique communication method and application scenarios of D2D communication, this paper will conduct further research. In general, although the above-mentioned researchers have designed the D2D relay communication schemes by integrating the physical domain and the social domain factors, and improved the D2D relay transmission performance, the hidden connections between the physical domain and the social domain have not been fully considered. There is still much room for improvement in D2D relay transmission performance.

III. SYSTEM MODEL

In this paper, D2D devices can reuse the uplink channel resources of cellular devices, so there is the same frequency interference between the D2D devices and the cellular devices. In addition, D2D devices may cause the transmission signal to be severely attenuated due to the distance between the building occlusion or the closing distance, resulting in poor communication quality. In order to ensure the quality of the user's service experience, a suitable relay node should be selected to assist D2D communication. On the one hand, relay nodes can enlarge the transmitted signal which has been attenuated, on the other hand, the link quality between transmitting devices and receiving devices is better by choose appropriate relay nodes. Figure 1 is the D2D relay communication scene in the cell.

Let the transmit power of all D2D devices to be P_t. The D2D direct communication rate $R_{U1,U2}$ between the transmitting device U1 and the receiving device U2 can be expressed as:

$$R_{U1,U2} = B_{CU1} \log_2(1 + \frac{P_t h_{U1,U2} d_{U1,U2}^{-\alpha}}{I_{CU1,U2} + \sigma^2}) \tag{1}$$

where, B_{CU1} is the uplink channel bandwidth of multiplexed cellular device CU1, $h_{U1,U2}$ is the channel gain of the channel between U1 and U2, $d_{U1,U2}^{-\alpha}$ is the path loss, $I_{CU1,U2}$ is the co-channel interference between CU1 and U2, σ^2 is Gaussian

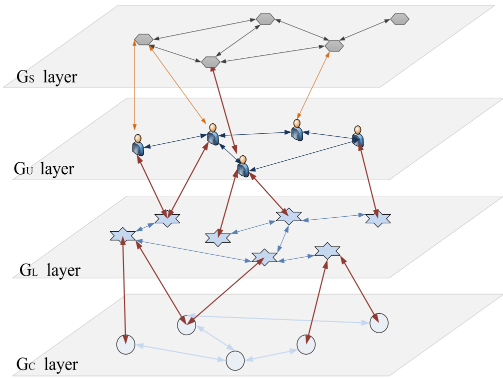

FIGURE 2. The constructed multidimensional information weighted supernetwork architecture.

channel noise power. The D2D relay communication mode is enabled when the transmission rate of the D2D direct communication is lower than the minimum transmission rate r_k^{th} acceptable to the user.

In half-duplex relay communication mode, D2D relay communication needs to be completed in two stages. The relay device first receives data from the source device (transmitting device) and then forwards the received data to the destination device (receiving device). The transmission rates $R_{U1,DR}$ and $R_{DR,U2}$ of the two stages can be easily calculated by (1). Therefore, the transmission rate of D2D relay communication can be expressed as:

$$R_{DR} = \frac{1}{2}\min(R_{U1,DR}, R_{DR,U2}) \tag{2}$$

IV. WEIGHTED SUPERNETWORK ARCHITECTURE BASED ON MULTIDIMENSIONAL INFORMATION

In order to fully exploit the social relationships between users to improve the stability of D2D relay communication, the comprehensive consideration of multi-dimensional information has become the research focus in social relations. However, as information has more dimensions, the structure of the network and the interrelationships between different pieces of information become more complex. Not only that, more and more research has added spatiotemporal information, that is, mining the information of all users in time and place to further improve the comprehensive measurement of social relations among users. Due to the small number of contributions of such information, it is easy to cause the data sparsity when such information is added into the measurement of social relations. Therefore, we introduce a supernetwork model to solve the measurement of multidimensional information in social network. The unobserved edge weights in the social networks are solved by supernetwork to explore the characteristics of the entire network. Figure 2 shows the weighted supernetwork architecture based on multidimensional information.

This paper combines spatiotemporal, user, location, and category factors to construct a four-layer supernetwork, called by weighted supernetwork architecture based on multidimensional information. The characteristics of each layer network are as follows:

A. FIRST LAYER: SPATIOTEMPORAL INFORMATION LAYER $G_S = (V_S, E_S, W_S)$

A spatiotemporal information layer G_S is an information network based on the relation between spatiotemporal nodes. Where V_S represents the set of all spatiotemporal nodes. If two or more users access the same location at a certain time, a spatiotemporal node will be formed. E_S represents the set of directed edges in all spatiotemporal nodes. W_S denotes the set of associated weights between all spatiotemporal nodes.

B. SECOND LAYER: USER INFORMATION LAYER $G_U = (V_U, E_U, W_U)$

The user information layer G_U is a relationship layer composed of all user nodes. Where V_U denotes a set of all user nodes, E_U denotes all directed edge for any two user nodes, and W_U denotes a set of association weights for any two user nodes.

C. THIRD LAYER: LOCATION INFORMATION LAYER $G_L = (V_L, E_L, W_L)$

In order to collect the user's location information, we assume that users can check in where they've been and share their check-in locations with friends. In this way, users' location activities can be truly reflected, and a close connection can be established between the online virtual world and the offline physical world. Therefore, the location information layer G_L is a location relationship layer composed of all check-in location nodes. Where V_L denotes all location nodes, E_L denotes a set of directed edges for any two location nodes, and W_L denotes a set of association weight between any two location nodes.

D. FOURTH LAYER: CATEGORY INFORMATION LAYER $G_C = (V_C, E_C, W_C)$

The category information layer G_C consists of associations between any category nodes. The category information is used to indicate the user's interest in offline world, such as a user often going to watch a movie. Where V_C denotes a set of all category nodes, E_C denotes a set of directed edges for any two category nodes, and W_C denotes a set of association weight between category nodes.

The construction of a four-layer supernetwork can clearly describe when and where each user does what. Next, the paper will quantify the edge weights in the supernetwork based on user influence, implicit association, user preference and node degree. The definition and quantification of edge weights can make the relationship between nodes in the network more accurate, which help to improve the interpretability.

V. QUANTIFICATION OF MULTIPLE TYPES OF EDGE WEIGHTS

On the basis of supernetwork architecture, there is also a certain relationship between layers. Next, we will define and quantify the edge weights within and between layers in four different weighting methods.

A. MEASUREMENT OF THE WEIGHT BETWEEN USERS

In a location-based social network, the impact of each user is different. If a friend has a very low influence on us, it is difficult for us to generate certain behaviors and connections with other people through the friend. Therefore, quantifying user-user edge weight $w(u, u')$ by user influence can improve model interpretability and accuracy. This paper mainly measures the influence of users by mining follow-up behavior in location-based social networks. If user u' makes a check-in at the location in which his friend u has checked in, user u' is considered to be following user u. Follow-up network $G_f = (V_f, E_f)$ is a directed network composed of all follow-up behavior, where V_f includes all users in follow-up network and E_f contains the directed edges of all following behaviors. At the same time, we divide user influence into user individual influence and inter-user influence, and they will be measured by follow-up network and follow-up behavior.

1) USER INDIVIDUAL INFLUENCE

User individual influence I_u is used to measure the impact of users on other users in the architecture due to their own behavior, which is a global measurement method. Generally, user individual influence will change dynamically with time. When users first touch new applications, most of them will actively generate a lot of check-in behaviors, thus follow-up edges present an upward trend. However, as time goes by, the user's activity on applications will decrease, and its influence will gradually weaken. For so long, the influence will decay to a lower stable value. Therefore, the impact of time factor is extremely important for user influence.

This paper first divides time into s different time slices, and the user's follow-up behavior in each time slice constitutes the corresponding follow-up network $(G_f^{t_0}, G_f^{t_1}, \ldots, G_f^{t_s})$. The final user individual influence is contributed by the individual influence in each time domain. The longer user personal influence is away from the present, the weaker it is. Considering the existence of isolated nodes in the network, we use the *LeaderRank* algorithm [35] to solve the user individual influence. The iterative formula of the *LeaderRank* algorithm is as follows:

$$I_u(t+1) = \sum_{u' \in N(u)} \frac{a_{u'u}}{k_{u'}^{out}} I_u(t) \tag{3}$$

where N_u represents the set of neighbor nodes of user u, and $k_{u'}^{out}$ represents the outbound degree of user u'.

LeaderRank also adds a Ground Node to achieve bidirectional connection with all nodes in network. In a stable state, it distributes the score of Ground Node evenly to all other nodes, so the final score of the node can be expressed as:

$$I_u = I_u(t_d) + I_g(t_d)/N \tag{4}$$

where $I_g(t_d)$ is the score of the Ground Node in steady state, and N is the number of users.

As time goes by, the user's influence will decrease, so the attenuation function defined in this paper is:

$$W_{ut_i} = \exp(-\ln 2 \times (t_c - t_i)/t_m) \tag{5}$$

where t_c represents the current time, t_i represents the i time slice, and t_m represents the half life of the reduced influence. Then the user individual influence value I_u at the current moment can be expressed as:

$$I_u = \sum_{i=0}^{k} I_{ut_i} \cdot W_{ut_i} \tag{6}$$

where I_{ut_i} represents the individual influence of the user u of the t_i time slice.

2) INTER-USER INFLUENCE

The inter-user influence $I_i(u, u')$ is used to measure the influence of user u on user u', and that is a measure of local perspective. In general, the more interactions between two users, the greater the impact between them. Follow-up behavior can be seen as an interaction between users and as a measure of inter-user influence. So, this paper uses the following check-in ratio I_c to measure the follow-up behaviors among users, which is defined as follows:

$$I_c(u, u') = \frac{K_{u',u}}{Checkin_u} \tag{7}$$

where, $K_{u',u}$ represents the total number of times the user u' follows the user u, and $Checkin_u$ represents the total number of times the user u has checked in.

Taking into account the user individual influence and the inter-user influence, the user influence $I(u, u')$ is:

$$I(u, u') = \partial_1 \cdot I_u + \partial_2 \cdot I_c(u, u') \tag{8}$$

I_u is the user individual influence, I_p is the proportion of the follow-up location, and I_c is the following check-in ratio, $\partial_1 + \partial_2 = 1$,and the values in our paper are $\partial_1 = 0.4$, $\partial_2 = 0.6$.

Based on the user influence, the user-user edge weight $w(u, u')$ can be defined. For the node pair $u - u'$, if the user u' to user u has high influence, the weight $w(u, u')$ should also be high, so the edge weight $w(u, u')$ between user u' and user u is show as:

$$w(u, u') = \frac{I(u', u)}{\sum_{v \in U_u} I(v, u)} \tag{9}$$

B. IMPLICIT ASSOCIATION

Implicit association refers to relationships that cannot be observed directly through the user's check-in information, such as the relationship among locations and the relationship among the categories. Reference [36] defines location relationship as the interest correlation point, and the position-position edge weight in this paper were modified based on the interest correlation point.

If a user continuously accesses two locations within a certain time slot, there is a certain implicit relationship between the two locations. Moreover, since most users like to visit locations that are close to where they've been [37], this article defines position-position edge weight by distance and implicit association.

$$w(p,p') = (1 - \frac{geodist(p,p')}{\sum\limits_{\forall z \in P} geodist(p,z)}) \cdot \frac{Count(p,p')+1}{Count_p+1} \tag{10}$$

where $geodist(p, p')$ is the distance between position node p and position node p', $Count(p, p')$ is the number of times that two position nodes are associated, and $Count_p$ is the maximum number of times all associated positions.

Since the spatiotemporal edge weight increases the time distance based on position edge weight, it is defined as follows:

$$w(t,t') = (1 - \frac{geodist(t,t')}{\sum\limits_{\forall z \in T} geodist(t,z)}) \cdot \frac{Count(t,t')+1}{Count_t+1} + (1 - \frac{timedist(t,t')}{\sum\limits_{\forall z \in T} timedist(t,t')}) \tag{11}$$

The formation of a spatiotemporal node refers to that two or more users access the same location at a certain time, so $geodist(t, t')$ represents the positional distance of two spatiotemporal nodes t, t', and $timedist(t, t')$ is the time distance of two spatiotemporal nodes t, t'.

If two different categories appear in multiple locations at the same time, there is a certain implicit relationship between the two categories. For example, the statistical data found that the category Bars and the category Nightlife often appear in the category attributes of multiple locations, implicitly indicating that there is a certain correlation between the two categories. According to the above description, the category-category edge weight of this paper is defined as follows:

$$w(c,c') = \frac{Count(c,c')+1}{Count_c+1} \tag{12}$$

where $Count(c, c')$ denotes the number of locations belonging to both category c and category c', and $Count_c$ represents the maximum number of locations belonging to both type c and some other type.

C. QUANTIFICATION OF EDGE WEIGHTS BETWEEN LAYERS

1) USER PREFERENCE

User preference reflects the degree of user's preference for location. If two users show keen interest in the same solution, they are likely to have a link relationship. In order to effectively integrate the preference information and improve the interpretability of the supernetwork model, this paper starts from the user's score to define and quantify the user-location edge weight $w(u, p)$ and the user-spatiotemporal edge weight $w(u, t)$.

In a location-based social network, the user's location score can intuitively reflect the degree of user's preference for location. For example, user u_1 scored at three positions like p_1, p_2, p_3, and gave scores of 5, 3, and 1, respectively. If we don't consider the user's rating attribute for this location, we assign a value of 1/3 to each user-location edge. In fact, this is not accurate. If user u_1 gives the location p_3 a score of 1, it indicates that the user is not satisfied with this place. At this time, the user-location edge weight $w(u_1, p_1)$ should be increased and the edge weight $w(u_1, p_3)$ should be reduced. Therefore, we should give higher weights to positions with the higher preferences. Based on reference[38], the user-location edge weight is define as follows:

$$w(u,p) = \frac{e^{r(u,p)}}{\sum\limits_{\forall p' \in P_u} e^{r(u,p)}} \tag{13}$$

where $r(u, p)$ represents the score of the user u at position p.

Based on the same principle, the user-spatiotemporal edge weight can also be defined by an exponential function. The formula is as follows:

$$w(u,t) = \frac{e^{r(u,t)}}{\sum\limits_{\forall t \in T} e^{r(u,t)}} \tag{14}$$

where $r(u, t)$ represents the score of the user u at spatiotemporal node t.

It should be noted that if the user has scored a location multiple times, this paper only uses the user's last rating as the scoring standard.

2) NODE'S DEGREE INFORMATION

The method of defining and quantifying edge weights by node degree information is similar to the resource allocation method, that is to say, when the nodes have more degrees of outbound, each outbound node will get relatively less resources.

The spacetime-user edge weight $w(t, u)$ is:

$$w(t,u) = \frac{1}{|U_t|} \tag{15}$$

where $|U_t|$ represents the number of users included in the spatiotemporal node.

- The weight of location-user edge weight $w(p, u)$ can be described as follows:

$$w(p,u) = \frac{n(p,u)}{\sum\limits_{\forall u \in U_p} n(p,u)} \tag{16}$$

where $n(p, u)$ is the number of times that user u accesses the location p, and $\sum_{\forall u \in U} n(p, u)$ is the total number of times that all users access the location p. U_p represents a set of users who have accessed location p.

- The location-category edge weight $w(p, c)$ is

$$w(p,c) = \frac{1}{|C_p|} \tag{17}$$

where $|C_p|$ indicates the number of categories to which the location p belongs.

TABLE 1. Weighted super-edge structure.

Number	Structure type	Specific type	Weight value
S1	Weighted super-triangle structure	Single weighted super-triangle structure	$W_{SE_{\mathrm{I}}}(u_i-u_k)\cdot W_{SE_{\mathrm{I}}}(u_k-u_j)$
S2			$W_{SE_{\mathrm{II}}}(u_i-p_k)\cdot W_{SE_{\mathrm{II}}}(p_k-u_j)$
S3			$W_{SE_{\mathrm{II}}}(u_i-t_k)\cdot W_{SE_{\mathrm{II}}}(t_k-u_j)$
S4		Synclastic double weighted super-triangle structure	$W_{SE_{\mathrm{II}}}(u_i-t_k)\cdot W_{SE_{\mathrm{II}}}(t_k-u_d)\cdot W_{SE_{\mathrm{II}}}(u_d-t_e)\cdot W_{SE_{\mathrm{II}}}(t_e-u_j)$
S5			$W_{SE_{\mathrm{II}}}(u_i-p_k)\cdot W_{SE_{\mathrm{II}}}(p_k-u_d)\cdot W_{SE_{\mathrm{II}}}(u_d-p_e)\cdot W_{SE_{\mathrm{II}}}(p_e-u_j)$
S6		Reverse double weighted super-triangle structure	$W_{SE_{\mathrm{II}}}(u_i-t_k)\cdot W_{SE_{\mathrm{II}}}(t_k-u_d)\cdot W_{SE_{\mathrm{II}}}(u_d-p_e)\cdot W_{SE_{\mathrm{II}}}(p_e-u_j)$
S7			$W_{SE_{\mathrm{II}}}(u_i-p_k)\cdot W_{SE_{\mathrm{II}}}(p_k-u_d)\cdot W_{SE_{\mathrm{II}}}(u_d-t_e)\cdot W_{SE_{\mathrm{II}}}(t_e-u_j)$
S8		Three-layer weighted super-triangle structure	$W_{SE_{\mathrm{III}}}(u_i-p_k-c_d)\cdot W_{SE_{\mathrm{III}}}(c_d-p_e-u_j)$
S9	weighted super-rectangular structure	Two-layer weighted super-rectangular structure	$W_{SE_{\mathrm{II}}}(u_i-p_k)\cdot W_{SE_{\mathrm{I}}}(p_k-p_d)\cdot W_{SE_{\mathrm{II}}}(p_d-u_j)$
S10			$W_{SE_{\mathrm{II}}}(u_i-t_k)\cdot W_{SE_{\mathrm{I}}}(t_k-t_d)\cdot W_{SE_{\mathrm{II}}}(t_d-u_j)$
S11		Three-layer weighted super-rectangular structure	$W_{SE_{\mathrm{III}}}(u_i-p_k-c_d)\cdot W_{SE_{\mathrm{I}}}(c_d-c_e)\cdot W_{SE_{\mathrm{III}}}(c_e-p_f-u_j)$
S12	weighted super-hybrid structure	Weighted super-hybrid structure I	$W_{SE_{\mathrm{II}}}(u_i-p_k)\cdot W_{SE_{\mathrm{II}}}(p_k-u_d)\cdot W_{SE_{\mathrm{I}}}(u_d-u_j)$
S13			$W_{SE_{\mathrm{II}}}(u_i-t_k)\cdot W_{SE_{\mathrm{II}}}(t_k-u_d)\cdot W_{SE_{\mathrm{I}}}(u_d-u_j)$
S14			$W_{SE_{\mathrm{I}}}(u_i-u_k)\cdot W_{SE_{\mathrm{II}}}(u_k-p_d)\cdot W_{SE_{\mathrm{II}}}(p_d-u_j)$
S15			$W_{SE_{\mathrm{I}}}(u_i-u_k)\cdot W_{SE_{\mathrm{II}}}(u_k-t_d)\cdot W_{SE_{\mathrm{II}}}(t_d-u_j)$
S16		Weighted super-hybrid structure II	$W_{SE_{\mathrm{II}}}(u_i-p_k)\cdot W_{SE_{\mathrm{I}}}(p_k-p_d)\cdot W_{SE_{\mathrm{II}}}(p_d-u_e)\cdot W_{SE_{\mathrm{I}}}(u_e-u_j)$
S17			$W_{SE_{\mathrm{II}}}(u_i-t_k)\cdot W_{SE_{\mathrm{I}}}(t_k-t_d)\cdot W_{SE_{\mathrm{II}}}(t_d-u_e)\cdot W_{SE_{\mathrm{I}}}(u_e-u_j)$
S18			$W_{SE_{\mathrm{I}}}(u_i-u_k)\cdot W_{SE_{\mathrm{II}}}(u_k-p_d)\cdot W_{SE_{\mathrm{I}}}(p_d-p_e)\cdot W_{SE_{\mathrm{II}}}(p_e-u_j)$
S19			$W_{SE_{\mathrm{I}}}(u_i-u_k)\cdot W_{SE_{\mathrm{II}}}(u_k-t_d)\cdot W_{SE_{\mathrm{I}}}(t_d-t_e)\cdot W_{SE_{\mathrm{II}}}(t_e-u_j)$

- The category-location edge weight $w(c,p)$ is described as follows:

$$w(c,p)=\frac{1}{|P_c|} \tag{18}$$

where $|P_c|$ represents the number of locations included in the category c.

VI. MEASUREMENT OF SOCIAL RELATIONSHIP

In the above two sections, this paper constructs a four-layer supernetwork, including spatiotemporal, user, location, and category. Then the edge weights in the supernetwork are quantified by using user influence, implicit incidence relation, user preference and node's degree information, and a four-layer weighted supernetwork model is successfully constructed. This section will discuss all the exist super-edge types and quantify the importance of each super-edge structure to determine the social relationships between users.

Definition 1 : The first type of super-edge is called SE_{I}. It refers to a super-edge containing only one type of node, and belongs to a special type of super-edge in the supernetwork. For example, a super-edge composed of user node u_1 and user node u_2 is called the first type of super-edge $SE_{\mathrm{I}}(u_1-u_2)$. Its weight is $W_{SE_{\mathrm{I}}}(u_1-u_2) = w(u_1,u_2)$. It indicates the relationship between nodes in the same layer. For example, the user layer refers to the friend relationship between users.

Definition 2: SE_{II} refers to the second type of super-edge, which indicates to the edge formed by the node pairs between two adjacent layers. It is characterized by containing only two heterogeneous nodes. For example, the super-edge formed by user node u_1 and location node p_1 is called the second type of super-edge $SE_{\mathrm{II}}(u_1-p_1)$ and the weight is $W_{SE_{\mathrm{II}}}(u_1-p_1) = w(u_1,p_1)$.

Definition 3: The third type of super-edge is called SE_{III}. It is the edges formed by three layers of adjacent layers, which is characterized by three heterogeneous nodes. For example, the super-edge of user node u_1, location node p_1 ,and category node c_1 is called the third type of super edges. Its weight value is defined as $W_{SE_{\mathrm{III}}}(u_1-p_1-c_1) = w(u_1,p_1)\cdot w(p_1,c_1)$.

It is worth noting that the super-edge constructed in this paper is directional, so the weight value satisfies $w(u_1,p_1) \neq w(p_1,u_1)$.

The weighted supernetwork model can not only show the association between homogeneous nodes, but also describe the association between heterogeneous nodes. The deeper the network layer is considered, the longer the association chain is, and the more it can reflect the fine-grained implicit association between nodes. In the previous method, the degree of association between nodes is calculated mainly by weighting the hyper-triangle structure [39]. This method can only capture additional associations simply, and it is difficult to reflect the relatively hidden associations of nodes. Therefore, this paper will construct multiple types of weighted super-edge structures, including weighted hyper-triangles, weighted super-rectangular and weighted hyper-hybrid structures, for mining implicit relationships between user nodes [40]. Specifically, all constructed super-edges for any two user nodes u_i, u_j and their corresponding weighted values are shown in table 1.

A. WEIGHTED HYPER-TRIANGLES STRUCTURE

The weighted hyper-triangular structure associates two super-edges through a common node between different super-edges to form a triangle-like structure and to measure the similarity between nodes.

According to the type of super-edge and the formed triangular structure, the weighted hyper-triangle structure is subdivided into the single weighted super-triangle structure, the double weighted super-triangle structure and the three-layer weighted hyper-triangle structure. The specific structure is shown as S1-S8 of Table 1.

B. WEIGHTED SUPER-RECTANGULAR STRUCTURE

The weighted hyper-triangle structure simply uses the common node of this layer or other layer nodes corresponding to this user node as a bridge to mine the association between any user nodes, but ignores whether other layer nodes corresponding to their two user nodes are related.

For example, when the spatiotemporal node t_k of the user node u_i is associated with the spatiotemporal node t_d of the user node u_j, $SE_{\mathrm{II}}(u_i - t_k)SE_{\mathrm{I}}(t_k - t_d)$,and $SE_{\mathrm{II}}(t_d - u_j)$ can be used to form a weighted super-rectangular structure, that is, the S10 structure. The semantic information of this structure is that users u_i and u_j prefer to be active at two related spatiotemporal nodes. Therefore, hidden user associations can be further exploited by weighting the super-rectangular structure. According to its definition, the weighted super-rectangular structure of any two user nodes u_i, u_j is shown in S9-S11 of Table 1.

C. WEIGHTED SUPER-HYBRID STRUCTURE

The weighted super-hybrid structure can be subdivided into the weighted super-hybrid structure I and the weighted super-hybrid structure II. A weighted super-hybrid structure I refers to add first type of super-edge on the basis of a single super-triangle structure. For example, the S13 consists of $SE_{\mathrm{II}}(u_i - t_k)$, $SE_{\mathrm{II}}(t_k - u_d)$, and $SE_{\mathrm{I}}(u_d - u_j)$. The semantic information of this structure indicates that u_j's friend u_d likes to be active at the same location as u_i at the same time. Weighted super-hybrid structure II indicates adding first type of super-edge on the basis of a weighted super-rectangular structure. For any two user nodes u_iu_j, the possible weighted super-hybrid structure is as shown S12-S19 in Table 1.

It can be seen from Table 1 that weighted super-edge structures are constructed. Taking the S1 structure as an example, it means the similarity between u_i and u_j calculated by the common node u_k. It is worth noting that different weighted super-edge structures have different semantic information. For example, the S2 structure embodies the meaning of location entropy [41]. It means that if two users have signed in at a place where many people have been to, it's hard to predict a friend relationship between the two. Because it may be a coincidence. But if two users often sign in at a place that few people have been to, it is likely that there is a certain relationship between them. Therefore, the popularity of a location also has an impact on user's relationship prediction, and this effect can be effectively captured by the S2 structure. The S7 structure is able to explore a short-term interest of the users. This short-term interest is interpreted as such interest that the user may only have at a specific time period. For example, a user goes to the cinema to watch a movie at 7:00 every Friday night, so this interest will only occur in a specific time period, but it will better reflect the user's personality. The S11 structure reflects that they often go to some locations with the same category, although two users have not been to the same location. This shows that two users have the same category preferences, which helps to mine the relationship between users.

Implicit semantic relationships between nodes can be exploited by constructing multiple types of weighted super-edge structures as described above. So, the social relationship value $S(u, v)$ of any two users u, v can be expressed as:

$$S(u, v) = \theta_1 W_{S1}(u, v) + \theta_2 W_{S2}(u, v) + \cdots + \theta_{19} W_{S19}(u, v) \tag{19}$$

where θ_i represents the degree of influence of the i-th weighted super-edge structure on the link prediction, and the *gradient descent algorithm* is used to update the parameter values. The parameter update process is as follows:

$$\theta_{i-new} = \theta_{i-old} + \lambda(y - \sum_{i=1}^{19} \theta_i W_{Si}) \times W_{Si} \tag{20}$$

where λ represents the step size of learning and y represents the associated value between users in the user layer. When the change value of each parameter is less than a certain threshold, the parameter will update to reach convergence, and the optimal parameter set θ^+ can be obtained.

VII. RELAY SELECTION ALGORITHM

In this section, we will combine the transmission rate of the relay communication and the extracted social relationship values to select the relay nodes that can satisfy the user's transmission requirements and ensure the transmission stability.

In this paper, we measure the selection of the relay node as an optimal social rate value to consider both the transmission rate and the social relationship value of the relay communication. The specific social rate value is defined as:

$$X_{DRi} = R_{DRi} \left(S \left(U1, DR_i \right) + S \left(DR_i, U2 \right) \right) / R_{U1,U2} \quad (21)$$

where X_{DRi} represents the social rate value of the relay node i, and $R_{U1,U2}$ represents the communication rate directly transmitted by the source node $U1$ and the target node $U2$. R_{DRi} represents the total transmission rate in relay communication mode. $S(U1, DR_i)$ and $S(DR_i, U2)$ are social relationship values calculated by (19). Through the above formulas, the social rate value of relay nodes in the candidate relay nodes set can be obtained, wherein the candidate relay nodes set is composed of nodes within the maximum coverage of the source node. Then the largest social rate value is selected as the real relay node. The specific algorithm steps are shown in Algorithm 1.

Algorithm 1 Based on Maximum Social Rate for Relay Selection Algorithm (MSRRS)

Input: transmitter U1, receiver U2, candidate node set U_R, and user's multidimensional information data

Output: an optimal relay node based on the optimal social rate value

/ / Divide the four-layer super networks

1: Construct a spatiotemporal node T based on the user's check-in location p and time t;

2: Build spatiotemporal layer G_T, user layer G_S, location layer G_L, and category layer G_C;

/ / Measure the social relationship values of any two users

3: Define edge weight based on user influence, implicit relationship, user preference, and node degree information, and quantize edge weight according to (3)-(18);

4: Construct three types of super-edges, SE_{I}, SE_{II}, SE_{II} and calculate the super-edge weights;

5: Based on the three types of super-edges, a weighted hyper-triangle structure, a weighted super-rectangular structure, and a weighted hyper-hybrid structure be constructed, and weights of the weighted super-edge structure W_S are calculated.

6. Calculate the social relationship value $S(u, v)$ of any two users according to (19) (20);

7. Calculate the transmission rate of the direct communication between the transmitter U1 and the receiver U2 and the relay transmission rate by add candidate relay node, according to the (1)(2);

8: Calculate the optimal social-rate value of all candidate relay links according to (21), and select the relay node output corresponding to the largest social rate value.

VIII. SIMULATION RESULTS AND ANALYSIS

These simulation experiments use MATLAB to analyze and verify the Based on Maximum Social Rate for Relay Selection Algorithm (MSRRS) proposed in this paper. The algorithm is applied to D2D communication with single cell communication, and compared with the results of the Based on Maximum Throughput for Relay Selection Algorithm (MTRS) and Random Relay Selection Algorithm (RRS). Among them, we analyzed transmission rate, social relationships and social stability, then verified the effectiveness and superiority of the proposed algorithm.

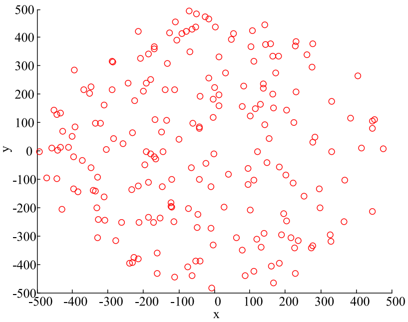

FIGURE 3. User distribution within the cell.

TABLE 2. Simulation parameters.

Parameters	Value
Cell radius	500m
Bandwidth of channel	180KHz
Terminal transmit power	23dBm
Noise power spectral density	-174dBm/Hz
Path attenuation coefficient	4
Number of relay users	[10,50]
Transceiver spacing	[50m,200m]

A. SIMULATION SCENE DESIGN

The coverage of single-cell is defined as a circular area with a radius of 500 meters, and user terminals are distributed in various locations of the cell by random seeding, as shown in Figure 3. Devices using D2D communication can reuse the uplink bandwidth of devices that are using cellular communications. Among them, in order to reduce the complexity of the experiment and highlight the key points of this paper, this paper sets the transmit power of the user equipment in the cell to a constant value of 23dBm. The other parameters are set as shown in Table 2.

B. ANALYSIS OF SIMULATION RESULTS

Since the path fading is mainly considered in this paper, the transmission quality of relay communication is particularly susceptible to the communication distance between users. In addition, the number of candidate relay nodes affects the number of relays selectable by the overall relay communication, thereby affecting the quality of selection of the selected relay node. Combining the above two aspects, this paper mainly compares the performance of transmission rate, social rate and social stability by changing the communication distance between users and the number of relay nodes in relay candidates to demonstrate the overall performance of the algorithm proposed in this paper. Among them, social

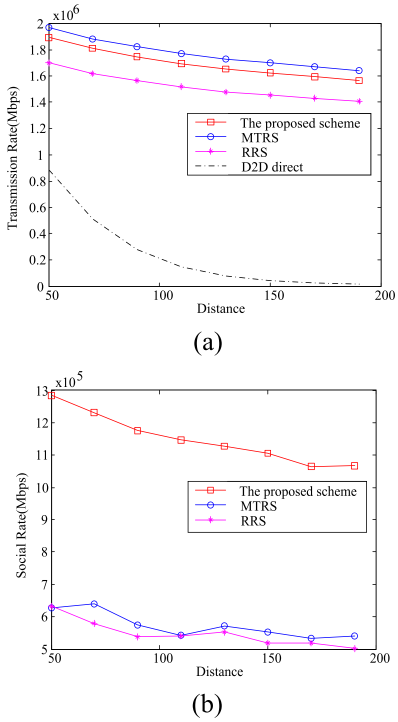

FIGURE 4. Effects of communication distance on the performance of three algorithms.

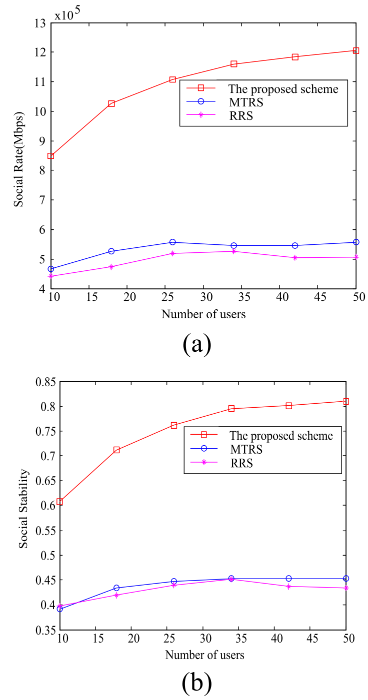

FIGURE 5. The impacts of the number of relay candidate nodes on various algorithms.

stability is used to express the overall social relationship strength of the source users, the destination users and the candidate relay users, which is independent of the communication rate and transmission distance in the current network. It is defined as $(S(U1, DR_i) + S(DR_i, U2))/S(U1, U2)$.

Figure 4 shows the effect of the transmission distance on the transmission rate and the optimal social-rate value of the relay communication, respectively. As can be seen from the Figure 4(a), As the transmission distance between the transmitting device and the receiving device increases, the transmission rate of the D2D direct transmission mode decreases rapidly. Especially after the transmission distance exceeds 120 meters, the transmission rate approaches 0 in D2D direct transmission mode. The top three curves in the Figure 4(a) are the transmission rates obtained by using the relay communication method, which are obviously superior to the D2D direct communication. Although the three relay methods have decreased with increasing distance, the decline is slow. The MSRRS mentioned in this paper is better than RRS, but lower than MTRS. The reason is that the MTRS algorithm is a relay node corresponding to selecting the highest relay transmission rate, and does not include the user social relationships in the selection of the relay nodes. As can be seen from Figure 4(b), as the distance increases, the two relay schemes of the comparison tend to be slower in social rate, but their social rate values are very low. The algorithm proposed in this paper is significantly better than the comparison algorithm in social rate values.

Figure 5 shows the effect of the number of relay candidate nodes on social rate and social stability, respectively. As can be seen from the Figure 5(a), as the number of relay candidate nodes increases, the social rate value of the three algorithms increases. Among them, the algorithm proposed in this paper is obviously superior to the other two algorithms, but it can be seen from the figure that the algorithm proposed in this paper is greatly affected by the number of relay candidate nodes. Therefore, if this algorithm is applied to a dense cellular network, it will perform well. The Figure 5(b) shows the effect of the number of candidate nodes on social stability. It can be seen from this figure that as the number of candidate relay nodes increases, the social stability of the three algorithms also increases, but the algorithm proposed in this paper is significantly better than the other two algorithms.

In summary, MSRRS proposed in this paper can effectively improve the overall transmission rate and transmission quality. This paper integrates multi-dimensional information to measure the strength of social relationships among users as comprehensively as possible and find hidden social relationship links through super-network architecture. Finally, compared with other algorithms, the proposed relay selection algorithm under optimal social-rate value has superior performance in transmission rate, social perception relationship and social stability.

IX. SUMMARY

D2D relay transmission has received wide attention to improve the communication quality of cellular edge users and to ensure stable transmission under highly dynamic wireless channels. In the existing D2D relay communication researches, most of them have introduced social relations to improve the stability of relay communication. However, how to integrate a variety of information to quantify the strength of social relations is a question worth considering. Because the more information that is incorporated, the more kinds of social relationships that are hidden between users. Based on this, this paper first proposes a supernetwork architecture based on multi-dimensional information, which is used to combine spatiotemporal, user, location and other multi-dimensional factors. Then, the intra-layer relationships weight and the inter-layer relationships weight in the supernetwork architecture are quantified, and multiple types of weighted super-edge structures are constructed based on these two weight relationships to capture a variety of hidden social relationships. Finally, based on the calculated social relationship strength and relay communication transmission rate, this paper proposes a social rate value to select the appropriate relay node. The proposed social rate value can effectively combine the social layer and the physical layer to achieve better performance of the selected relay node in terms of transmission rate and transmission stability. The simulation results show that the relay node selected by MSRRS proposed in this paper have better performance in the transmission rate of relay communication, and are better than other algorithms in terms of stability.

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