



Particle Swarm Optimization Based Location Recommendation for D2D Communication Underlying LTE Cellular Networks

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Abstract. In this paper, we present a particle swarm optimization based location recommendation scheme (PSO-LR) for Device-to-Device (D2D) Communication underlying Long Term Evolution (LTE) cellular networks. The proposed scheme enables D2D users to move to new locations which provide better link qualities and a higher system capacity. Also, it can balance resource allocation between cellular users and D2D users. The simulation results illustrate that the proposed PSO-LR scheme can effectively improve the total system capacity by location recommendation for D2D users, and reduce both the distance and time of location recommendation by comparison with other location recommendation scheme [11].

Keywords: Device-to-Device (D2D) communication
3GPP Long Term Evolution (LTE) · Interference mitigation

1 Introduction

Recently, Device-to-Device (D2D) communication has been widely investigated for the growing demands of Internet of Things (IoT). Different from traditional D2D techniques like Bluetooth or Wi-Fi, D2D communication underlying Long Term Evolution (LTE) cellular networks is able to use operator legal license band for progressing high-speed and large-scale proximity discovery or direct communication [1]. D2D communication underlying LTE cellular networks can improve power-saving efficiency by enabling a direct data transmission between User Equipment (UE) within a short range without the relay by Base Station (BS). Furthermore, it can enhance the spectrum utilization by frequency reuse, and thus improve the total system capacity.

However, D2D communication might cause inter-interferences to cellular networks and degrade the overall system performance. The interferences in a D2D communication underlying LTE cellular networks can be classified into two types: cross-tiered (i.e., between the D2D communication and cellular networks) and co-tiered (i.e., solely between D2D communication) [2]. There have been some recent works on the mitigation of interferences and/or the cooperation of resource allocation between macrocell

user equipment (MUE) and D2D user equipment (DUE) [1–10]. In [3], the authors discuss the cross-tiered interference problem between the D2D communication and 3G Wideband Code Division Multiple Access (WCDMA) cellular networks. In [4–10], the authors investigate the interference problem of D2D communication underlying Long Term Evolution (LTE) cellular networks. [7] concludes that the a severe interference situation can be mitigated using orthogonal resource distribution. However, using orthogonal resource distribution restricts the frequency reuse and hence degrades spectrum utilization efficiency. [8] investigates that the mutual interference between D2D Communication and Cellular Networks can be limited to a certain area. It is mentioned that D2D Communication is similar to the secondary user in cognitive networks. The difference between D2D Communication and the secondary user is that the latter will not be controlled by the primary user whereas D2D communication can be controlled by cellular networks. [9] discusses that in downlink of LTE, all the resources can be divided into center part and edge part. Edge part is for partial frequency reuse. If D2D communication uses edge part of resources, the interference can be limited to this area.

In this paper, we tackle the cross-tiered interference problem between the D2D communication and cellular networks, and propose a particle swarm optimization (PSO) based location recommendation scheme for D2D Communication underlying cellular networks. PSO is often used in the field of automatic control [12, 13]. In this paper, we apply PSO in location recommendation for D2D users to reduce the interference between D2D communication and cellular networks and hence improve the link qualities of both MUE users and D2D users. The results of simulations show that comparing with our existing scheme [11], the proposed PSO location recommendation scheme effectively reduces both the cost and time of location recommendation. The rest of this paper is organized as follows. Section 2 illustrates the proposed PSO location recommendation scheme. Section 3 explains the simulation setup and results. Finally, the conclusion is given in Sect. 4.

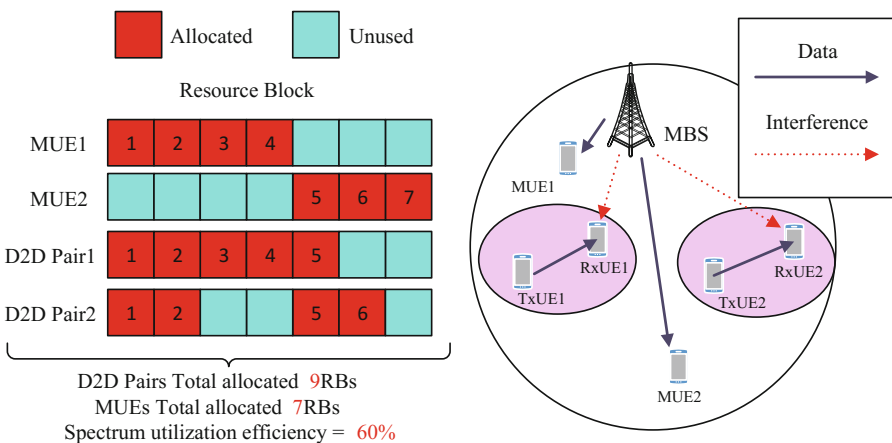


Fig. 1. Example of D2Ds with the proposed PSO LR scheme.

2 Proposed PSO Location Recommendation Scheme

To illustrate our resource allocation scheme and PSO Location Recommendation, consider the scenario shown in Fig. 1. The Transmission User Equipment (TxUE) of D2D communication can share the spectrum resources with cellular networks when it transmits data to the Receiver User Equipment (RxUE). However, TxUE will produce mutual interference to MUE 2 because MUE 2 is within the transmission range of TxUE. Now, we consider the use of location recommendation for D2D users as shown in Fig. 2. When D2D communication pairs move, the interference from TxUE to MUE 2 is mitigated, and the total system capacity can be increased. The example illustrates that a location recommendation approach for D2D users can improve the overall transmission efficiency.

As Fig. 2 shows, location recommendation for D2D users can affectively increase the system capacity of cellular networks and D2D communication. In general, the location recommendation problem can be expressed as:

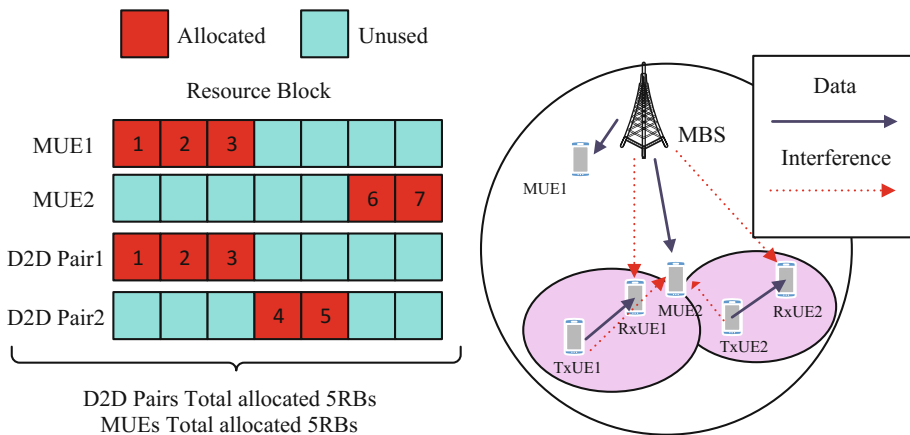


Fig. 2. Example of D2Ds in a co-channel interference scenario.

$$\hat{I} = F(I, \varphi, \psi) \tag{1}$$

where \hat{I} represents the recommended location for D2D users; I represents the current location of D2D users; φ and ψ represents the current and the desired system capacity of cellular networks and D2D communication, respectively. First, we mark m coordinate points in the space of interest, measure the system capacity in each point, and record that in the database. Once the system capacity in the current point is inadequate, D2D users will be recommended to move to another location which provides sufficient system capacity. In this paper, the location recommendation approach is implemented based on a particle swarm optimization technique [13]. The fitness function in particle swarm optimization can be expressed as:

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01: Construct and initialize the capacity map  $\{(I_1, \varphi_1), (I_2, \varphi_2), \dots, (I_m, \varphi_m)\}$ 
02:  $D2D_h$  informs the serving BS of  $(I_h, \varphi_h) \rightarrow (\varphi_h, \psi_h)$ 
03: If  $\varphi_h < \psi_h$ 
04: For  $k = 1 : m$ 
05:   Export  $(I_k, \varphi_k)$ 
06:   Set  $\Lambda$  as the set of  $\{(I_k^*, \varphi_k^*)\}$  in which  $\varphi_k \geq \psi_h$ 
//  $\varphi_k^*$  is adequate to the desired capacity level
07: End For
08: If  $\Lambda \neq \phi$ 
// Calculate the moving distance from the current location  $I_h$  to each location  $I_k^*$  in  $\Lambda$ ,  $d_{h,k}$ 
09:   Initialize particles swarm optimization
10:   Repeat
11:     For each particle  $i$  in  $S$  do
// Construct and initialize the particle  $S = \{(x_1, pb_1), (x_2, pb_2), \dots, (x_i, pb_i)\}$ 
12:       If  $f(x_i) < f(pb_i)$  then
// update the particle's best position by Fitness Eq. (5)
13:          $pb_i = x_i$ 
14:       End If
15:       If  $f(pb_i) < f(gb)$  then
// update the global best position
16:          $gb = pb_i$ 
17:       End If
18:     End For
19:     For each particle  $i$  in  $S$  do
// update particle's velocity and position
20:       For each dimension  $d$  in  $D$  do
21:         Execute Eq. (3) and (4)
22:       End For
23:     End For
24:      $n = n + 1$  // advance iteration
25:   Until  $n < MAX\_ITERATIONS$ 
26:    $\hat{I} = gb$ 
27: End if
28: Else  $\Lambda = \phi$ 
29: Return  $I_h$ 
30: Return  $\hat{I}$ 
// Go to the new location  $\hat{I}$ 
31: End if
32: End

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Fig. 3. The proposed particle swarm optimization location recommendation algorithm (PSO-LR).

$$f(d_{\text{move}}) = \begin{cases} w_{\text{fit}}(C_{\text{D2D_particle}})(d_{\text{move}})^{-1} & , C_{\text{D2D_after}} - C_{\text{D2D_before}} > C_{\text{D2D_target}} \\ 0 & , \text{elsewhere} \end{cases} \tag{2}$$

where w_{fit} is the fitness weight; $C_{\text{D2D_particle}}$ is the system capacity where the particle locates; $C_{\text{D2D_before}}$ is hypotheticalal system capacity before D2D users move; $C_{\text{D2D_after}}$ is hypotheticalal system capacity after D2D users move; $C_{\text{D2D_target}}$ is the target value of increased system capacity after a move. The objective of (2) is to provide a location recommendation which meets the situation $C_{\text{D2D_before}} - C_{\text{D2D_after}} > C_{\text{D2D_target}}$. To combine PSO into the location recommendation approach, we use Eqs. (3) and (4) presented in [12],

$$v_{i,d}(n+1) = \zeta v_{i,d}(n) + C_1(\text{rnd}_{0,1}) [pb_{i,d} - x_{i,d}(n)] + C_2(\text{rnd}_{0,1}) [gb_d - x_{i,d}(n)], \tag{3}$$

$$x_{i,d}(n+1) = x_{i,d}(n) + v_{i,d}(n+1) \cdot T, \tag{4}$$

where i represents the particle’s index; d represents the considered dimension; n is the number of iteration; C_1 represents the acceleration constant for the cognitive component; C_2 is the acceleration constant for the social component; T represents the systematic sampling time.

Once we complete the design of fitness function, the PSO-LR scheme will initialize all particles with random location $x_{i,d}$ and velocity $v_{i,d}$, and start to evaluate the fitness value of all particles. We divide our evaluation into two steps. In the first step, the current fitness value of each particle is compared with the best location $pb_{i,d}$ till now. If the current fitness value is better, $pb_{i,d}$ is updated with the current location. In the second step, the current fitness value of each particle is compared with the best overall location of particle swarm gb_d till now. If the current fitness value is better, gb_d is updated with the current location.

After updating particles’ speed $v_{i,d}$ and location $x_{i,d}$ in Eqs. (3) and (4), PSO-LR will check whether the stop criteria is satisfied. If not, it will return to evaluation of the first phase, or select the position that has the shortest moving distance to D2D users.

Finally, since the shortest recommended distance does not represent the performance of the whole system, in order to get more accurate analysis to reinforce our proposed algorithm, we design a cost function for location recommendation, which can be expressed as Eq. (5),

$$\begin{aligned} LR_{\text{cost}}(w_{\text{cost}}, c_{\text{ave}}, r_{\text{ave}}, t_{\text{ave}}, d_{\text{ave}}) \\ = w_{\text{cost}}(c_{\text{ave}} \cdot r_{\text{ave}})^{-1} \cdot t_{\text{ave}} \cdot d_{\text{ave}}, \end{aligned} \tag{5}$$

where d_{ave} represents the average recommendation distance; w_{cost} represents the cost weight; c_{ave} represents the growth rate of system capacity; r_{ave} represents the increasing rate of resource utilization; t_{ave} represents the average calculation time. With the cost function, we can analyze the total effect of the advantages and disadvantages that PSO-LR produces. The pseudo code of the proposed PSO-LR scheme is shown in Fig. 3.

3 Performance Evaluation and Discussion

In this section, we conduct simulation scenarios of D2D communications underlying LTE cellular networks to demonstrate the effectiveness of the proposed PSO-LR schemes. The simulation is programmed using C++ by following the LTE standard [14]. The system parameters and their values are listed in Table 1. The simulation setup assumes a square area where the D2D users are randomly deployed. We compare the performance of the proposed PSO-LR scheme with that of our existing scheme [11] using brute force for producing location recommendation. The co-channel reuse scheme is used for resource allocation (i.e., the use of frequency spectrum will prevent interference as well as possible) to clearly examine the achieved performances with different LR schemes. The performance metrics are indexed as the recommended distance and recommended cost.

Table 1. Simulation parameters

Notation	Parameter	Value
$D_{TxUE_j, RxUE_j}$	The distance between D2D (meter)	10
k	Number of MUEs	30
h	Number of D2D pairs	5
r	Number of resource block	30
$P_{MBS, RxUE_j}$	Transmit power of BS (dBm)	46
$P_{TxUE_j, k}$	Transmit power of TxUE (dBm)	23
N	Noise power (dBm)	-174
α	Path-loss exponent	5
C_{D2D_target}	Location recommendation capacity (bps)	50
W_{fit}	Fitness weights	10000
W_{cost}	Cost weights	0.01
C_1	Constant value	2
C_2	Constant value	2
d	Dimensions (x, y)	2
i	Number of particles	45
n	Iterations	200-2000

According to our simulation scenarios, we respectively compare the data in different iteration number of brute-force LR with that of our PSO-LR scheme. We use both map sizes 1000 m * 1000 m (Case 1) and 2000 m * 2000 m (Case 2) with 5 pairs of D2D communication. The simulation results are illustrated with the average data in one thousand times.

The recommended distances using the proposed PSO-LR scheme and brute-force LR scheme [11] with different map sizes are shown in Fig. 4. As Fig. 4 shows, the recommended distance with PSO-LR is significantly lower than that with the brute-

force LR scheme. Also, the more iteration number is, the shorter recommended distance is. Since the map size of Case 2 is bigger than that in Case 1, it has a slower convergence speed.

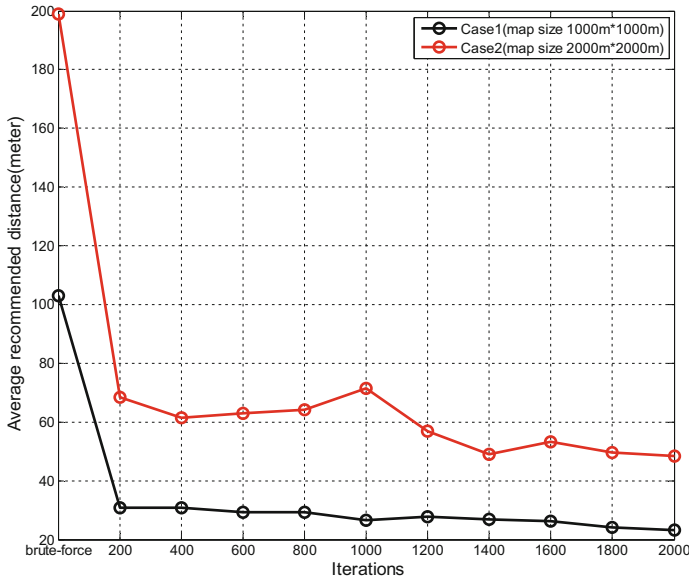


Fig. 4. Average recommended distance (meter).

The average execution time with different LR schemes are shown in Fig. 5. It is shown that the recommended times with PSO-LR are far less than that with the brute-force LR scheme. Also, in Case 2 with a bigger map, the advantage of shorter recommended time will be more obvious when using our PSO-LR scheme.

Figure 6 compares the average system capacity with the proposed PSO-LR scheme and brute-force LR scheme. It is shown that the system capacity with PSO-LR is merely lower than that brute-force LR (about 3.5% and 2.6% in Case 1 and Case 2, respectively). Although the increased system capacity with PSO-LR is beyond that brute-force LR, PSO-LR still can effectively increase the overall system capacity by location recommendation. Figure 7 shows the average resource reuse utilization ratio with the proposed PSO-LR scheme and brute-force LR scheme. It is shown that the resource reuse utilization ratio with PSO-LR is merely worse than that brute-force LR. The performance difference between PSO-LR and brute-force LR in Case 2 with a bigger map is less than that in Case 1.

Finally, we collect the recommended distance, execution time, capacity increase utilization ratio and resource reuse utilization ratio mentioned above to evaluate the cost in Eq. (5) to analyze the total effect of the advantages and disadvantages that PSO-LR produces. As Fig. 8 shows, our PSO-LR scheme is superior to brute-force LR scheme in terms of lower cost. From the simulation results shown in Figs. 4, 5, 6, 7 and

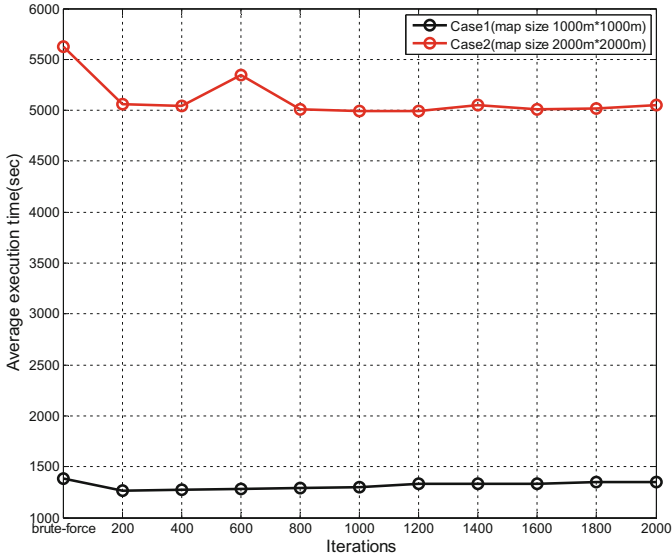


Fig. 5. Average execution time (sec).

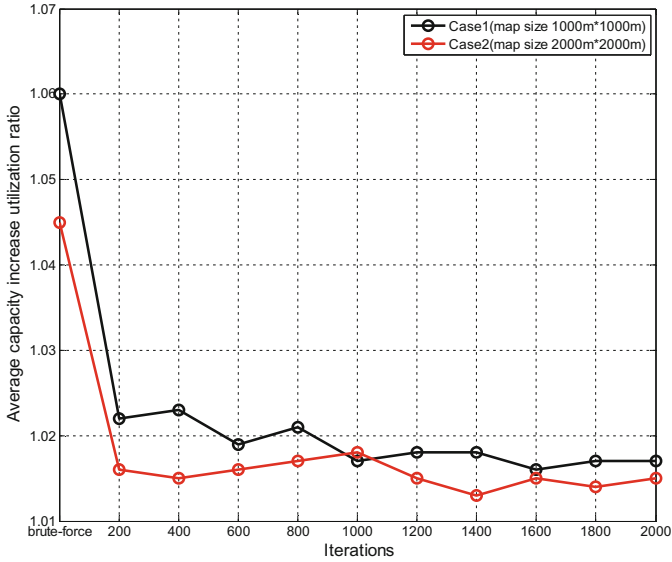


Fig. 6. Average capacity increase utilization ratio.

8, it is demonstrated that by comparison with brute-force LR scheme, the proposed PSO-LR scheme can effectively decrease the recommended distance and recommended time with a minor degradation of system capacity for D2D Communication underlying LTE cellular networks.

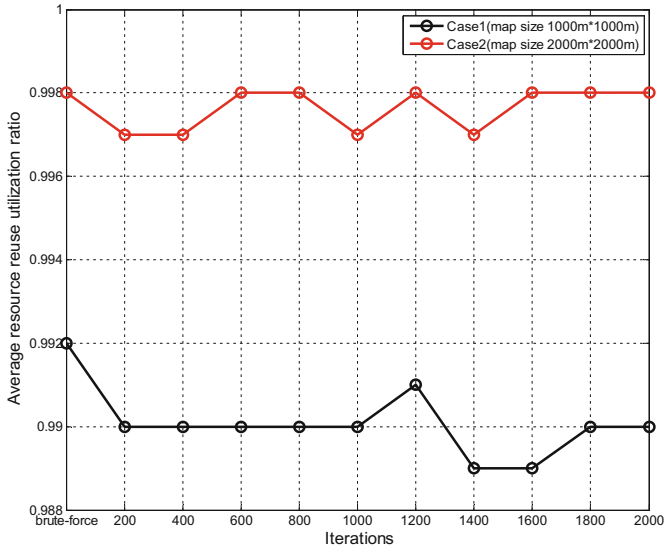


Fig. 7. Average resource reuse utilization ratio.

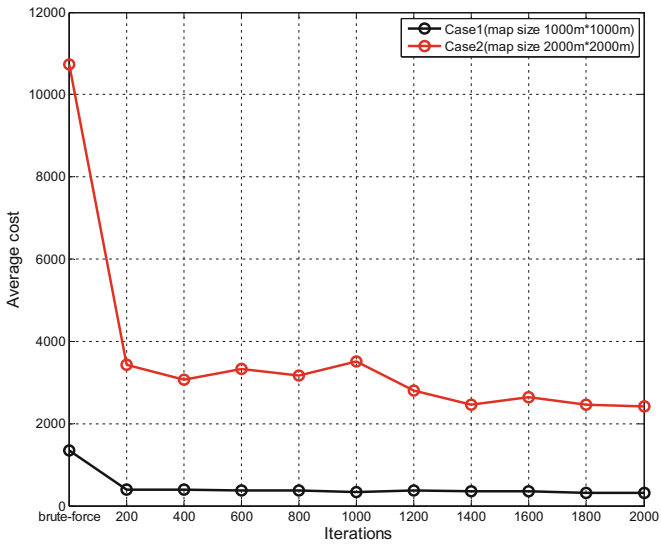


Fig. 8. Average cost.

4 Conclusion and Future Work

In this paper, we present a particle swarm optimization based location recommendation scheme (PSO-LR) for D2D Communication underlying LTE cellular networks. The proposed scheme enables D2D users to move to new locations which provide better link qualities and a higher system capacity. Also, it can balance resource allocation between cellular users and D2D users. The simulation results illustrate that the proposed PSO-LR scheme can effectively improve the total system capacity by location recommendation for D2D users, and reduce both the distance and time of location recommendation by comparison with other location recommendation scheme [11]. Our future research will investigate the joint problem of the location recommendation for D2D users combined with the deployment of cellular base stations.

Acknowledgment. The authors would like to thank the financial support provided by National Science Council (MOST 106-2221-E-003-023, and MOST 107-2634-F-155-001).

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