Task Allocation Scheme for Cyber Physical Social Systems

Zhou Su[+], Minghui Dai[+], Qifan Qi[+], Yuntao Wang[+], Qichao Xu[+], and Qing Yang[++]

[+]School of Mechatronic Engineering and Automation, Shanghai University, Shanghai 200444, P. R. China

[++]Computer Science and Engineering Department, University of North Texas, Denton, TX, USA

Abstract—Cyber-physical social system (CPSS) has emerged to integrate the interaction between the physical, cyber, and social world. However, due to the ever-increasing amount of sensing data and the limited resources of mobile systems, how to allocate the tasks by crowd sensing to enable a high-confidence CPSS becomes a new challenge. Therefore, in this paper we propose a novel game theoretic approach to allocate tasks with the trust and incentives in CPSS. Firstly, with the analysis of social tie of mobile users, a trust evaluation mechanism is developed to evaluate the reputation of mobile users. Secondly, by introducing a virtual currency, the incentive mechanism is designed to encourage mobile users to undertake the tasks by crowd sensing. Thirdly, based on the interaction of task requester and mobile users, a bargaining game model is presented to allocate tasks where the optimal price can be determined by the subgame perfect Nash equilibrium. Finally, extensive simulations are carried out to demonstrate that the proposal can outperform other conventional methods.

Index Terms—Cyber-physical social systems, Task allocation, Bargaining game.

1 Introduction

Cyber-physical social system (CPSS) has been a promising paradigm to seamlessly integrate the cyber, physical, and social world. With the advance of CPSS, more and more users can take a variety of mobile devices to interact with each other [1], [2], [3]. In the CPSS, various sensors are equipped to analyze physical phenomena, monitor computational entities and make decisions based on sensing information [4], [5], [6], [7], [8]. Nowadays, the CPSS has received increasing demands and keen research attentions.

To enable a high-confidence CPSS for better benefits, crowd sensing is advocated in recent years. Instead of collecting data from a fixed mobile user, multiple social users are encouraged to provide sensing data to the CPSS [9], [10], [11], [12]. With the crowd sensing, the CPSS can collect sensing data of human society in an interactive and automatic way [13], [14], [15]. These sensing data are excavated and analyzed by remote data servers and practitioners, which can provide sensing services to individuals, social groups, the third parties, etc [16], [17], [18], [19].

However, with the ever-increasing scale of CPSS, the task allocation becomes a new challenge for crowd sensing in the CPSS with the following reasons. On one hand, due to the large number of mobile devices equipped with sensors and controlled by different individual users, it is difficult to depend on a single mobile user who has limited resources to undertake the sensing tasks. How to encourage multiple mobile users to cooperatively undertake the tasks should be considered [20], [21], [22], [23], [24]. One the other hand, because of the unstability of networks and the uncertainty of mobile users, the quality of sensing data may be low even unfaithful sometimes [25], [26]. How to provide the accurate sensing data with high-quality needs to be discussed.

Although the existing works have studied the optimization in crowd sensing for CPSS, most of them cannot be directly used for task allocation by crowd sensing in CPSS [27], [28]. Firstly, mobile users may be selfish and have a low will to undertake the sensing task as it consumes their energy and resources. An incentive mechanism is needed for mobile users to encourage them to undertake the tasks in the crowd sensing. Secondly, a user with high reputation is likely to provide high-quality sensing data in CPSS. A novel trust mechanism should be designed to evaluate the reputation of mobile users. Finally, as different mobile users have different relationship, the social tie should be considered to model the interaction among them in order to allocate the tasks efficiently. Therefore, how to develop an efficient task allocation scheme for crowd sensing in the CPSS is still an open and vital issue.

Therefore, in this work, we study the task allocation in CPSS with trust management and social tie. Our work is different from the conventional models for crowd sensing [29], [30], [31], where the social tie among mobile users in CPSS is not focused on to encourage mobile users to provide sensing content cooperatively and the secure task allocation in CPSS such as the trust mechanism is not mentioned either. Firstly, by considering the reputation and social interaction among mobile users, we design the trust mechanism to guarantee the security of CPSS for sensing. Secondly, a credit clearance center is introduced to manage the virtual currency of mobile users. Mobile users can obtain virtual currency as incentives by providing high-quality of sensing services to the task requester. Finally, based on the

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSE.2018.2867080, IEEE Transactions on Network Science and Engineering

interaction between the task requester and mobile users, a game theoretical model is presented to allocate tasks. In a nutshell, the main contributions of this work are three-fold as follows.

- **Trust Evaluation:** We establish a mechanism to evaluate the trust of mobile users in the CPSS. The trust value is obtained from the historic interaction among mobile users according to the social tie. The task requester can allocate the sensing task to mobile users with high reputation to improve the quality of sensing data.
- **Incentive Scheme:** The virtual currency is introduced to stimulate mobile users to participate in the CPSS. Mobile users who are active to undertake the tasks can obtain the virtual currency as incentives.
- **Task Allocation:** We develop a bargaining game model based on the interaction between the task requester and mobile users. The optimal price for task allocation can be determined by the subgame perfect Nash equilibrium.

This remainder of this paper is organized as follows. In Section 2, the related work is given. Section 3 presents the system model. Section 4 introduces the task allocation with incentive mechanism. Performance simulations are shown in Section 5. Finally, we give the conclusion in Section 6.

2 Related work

2.1 Mobile Crowd Sensing

To improve the performance of task allocation scheme, various studies have been done in crowd sensing applications and systems. Jayaraman *et al*. [32] study a context aware distributed mobile data analytics platform. The authors propose a cost model for a typical distributed data analytics application, which enables efficient data analytics in the fog by providing a standardized component-oriented approach. Yang *et al*. [33] develop two system models: the platform-centric model where the platform provides a reward shared by participating users, and the user-centric model where users have more control over their received payment. He *et al*. [34] consider a standard mobile crowd sensing model to design an incentive scheme. The notion of walrasian equilibrium is employed as a comprehensive metric. Song *et al*. [35] propose an auction-based budget feasible mechanism. The mechanism consists of a winner selection rule and a payment determination rule. Thereby an incentive mechanism is designed to stimulate mobile users to contribute to the system.

Li *et al*. [36] study the mobile crowd sensing and develop a software defined opportunistic network scheme to solve the optimal decision of mobile devices and the sensing service provider. Then an incentive mechanism for data forwarding and collection in a software defined opportunistic network is designed. Wang *et al*. [37] present a points-of-interest trajectory prediction method that uses a semi-markov process to determine the probability distribution of users' arrival times. The authors propose an efficient prediction-based user recruitment for mobile crowd sensing. The users are separated into two groups corresponding to different price plans: pay as you go and pay monthly. Sei *et al*. [38] study the aggregator in crowd sensing systems. A new data-collection scheme is proposed to estimate data distributions. The aggregator can estimate data distributions more accurately than other randomization methods.

2.2 Mobile Social Networks

Xu *et al*. [39] discuss the social relationships in mobile social networks (MSNs). The social relationships are divided into four types: blood relationship, geographical relationship, work relationship, and interest relationship. An analytical model is developed to evaluate the influences of multiple relationships on the information spreading process. Li *et al*. [40] develop a novel framework where each sub-network has its own currency and can earn currency by providing other sub-networks with relay service. Thereby a bargaining game based on cooperative scheme is proposed for relay service in heterogeneous content centric networks. Xu *et al*. [41] present a novel virtual currency to pay for the relay service. Each node has a certain currency and can earn the currency as a relay for other nodes. In addition, a model between the bundle carrier and the relay node is developed to obtain the optimal transaction pricing. Mahmoud *et al*. [42] study the centralized and decentralized network models to securely outsource data. The authors develop searchable encryption scheme and cryptography construct to enable the server to match the topics.

Wang *et al*. [43] study the collaboration agent for each subtask of each complex task. A distributed multiagent-based task allocation model is presented to maximize the objective of social effectiveness. Hao *et al*. [44] aggregate the prestige-based trust value, the social context aware trust value, the spatio-temporal factors related trust values and the risk of trust between mobile users in MSNs to generate an overall trust value between them. Then a new fuzzy inference mechanism is proposed for inferring trust semantically from one mobile user to another. Sharma *et al*. [45] develop a pervasive trust management framework for pervasive social networking. The framework can generate high trust value between the users with a lower cost of monitoring.

Different from the above works, this paper incorporates the trust mechanism into task allocation scheme in CPSS. The trust mechanism can improve the quality of sensing data, while the task allocation scheme with incentives can increase the number of tasks to undertake by crowd sensing.

3 System Model

We focus on the fundamental and simplest case of the CPSS as in Fig. 1. Accordingly, we present the model of the crowd sensing involved in this section, including the user model, network model and incentive model.

3.1 User Model

Mobile users are interacted with each other via short-range wireless communication in the CPSS. There are I mobile users which are denoted by $\mathcal{I} = \{1, 2, \cdots, i, \cdots, I\}$. The inter-meeting time between user i and user j follows the exponential distribution with the parameter $\lambda_{i,j}$. All users in the network can generate sensing tasks based on

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSE.2018.2867080, IEEE Transactions on Network Science and Engineering

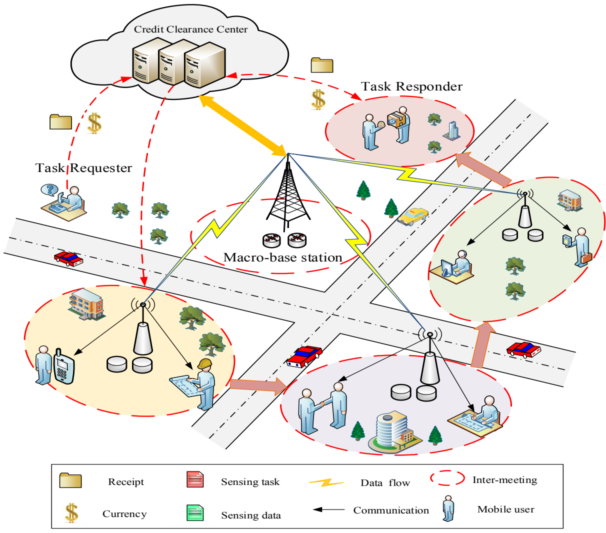


Fig. 1. Cyber-physical social systems.

the Poisson distribution with the parameter γ_i [46]. There are different social relationships between two mobile users. The set of relationships between two users is denoted as $\mathcal{K} = \{1, 2, \cdots, k, \cdots, K\}$. Let $e_k\ (k \in K)$ be the credibility value between two users with a relation k, we have $e_1 > e_2 > \cdots > e_K$ [39]. Let $\mathbf{l}_{i,j} = (l_{i,j,1}, l_{i,j,2}, \cdots, l_{i,j,K})$ denote the relation vector between user i and user j. The social relation k is determined by the types between two mobile users in the CPSS. $l_{i,j,k} = 1$ implies that user i and user j have the relation with k. If $l_{i,j,k} = 0$, it indicates that two users do not have the relation. Then, the direct trust value between user i and user j becomes

$$o_{i,j} = \mathbf{l}_{i,j} \cdot \mathbf{e}^{\mathrm{T}} \tag{1}$$

where

$$\mathbf{e} = (e_1, e_2, \cdots, e_K) \tag{2}$$

3.2 Network Model

Each mobile user can generate sensing tasks in the CPSS. A user needs to seek help from his/her friends when the sensing task cannot be finished by himself/herself. Here, the sensing tasks are classified into two types denoted by N_i and M_i, respectively. The set $\mathrm{N}_i = \{n_{i,1}, n_{i,2}, \cdots, n_{i,\mathrm{N}_i}\}$ indicates that the sensing task can be finished by the user himself/herself. Whereas the sensing task that cannot be finished by himself/herself is denoted by the set $\mathrm{M}_i = \{m_{i,1}, m_{i,2}, \cdots, m_{i,\mathrm{M}_i}\}$. For each sensing task m, it has the time-to-live (TTL) , denoted by T_m. It means that the sensing task is invalided when the time exceeds T_m. Task m has its sensing time $t_{i,m}$ for user i. The sensing time for users to finish the same task m is different from each other, which is related to the characteristics of users and devices. Let $g_{j,m}$ denote the minimum remaining time for user j to finish the sensing task m, then we have

$$g_{j,m} = (T_m - T_0) - t_{j,m} \tag{3}$$

Here, T_0 is the current time. The time for user j to finish the sensing task in set N_j is t_{j,N_j}, which is denoted as

$$t_{j,\mathrm{N}_j} = \sum_{m \in \mathrm{N}_j} t_{j,m} \tag{4}$$

Considering that user i generates sensing task m at time T_0. The probability of adding sensing task m to set N_i becomes

$$p_{m,\mathrm{N}_i} = \begin{cases} 1 & if \;\; g_{i,m} \geq t_{i,\mathrm{N}_i} \\ 0 & otherwise \end{cases} \tag{5}$$

$p_{m,\mathrm{N}_i} = 0$ indicates that sensing task m is added to the set M_i. By considering the inter-meeting time between user i and user j, user i will allocate sensing task m to user j if $g_{j,m} \geq t_{j,\mathrm{N}_j} + \frac{1}{\lambda_{i,j}}$ when user i encounters user j. Here, $g_{j,m} \geq t_{j,\mathrm{N}_j} + \frac{1}{\lambda_{i,j}}$ represents the constraint to add the sensing task m to the set N_i.

3.3 Incentive Model

Since it consumes the energy and resources for mobile users to undertake the sensing tasks, mobile user may have a low will to undertake the sensing task due to the selfishness. Therefore, in this section, we introduce the virtual currency as an incentive for mobile users who finish the sensing task. A third-party management agency, called credit clearance center (CCC), is used to manage the virtual currency of users. All users are registered in the CCC.

Here, user i allocates the sensing task m to user j when they encounter each other. At the same time, a receipt is sent to user j, which contains the information of the price between user i and user j, the number of currency $TF_{m,i,j}$ and the code with respect to the sensing task m. The receipt is transferred to the CCC when user j accesses to the CPSS. User j submits the sensing data to user i after he/she finishes the sensing task m and encounters user i. Similarly, user i submits an acknowledgement (ACK) to the CCC when user i accesses to the CPSS. The virtual currency based on the receipt will be sent to user j from user i's account when CCC confirmed correctly. After finishing the sensing task m, we have the following account balance for user i and user j

$$VC_i = VC_i^{'} - TF_{m,i,j} \tag{6}$$

$$VC_j = VC_j^{'} + TF_{m,i,j} \tag{7}$$

Here, VC_i and VC_j denote the number of current virtual currency of user i and user j, respectively. $VC_i^{'}$ and $VC_j^{'}$ represent the number of virtual currency of user i and user j before the trade, respectively.

4 Task Allocation with Incentive Mechanism

In this section we introduce the task allocation between the requester and mobile user and the incentive mechanism based on the bargaining game.

4.1 Trust Evaluation

The trust evaluation mechanism includes direct trust and indirect trust. The indirect trust is calculated by collecting the recommendation information from other users. In the CPSS, user i and user j have the same neighbor users $j^{'} = \left\{ j^{'}_{1}, j^{'}_{2}, \cdots, j^{'}_{I} \right\}$. Let $\omega_{i,j'}$ denote the number of successful interactions between user i and user $j^{'}$, while $\varpi_{i,j'}$ means the contrary. $W_{i,j'}$ indicates the number of interactions between user i and user $j^{'}$ in the unit time ΔT. By calculating the reliability value of each case, we have

$$P_{i,j'} = \frac{\omega_{i,j'}}{W_{i,j'}} \tag{8}$$

$$P^{'}_{i,j'} = \frac{\varpi_{i,j'}}{W_{i,j'}} \tag{9}$$

Here, $P_{i,j'}$ and $P^{'}_{i.j'}$ indicate that the reliability value of successful interaction and failure interaction between user i and user $j^{'}$, respectively. Similarly, the reliability value of successful interaction between user $j^{'}$ and user j can be calculated as

$$P_{j',j} = \frac{\omega_{j',j}}{W_{j',j}} \tag{10}$$

The reliability value of failure interaction between user $j^{'}$ and user j is shown as

$$P^{'}_{j',j} = \frac{\varpi_{j',j}}{W_{j',j}} \tag{11}$$

Let $\Theta = \{T, \bar{T}\}$ denote the set of possible status of users in CPSS, where $\{T\}$ indicates that one user trusts others. Whereas $\{\bar{T}\}$ means the contrary. The indirect trust vector $IT_{i,j}$ is defined as

$$IT_{i,j} = \left(\pi\left(T\right), \pi\left(\bar{T}\right), \pi\left(T, \bar{T}\right)\right) \tag{12}$$

Here, $\pi\left(T\right)$ and $\pi\left(\bar{T}\right)$ mean that the support degree of trust and distrust, respectively. $\pi\left(T, \bar{T}\right)$ denotes the uncertainty degree due to the lack of information. The values of trust, distrust and uncertainty degree range in $[0, 1]$. Therefore, the indirect trust vector can be determined by

$$\left\{ \begin{array}{l} \pi\left(T\right) = P_{i,j} = P_{i,j'} \times P_{j',j} \\ \pi\left(\bar{T}\right) = P^{'}_{i,j} = P^{'}_{i,j'} \times P^{'}_{j',j} \\ \pi\left(T, \bar{T}\right) = 1 - \pi\left(T\right) - \pi\left(\bar{T}\right) \end{array} \right. \tag{13}$$

According to (12), the indirect trust value between user i and user j is the combination of the reliability functions, which can be calculated as

$$o^{'}_{i,j}\left(T\right) = \frac{\sum\limits_{\ell_1 \cap \cdots \cap \ell_I = T} \pi_1\left(\ell_1\right)\pi_2\left(\ell_2\right)\cdots\pi_I\left(\ell_I\right)}{1 - \sum\limits_{\ell_1 \cap \cdots \cap \ell_I = \emptyset} \pi_1\left(\ell_1\right)\pi_2\left(\ell_2\right)\cdots\pi_I\left(\ell_I\right)} \tag{14}$$

where $\ell_i \in \{T, \bar{T}\}$ denotes the possible status of user.

4.2 Node Reputation

Based on the historical interaction information, the reputation of user i to user j can be obtained from the evaluation value of sensing task. We consider that user i and user j encounter at time t_0. $\mathrm{Q}_{i,j} = \{q_1, q_2, \cdots, q_{Q_{i,j}}\}$ is defined as the set of sensing tasks that user j received from user i. For each task $q_k \in \mathrm{Q}_{i,j}$, it has the following two cases:

Case 1: Task q_k is uncompleted within its TTL, i.e., $t^{back}_{q_k} > T_{q_k}$. Here, $t^{back}_{q_k}$ is the time that user i receives the sensing data of task q_k from user j. In this case, the reputation of user i to user j decreases as below

$$\tau^{'}_{q_k} = -\eta_i(t^{back}_{q_k} - T_{q_k}) \tag{15}$$

where $\tau^{'}_{q_k}$ is the change of reputation value and η_i is the adjustment coefficient of user i.

Case 2: Task q_k is completed within its TTL, i.e., $t^{back}_{q_k} \leq T_{q_k}$. Then, user i gives an evaluation value to the sensing data. We define $\kappa_{q_k} \in [0, 1]$ as the evaluation value of task q_k. The reputation changing value in this case is

$$\tau^{''}_{q_k} = \mu_i\left(\kappa_{q_k} - \kappa\right) \tag{16}$$

where μ_i is the adjustment coefficient of user i and κ is the evaluation threshold of user i. If $\kappa_{q_k} > \kappa$, the evaluation value of sensing data is higher than the threshold value of mobile user i. The reputation of user j will increase if the evaluation value of sensing data is higher than the threshold. Otherwise, the reputation of user j decreases and the reputation changing value is $\tau^{''}_{q_k}$.

Combining case 1 with case 2, the change of reputation value caused by task q_k is

$$\tau_{q_k} = \left\{ \begin{array}{ll} \tau^{'}_{q_k} = -\eta_i(t^{back}_{q_k} - T_{q_k}) & if\ t^{back}_{q_k} > T_{q_k} \\ \tau^{''}_{q_k} = \mu_i(\kappa_{q_k} - \kappa) & otherwise \end{array} \right. \tag{17}$$

Therefore, by considering the direct trust, indirect trust and the reputation value of sensing task, the trust value of user i to user j can be obtained by

$$tr_{i,j} = \alpha \frac{o_{i,j}}{\sum_{k=1}^{K} e_k} + \beta o^{'}_{i,j}\left(T\right) + \varepsilon \frac{1}{Q_{i,j}} \sum_{k=1}^{Q_{i,j}} \tau_{q_k} \tag{18}$$

where $\alpha, \beta, \varepsilon$ are weight parameters and $\alpha + \beta + \varepsilon = 1$.

The candidate of user i, who wants to allocate the sensing task to other users, is to finish the sensing task with high quality within its TTL. Thus, user i always wants to allocate sensing tasks to the user with high trust value. Here, we introduce the trust threshold of user i at time t_0, which is associated to the remaining time of task. We have

$$th_{i,t_0} = \xi_i \frac{1}{|\mathrm{M}_i|} \sum_{m \in \mathrm{M}_i} g_{i,m} \tag{19}$$

where ξ_i is the adjustment coefficient of user i. From (19), we can know that the trust threshold th_{i,t_0} is small when the remaining time $g_{i,m}$ of the task is short. Therefore, user i allocates the sensing task to user j only when the trust value of user j is higher than the threshold (i.e., $tr_{i,j} \geq th_{i,t_0}$).

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSE.2018.2867080, IEEE Transactions on Network Science and Engineering

4.3 Task Allocation

For user i, he/she allocates sensing tasks to user j from the set M_i if user j is credible, which means $tr_{i,j} \geq th_{i,t_0}$. Since user i wants to finish all tasks within TTL, he/she always allocates the tasks which have the short remaining time at first. As user j does not want to decrease his/her reputation value, user j only receives the tasks that he/she can finish within the task's TTL. Therefore, we have the following two rules for the task allocation:

1) User j only receives the task m which can be finished within the task's TTL, i.e., the task m can be added to the set N_j.
2) The task m in set M_i with short remaining time is allocated to other user with a high priority.

As for the task allocation scheme, if mobile user j is credible to task requester i, the task requester i will allocate the task to mobile user j. There are two constraints to be satisfied: 1) The requester i firstly allocates the task within a short remaining time. 2) Mobile user j only receives the task which can be finished within the task's TTL. With the task removing and task adding, we can obtain set $\mathrm{N2}^*$ that the task requester i allocates the task to mobile user j.

Based on the two rules, we propose a minimum remaining time (MRT) algorithm for task allocation in Algorithm 1. The algorithm contains two parts: the task removing and the task adding. In Algorithm 1, N1 is the set that user i needs to allocate tasks to other users, N2 is the set that user i wants to allocate tasks to user j. At the initialization phase, we have $\mathrm{N1} = \mathrm{M}_i, \mathrm{N2} = \emptyset$.

In the task removing process: based on rule 1, user j only receives the task which he/she can finish within the task's TTL. By considering the task in set N_j and set N2, the arranging time that user j needs to finish those tasks is

$$t_j^{arr} = t_{j,\mathrm{N}_j} + t_{j,\mathrm{N2}} \tag{20}$$

t_{j,N_j} and $t_{j,\mathrm{N2}}$ are the time that user j finishes those tasks in the set N_j and set N2, respectively. Then we have

$$t_{j,\mathrm{N2}} = \sum_n t_{j,n}, n \in \mathrm{N2} \tag{21}$$

For task $m \in \mathrm{N1}$, if user j cannot finish the task within its TTL, i.e., task m does not satisfy rule 1. Thus, task m will be removed from the set N1. The process is denoted as

$$\mathrm{N1} = \begin{cases} \lceil \mathrm{N1}, m \rceil & if \;\; g_{j,m} < t_j^{arr} + \frac{1}{\lambda_{i,j}} \\ \mathrm{N1} & otherwise \end{cases} \tag{22}$$

Here, $\lceil \Delta, \times \rceil$ means to remove element $\times$ from set Δ. After removing all the tasks which do not satisfy rule 1 from the set N1, we return to the task adding process.

In the task adding process: if set N1 is non-null based on rule 2, the tasks which have short remaining time will be allocated to user j, i.e., the task is added into the set N2. Since all tasks in the set N1 are sorted by the ascending sequence according to their remaining time, the first element in the set N1 will be allocated to user j. Let $\mathrm{N1}(1)$ represent the first element in set N1, we have

$$\mathrm{N2} = \begin{cases} \lfloor \mathrm{N2}, \mathrm{N1}(1) \rfloor & if \;\; \mathrm{N1} \neq \emptyset \\ \mathrm{N2} & otherwise \end{cases} \tag{23}$$

$$\mathrm{N1} = \begin{cases} \lceil \mathrm{N1}, \mathrm{N1}(1) \rceil & if \;\; \mathrm{N1} \neq \emptyset \\ \mathrm{N1} & otherwise \end{cases} \tag{24}$$

Here, $\lfloor \Delta, \times \rfloor$ means to add element $\times$ to set Δ. The processes of task removing and task adding are repeated until set N1 is null. Therefore, we can obtain the task set $\mathrm{N2}^* = \mathrm{N2}$ that user i allocates to user j.

Algorithm 1 : MRT Algorithm (user i to user j)

```
Input: N_j, M_i = {m_{i,1}, m_{i,2}, ..., m_{i,M_i} : g_{i,m_{i,1}} ≤ g_{i,m_{i,2}} ≤ ... ≤ g_{i,m_{i,M_i}}}
Initialization: N1 = M_i, N2 = ∅
Repeat the iteration
while N1 ≠ ∅ do
  compute t_j^arr by Eq. (20)
  for each task m in N1 do
    if g_{j,m} < t_j^arr + λ_{i,j} then
      update N1 by Eq. (22)
    else
      break the loop
    end if
  end for
  if N1 ≠ ∅ then
    add N1 (1) to N2 by Eq. (23)
    remove N1 (1) from N1 by Eq. (24)
  end if
  Output: N2* = N2
end while
```

4.4 Bargaining Game

When user i encounters user j who is credible to user i, user i may allocate sensing task from set $\mathrm{N2}^*$ to user j. Here, the transaction process is modeled as a bargaining game, where user i is the buyer who wants to buy the sensing service and user j is the seller who sells his/her sensing service.

There are two players defined as $\{B, S\}$ in the bargaining game. They represent the buyer and the seller, respectively. Here, user i is the buyer and the reserve price (i.e., the highest price) that he/she can pay for the transaction is

$$\begin{gathered} r_B = r_{i,\mathrm{N2}^*} = \min\{VC_i, V_i\} \\ V_i = \rho_i \times |\mathrm{M}_i| \times \sum_{m=1}^{|\mathrm{N2}^*|} t_{j,\mathrm{N2}^*(m)} \times \upsilon_i \left(\frac{1}{|\mathrm{N2}^*|} \sum_{m=1}^{|\mathrm{N2}^*|} g_{i,m} \right)^{-1} \end{gathered} \tag{25}$$

where ρ_i is the reserve coefficient of buyer i and υ_i is the coefficient of remaining time, respectively. Eq. (25) indicates that the reserve price of buyer i will be high if the sensing time of task in set $\mathrm{N2}^*$ is long. Moreover, if the average remaining time of task in set $\mathrm{N2}^*$ is short, the task in set $\mathrm{N2}^*$ is urgent to finish and the reserve price of user i for the task is high.

Similarly, user j acts as the seller in the game and the reserve price is

$$r_S = r_{j,\mathrm{N2}^*} = \rho_j \times tr_{i,j} \times \sum_{m=1}^{|\mathrm{N2}^*|} t_{j,\mathrm{N2}^*(m)} \tag{26}$$

Here, ρ_j is the reserve coefficient of seller j. Eq. (26) represents that the reserve price of user j is high if the sensing time of the task in set $\mathrm{N2}^*$ is long or the trust value of user j is high. Furthermore, if user j has less virtual currency, he/she may be more urgent to earn virtual currency and give a low reserve price to make sure that the transaction is successful.

Based on the reserve price of buyer i and seller j, there are three cases which are $r_{j,\mathrm{N2}^*} > r_{i,\mathrm{N2}^*}$, $r_{j,\mathrm{N2}^*} = r_{i,\mathrm{N2}^*}$ and $r_{j,\mathrm{N2}^*} < r_{i,\mathrm{N2}^*}$, respectively. In the case $r_{j,\mathrm{N2}^*} > r_{i,\mathrm{N2}^*}$, the reserve price of buyer i is lower than the reserve price of seller j. The transaction will be canceled. In the case $r_{j,\mathrm{N2}^*} = r_{i,\mathrm{N2}^*}$, the transaction will be ended and the price of the transaction is $r_{i,\mathrm{N2}^*}$. In the case $r_{j,\mathrm{N2}^*} < r_{i,\mathrm{N2}^*}$, the optimal price of the transaction is obtained by the bargaining game. In the bargaining game, two players make the bargaining to divide a "cake", which is denoted as

$$C = r_B - r_S \tag{27}$$

Then the utilities of seller S and buyer B can be expressed by

$$u_B(x_B) = x_B C \tag{28}$$

$$u_S(x_S) = x_S C \tag{29}$$

Here, $u_B(\cdot)$ and $u_S(\cdot)$ are the utility functions of buyer and seller, respectively. x_B and x_S are the proportion of the "cake" which is divided by the buyer and seller, respectively. We have

$$x = \{(x_S, x_B) : x_S + x_B = 1, x_S \geq 0, x_B \geq 0\} \tag{30}$$

In the bargaining game, two players give their dividing offer in turn. We consider that the seller gives the offer first, i.e., the seller S gives the offer $x_1 = (x_S^1, x_B^1)$ in round 1. The buyer B decides whether to accept the offer or not. If the buyer B accepts offer x_1, the bargaining game between buyer B and seller S is over. The "cake" C is divided by the offer x_1. Otherwise, the bargaining game comes to round 2. In round 2, the buyer B gives his/her offer $x_2 = (x_S^2, x_B^2)$. If the seller S accepts the offer x_2, the bargaining game is over and they divide the "cake" C by the offer x_2. Otherwise, the bargaining game comes to the next round and the seller S starts to give the offer. The bargaining game is continued until one player accepts the dividing offer which is proposed by another player.

Since the bargaining process brings some costs, i.e., time, between buyer and seller, there are discounts for the utility between buyer B and seller S. Here, we define δ_B and δ_S ($\delta_B, \delta_S \in [0,1]$) as the discount factor for buyer B and seller S, respectively. For buyer B, he/she is more concerned with the remaining time of task. In other words, he/she wants the task to be finished as soon as possible. Thus, the discount factor satisfies

$$\frac{d\delta_B\left(\frac{1}{|\mathrm{N2}^*|}\sum_{m=1}^{|\mathrm{N2}^*|} g_{i,m}\right)}{d\left(\frac{1}{|\mathrm{N2}^*|}\sum_{m=1}^{|\mathrm{N2}^*|} g_{i,m}\right)} > 0, \delta_B(0) = 0,\ \delta_B(\infty) = 1 \tag{31}$$

Here, we set the discount factor of the buyer B as

$$\delta_B = \frac{e^{v\theta} - e^{-v\theta}}{e^{v\theta} + e^{-v\theta}} \tag{32}$$

where v is the patience coefficient of the buyer.

$$\theta = \frac{1}{|\mathrm{N2}^*|}\sum_{m=1}^{|\mathrm{N2}^*|} g_{i,m} \tag{33}$$

The discount factor of seller S is related to the number of tasks in set N_j. If there are many tasks in N_j, seller S may have less patience on bargaining process with the result that the discount factor is low. For the discount factor δ_S, we have

$$\frac{d\delta_S(e^{\gamma_j}|\mathrm{N}_j|)}{d(e^{\gamma_j}|\mathrm{N}_j|)} < 0, \quad \delta_S(0) = 1,\ \delta_S(\infty) = 0 \tag{34}$$

Similarly, δ_S is set as

$$\delta_S = 1 - \frac{e^{\mu\theta'} - e^{-\mu\theta'}}{e^{\mu\theta'} + e^{-\mu\theta'}} \tag{35}$$

where μ is the patience coefficient of the seller.

$$\theta' = e^{\gamma_j}|\mathrm{N}_j| \tag{36}$$

Thus, at round k, the utilities of seller S and buyer B can be calculated separately as

$$u_S^k(x_S^k) = \delta_S^{k-1} x_S^k C \tag{37}$$

$$u_B^k(x_B^k) = \delta_B^{k-1} x_B^k C \tag{38}$$

Here, $u_S^k(\cdot)$ and $u_B^k(\cdot)$ are the utility functions of seller S and buyer B at round k, respectively. With the discount factors, both buyer B and seller S want to reach an agreement as quickly as possible. Therefore, we have the following theorem.

Theorem 1: There exists a unique subgame perfect Nash equilibrium for the proposed bargaining game, where the bargaining game can be ended in round 1 with the following agreement

$$x_S^* = \frac{1 - \delta_B}{1 - \delta_B\delta_S} \tag{39}$$

$$x_B^* = \frac{\delta_B - \delta_B\delta_S}{1 - \delta_B\delta_S} \tag{40}$$

Proof: For seller S, he/she gives the offer at each odd round. Since the offer given by the seller S at each round is equivalent to the first round, the infinitely repeated game can be seen as a bargaining game with three rounds [41]. Here, x_S^* is denoted as the best offer for the seller S in round

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSE.2018.2867080, IEEE Transactions on Network Science and Engineering

3. With a backward induction method, the proportion that seller S requests in round 3 satisfies

$$x_S^3 = x_S^* \tag{41}$$

$$x_B^3 = 1 - x_S^* \tag{42}$$

Thus, at round 3, the utility of seller S and buyer B can be obtained separately by

$$u_S^3 = \delta_S^2 x_S^* C \tag{43}$$

$$u_B^3 = \delta_B^2 (1 - x_S^*) C \tag{44}$$

Back to round 2, the buyer B gives his/her offer. Here, as we have $x_S^2 = x_B, x_B^2 = 1 - x_B$, the utilities of seller S and buyer B at the current round become

$$u_S^2 = \delta_S x_B C \tag{45}$$

$$u_B^2 = \delta_B (1 - x_B) C \tag{46}$$

If $x_B \geq \delta_S x_S^*$ holds when $u_S^2 \geq u_S^3$, seller S will accept the offer at the current round. Otherwise, the bargaining game comes to round 3. Thus, the utility of buyer B is

$$u_B = \begin{cases} u_B^2 = \delta_B (1 - x_B) C & if\ x_B \geq \delta_S x_S^* \\ u_B^3 = \delta_B^2 (1 - x_S^*) C & otherwise \end{cases} \tag{47}$$

Here, $\delta_B \in [0, 1]$ and the best offer of buyer B is $x_B = \delta_S x_S^*$ at round 2.

Back to round 1, the seller S gives his/her offer. From the above analysis, we know that seller S insists that x_S^* is the best offer in this round. The utilities of both sides become

$$u_S^1 = x_S^* C \tag{48}$$

$$u_B^1 = (1 - x_S^*) C \tag{49}$$

Similarly, only if $u_B^1 \geq u_B^2$, i.e., $1 - x_S^* \geq \delta_B (1 - x_B)$, the buyer B will accept the offer at the current round. It is obviously that the task allocation strategy $1 - x_S^* = \delta_B (1 - x_B)$ is the best offer for seller S. The best offer can be obtained by

$$x_S^* = 1 - \delta_B (1 - x_B) = 1 - \delta_B (1 - \delta_S x_S^*) \tag{50}$$

$$x_S^* = \frac{1 - \delta_B}{1 - \delta_B \delta_S} \tag{51}$$

Therefore, the optimal price of the transaction in the case $r_{j,\mathrm{N2}^*} < r_{i,\mathrm{N2}^*}$ is

$$r^* = r_{j,\mathrm{N2}^*} + \frac{1 - \delta_B}{1 - \delta_B \delta_S} C \tag{52}$$

This completes our proof.

5 Performance Evaluation

5.1 Simulation Setup

In the simulation, there are 100 mobile users in the CPSS. We consider that there are only 5% mobile users to generate sensing tasks over time in the CPSS [47]. The rate of task-generating γ_i follows the uniform distribution in $[0, 1]$ [47]. The average frequency that two users encounter each other is 0.2 times per hour [46]. Similarly, the average completion time t_m of each task is $[10, 20, \cdots, 50]$(hours) [47]. The sensing time of task m for users is $[0.9t_m, 1.1t_m]$. The TTL of task m is $2t_m$. The adjustment coefficients η_i and μ_i of mobile user i are 0.1, 0.8, respectively. The adjustment coefficient ξ_i of the reputation threshold is 0.005.

In addition, there are five kinds of social relationships between two mobile users. The credibility value between two users is set to be $e_1 = 1$, $e_2 = 0.8$, $e_3 = 0.6$, $e_4 = 0.4$, $e_5 = 0.2$, respectively. Moreover, based on the different social ties between two mobile users, the evaluation value of the requester for the quality of sensing data follows the uniform distribution in $[0.7, 1.0]$, $[0.6, 1.0]$, $[0.5, 1.0]$, $[0.4, 1.0]$, $[0, 1.0]$, respectively. The simulation results are obtained by repeating the experiment until 100 times.

5.2 Performance Evaluation

Since the evaluation threshold κ has an effect on the trust value of users, the simulations are carried out by comparing the performance of the proposed algorithm on the value of κ. Fig. 2 shows the number of finished tasks within TTL under different value of κ. From Fig. 2, we can observe that the number of finished tasks within TTL increases over time. In addition, the large value of κ implies that the number of finished tasks is few. The reason is that the update of user's reputation value is controlled by the value of κ. The requester does not select a user whose reputation value is less than the evaluation threshold to finish the task. When the number of mobile users employed by the requester decreases in the CPSS, the number of finished tasks within TTL is also reduced.

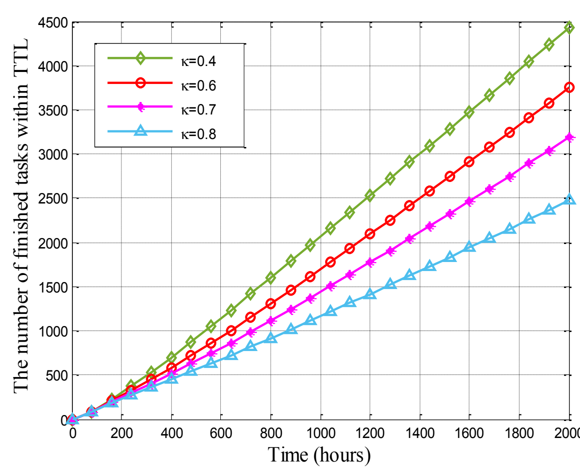


Fig. 2. The number of finished tasks with different value of κ.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TNSE.2018.2867080, IEEE Transactions on Network Science and Engineering

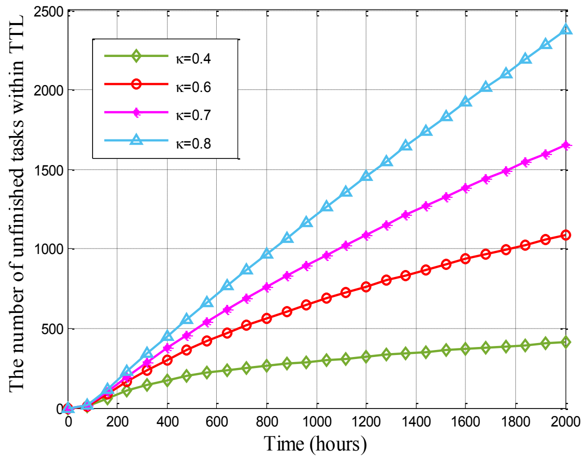


Fig. 3. The number of unfinished tasks with different value of κ.

Fig. 3 depicts the number of unfinished tasks within TTL under different value of κ. It can be seen from the figure that the number of unfinished tasks within TTL increases over time. Moreover, the large value of κ implies that the number of unfinished tasks is large. The reason is that the requester does not select a user whose reputation value is less than the evaluation threshold to finish the task. If the number of users to finish the task is reduced, the number of unfinished tasks within TTL increases.

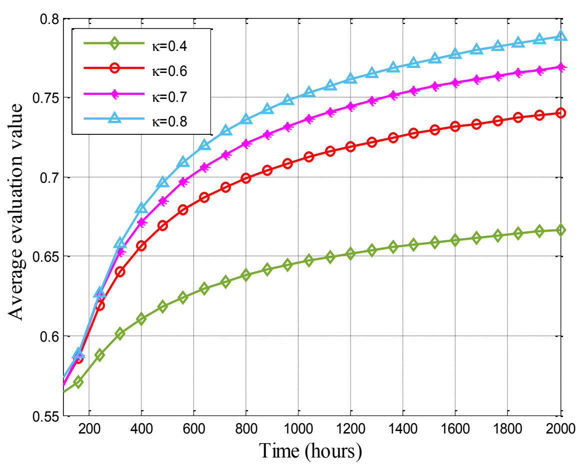


Fig. 4. The average evaluation value with different value of κ.

Fig. 4 illustrates the average evaluation value with different value of κ. Note that the average evaluation value changes slowly and gradually when it reaches the stable κ. Moreover, the large value of κ means that the average evaluation value is large. This is because the reputation value is controlled by the value of κ. If the user's reputation value is high, the task will be finished with high quality and the average evaluation value becomes large.

From the above analysis, we obtain that different values of κ have different effects on the mobile CPSS. Specifically, the high value of κ can improve the evaluation value of the sensing data, but increase the number of unfinished tasks.

In Fig. 5, we compare the performance of the algorithm with different value of ξ_i. From Fig. 5, we can obtain that the number of finished tasks within TTL increases over time. In addition, the large value of ξ_i indicates that the number of finished tasks is small. The reason is that the trust threshold value is controlled by the value of ξ_i. The requester does not select a user whose reputation value is less than the trust threshold. If the value of ξ_i is high, the number of users to finished task is reduced. Therefore, the number of finished tasks within TTL reduces.

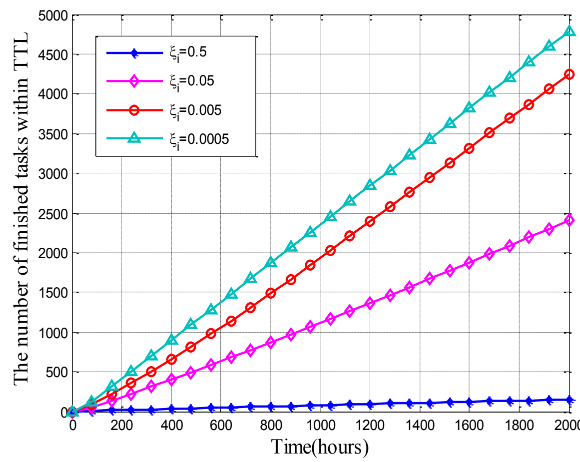


Fig. 5. The number of finished tasks with different value of ξ_i.

In Fig. 6, we compare the performance of the algorithm on different value of TTL. From Fig. 6, we can observe that the number of finished tasks within TTL increases over time. Note that the large value of TTL indicates that the number of finished tasks is high. This is because the task's TTL is used to measure the valid time of the task. If the task's TTL is longer, the number of finished tasks is higher.

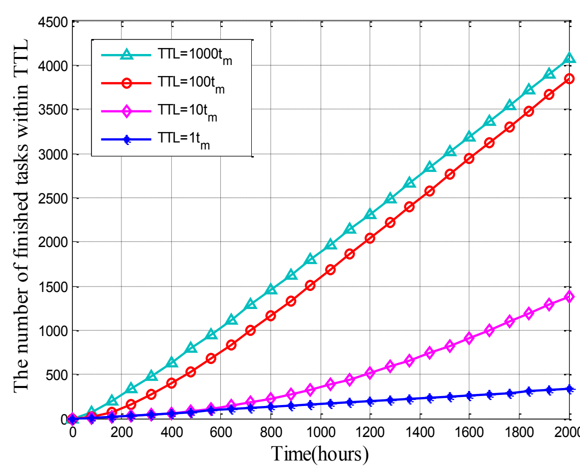


Fig. 6. The number of finished tasks with different value of TTL.

In Fig. 7 – Fig. 9, we investigate the performance of the algorithm when the value of κ is 0.5. The proportion of selfish user in the CPSS is set to be 50%. We compare the proposed algorithm with two other algorithms: the random selection with MRT (RSWM) algorithm and the random selection without MRT (RSWOM) algorithm. In RSWM scheme, the requester randomly selects a user to finish the task and the task is allocated by MRT algorithm. In RSWOM scheme, the requester randomly selects a user to finish the task and the task is not allocated by MRT algorithm.

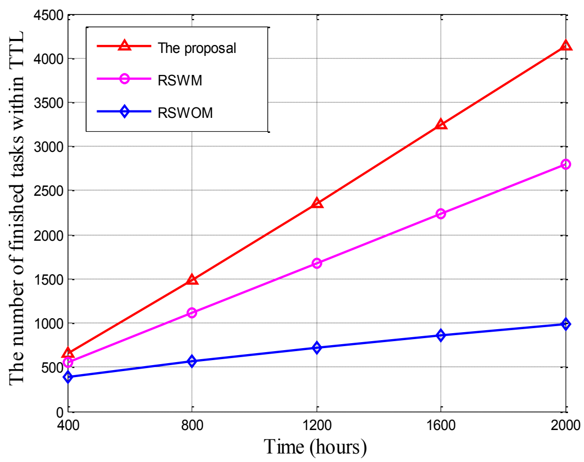


Fig. 7. The number of finished tasks in three algorithms.

Fig. 7 shows the number of finished tasks within TTL in three algorithms. From Fig. 7, we can obtain that our proposal outperforms the other two conventional algorithms in terms of the number of tasks. It is because the bargaining game facilitates the transaction between two mobile users with the incentives. Mobile users become more active to provide sensing tasks to obtain more virtual currency where the efficiency of sensing can be improved. Similarly, it can be seen that the number of finished tasks by RSWM algorithm is more than that by RSWOM algorithm. The reason is that the task allocation based on MRT algorithm can improve the number of finished tasks.

Fig. 8 indicates the number of unfinished tasks within TTL in three algorithms. From the figure, we can see that the number of unfinished tasks in the proposed algorithm is much lower than other algorithms. The reason is that the proposed algorithm can improve the number of finished tasks. Therefore, the number of unfinished tasks is reduced within TTL. Similarly, it can be seen that the number of unfinished tasks by RSWM algorithm is much lower than that by RSWOM algorithm. The reason is that the task can be effectively allocated to users according to the MRT algorithm, with the result to decrease the number of unfinished tasks.

Fig. 9 indicates the average evaluation value of sensing data changes over time in three algorithms. In Fig. 9, we observe that the evaluation value of sensing data can be significantly improved by setting the reputation threshold of the requester. This is because the requester only selects the user whose reputation value is higher than the reputation

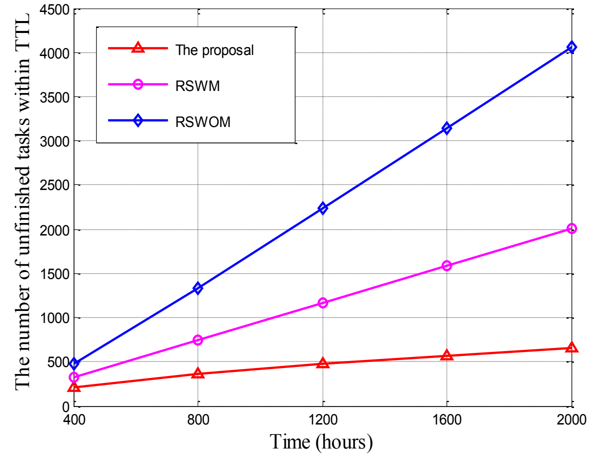


Fig. 8. The number of unfinished tasks in three algorithms.

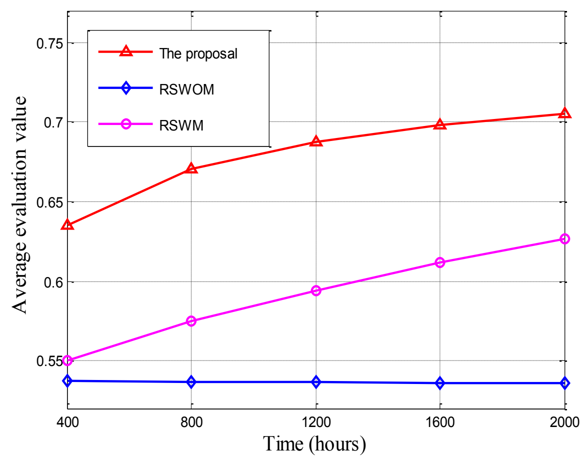


Fig. 9. The average evaluation value of sensing data changes over time in three algorithms.

threshold to finish the task. Therefore, the quality of sensing task is high and the evaluation value of the sensing task is also large.

From the above simulation analysis, we can conclude that the proposed algorithm outperforms other two schemes in terms of both the number of finished tasks and the quality of tasks. Our proposal can effectively improve the number of finished tasks. In addition, the performance of the proposed algorithm is more effective when the number of users in the CPSS is larger.

6 CONCLUSION

In this paper, we have proposed a novel task allocation scheme for crowd sensing in CPSS by using a game theoretical approach. Firstly, a trust mechanism has been proposed to evaluate the reputation of mobile users, based on the historical interaction among mobile users. Secondly, the virtual currency management has been introduced to stimulate mobile users to participate in crowd sensing to undertake the tasks with incentives. Thirdly, the interaction between the task requester and mobile users has been modeled by the bargaining game. The optimal price to provide sensing service can be obtained by a subgame perfect Nash equilibrium. In addition, simulation results have shown that our scheme outperforms other conventional schemes in terms of the number of tasks and the quality of tasks.

As for the future work, a secure task relay between the task requesters and mobile users will be studied to protect the privacy of mobile users.

Acknowledgement

This work is supported in part by NSFC (no. 91746114, 61571286, 61633016, 61533010), Shanghai Key Laboratory of Power Station Automation Technology, National Science Foundation (NSF) through grant CNS-1644348.

References

[1] Y. Guo, X. Hu, B. Hu, J. Cheng, M. Zhou, and R. Y. K. Kwok, "Mobile cyber physical systems: current challenges and future networking applications," *IEEE Access*, vol. 6, pp. 12360-12368, Dec. 2017.

[2] K. Navaie, and H. Aghvami, "Dependable information exchange for next generation mobile cyber-physical systems," *IEEE Wireless Communications*, vol. 24, no. 5, pp. 150-156, Oct. 2017.

[3] X. Sheng, J. Tang, X. Xiao, and G. Xue, "Sensing as a service: challenges, solutions and future directions," *IEEE Sensors Journal*, vol. 13, no. 10, pp. 3733-3741, May. 2013.

[4] Y. Hui, Z. Su, and S. Guo, "Utility based data computing scheme to provide sensing service in Internet of Things," *IEEE Transactions on Emerging Topics in Computing*, DOI: 10.1109/TETC.2017.2674023, 2017.

[5] X. Liu, Y. Liu, A. Liu, and L. Yang, "Defending on-off attacks using light probing messages in smart sensors for industrial communication systems," *IEEE Transactions on Industrial Informatics*, DOI: 10.1109/TII.2018.2836150, 2018.

[6] Q. Xu, Z. Su, Q. Zheng, and B. Dong, "Secure content delivery with edge nodes to save caching resources for mobile users in green cities," *IEEE Transactions on Industry Informatics*, DOI: 10.1109/TII.2017.2787201, 2017.

[7] Z. Li, Y. Liu, A. Liu, S. Wang, and H. Liu, "Minimizing convergecast time and energy consumption in green Internet of Things," *IEEE Transactions on Emerging Topics in Computing*, DOI: 10.1109/TETC.2018.2844282, 2018.

[8] Z. Su, Y. Hui, Q. Xu, T. Yang, J. Liu, and J. Jia, "An edge caching scheme to distribute content in vehicular networks," *IEEE Transactions on Vehicular Technology*, DOI:10.1109/TVT.2018.2824345, 2018.

[9] A. Kamilaris, and A. Pitsillides, "Mobile phone computing and the Internet of Things: A survey," *IEEE Internet of Things Journal*, vol. 3, no. 6, pp. 885-898, Dec. 2016.

[10] Y. Jiang, and F. Leung, "Mobile phone identification from speech recordings using weighted support vector machine," *2016 42nd Annual Conference of the IEEE Industrial Electronics Society*, pp. 963-968, 2016.

[11] E. Maby, R. Le Bouquin Jeannes, and G. Faucon, "Short-term effects of GSM mobiles phones on spectral components of the human electroencephalogram," *2006 International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 3751-3754, 2006.

[12] C. Han, L. Jia, and D. Peng, "Model predictive control of batch processes based on two-dimensional integration frame," *Nonlinear Analysis: Hybrid Systems*, vol. 28, pp. 75-86, 2018.

[13] D. Wang, T. Abdelzaher, and L. Kaplan, "Surrogate mobile sensing," *IEEE Communications Magazine*, vol. 52, no. 8, pp. 36-41, 2014.

[14] A. Triantafyllidis, C. Velardo, D. Salvi, S. Shah, V. Koutkias, and L. Tarassenko, "A survey of mobile phone sensing, self-reporting, and social sharing for pervasive healthcare," *IEEE Journal of Biomedical and Health Informatics*, vol. 21, no. 1, pp. 218-227, Jan. 2017.

[15] M. Louta, K. Mpanti, G. Karetsos, and T. Lagkas, "Mobile crowd sensing architectural frameworks: A comprehensive survey," *2016 7th International Conference on Information, Intelligence, Systems Applications (IISA)*, pp. 1-7, 2016.

[16] Z. Su, Q. Xu, J. Luo, H. Pu, Y. Peng, and R. Lu, "A secure content caching scheme for disaster backup in fog computing enabled mobile social networks," *IEEE Transactions on Industrial Informatics*, pp. 1-1, DOI: 10.1109/TII.2018.2849984, 2018.

[17] X. Sheng, J. Tang, J. Wang, C. Gao, and G. Xue, "SOR: an objective ranking system based on mobile phone sensing," *IEEE 34th International Conference on Distributed Computing Systems*, pp. 114-123, 2014.

[18] X. Duan, C. Zhao, S. He, P. Cheng, and J. Zhang, "Distributed algorithms to compute walrasian equilibrium in mobile crowdsensing," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 5, pp. 4048-4057, DOI: 10.1109/TIE.2016.2645138, 2017.

[19] Z. Su, and Q. Xu, "Security-aware resource allocation for mobile social big data: a matching-coalitional game solution," *IEEE Transactions on Big Data*, DOI: 10.1109/TBDATA.2017.2700318, 2017.

[20] B. Guo, Y. Liu, W. Wu, Z. Yu, and Q. Han, "ActiveCrowd: a framework for optimized multitask allocation in mobile crowdsensing systems," *IEEE Transactions on Human-Machine Systems*, vol. 47, no. 3, pp. 392-403, Jun. 2017.

[21] B. Guo, H. Chen, Q. Han, Z. Yu, D. Zhang, and Y. Wang, "Worker-contributed data utility measurement for visual crowdsensing systems," *IEEE Transactions on Mobile Computing*, vol. 16, no. 8, pp. 2379-2391, Aug. 2017.

[22] Z. Zhang, S. He, J. Chen, and J. Zhang, "REAP: an efficient incentive mechanism for reconciling aggregation accuracy and individual privacy in crowdsensing," *IEEE Transactions on Information Forensics and Security*, DOI: 10.1109/TIFS.2018.2834232, 2018.

[23] Q. Xu, Z. Su, S. Yu, and Y. Wang, "Trust based incentive scheme to allocate big data tasks with mobile social cloud," *IEEE Transactions on Big Data*, DOI: 10.1109/TBDATA.2017.2764925, 2017.

[24] Z. Su, Q. Xu, Q. Yang, and F. Hou, "Edge caching for layered video contents in mobile social networks," *IEEE Transactions on Multimedia*, vol. 19, no. 10, pp. 2210-2221, 2017.

[25] Z. Zheng, F. Wu, X. Gao, H. Zhu, S. Tang, and G. Chen, "A budget feasible incentive mechanism for weighted coverage maximization in mobile crowdsensing," *IEEE Transactions on Mobile Computing*, vol. 16, no. 9, pp. 2392-2407, Sep. 2017.

[26] X. Gong, X. Chen, J. Zhang, and H. Poor, "Exploiting social trust assisted reciprocity (STAR) toward utility-optimal socially-aware crowdsensing," *IEEE Transactions on Signal and Information Processing over Networks*, vol. 1, no. 3, pp. 195-208, Sep. 2015.

[27] J. Xu, J. Xiang, and D.Yang, "Incentive mechanisms for time window dependent tasks in mobile crowdsensing," *IEEE Transactions on Wireless Communications*, vol. 14, no. 11, pp. 6353-6364, Nov. 2015.

[28] X. Zhang, Z. Yang, W. Sun, Y. Liu, S. Tang, K. Xing, and X. Mao, "Incentives for mobile crowd sensing: a survey," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 1, pp. 54-67, 2016.

[29] K. Ota, M. Dong, J. Gui, and A. Liu, "QUOIN: incentive mechanisms for crowd sensing networks," *IEEE Network*, vol. 32, no. 2, pp. 114-119, 2018.

[30] D. Zhao, X. Li, and H. Ma, "Budget-feasible online incentive mechanisms for crowdsourcing tasks truthfully," *IEEE/ACM Transactions on Networking*, vol. 24, no. 2, pp. 647-661, 2016.

[31] X. Zhu, J. An, M. Yang, L. Xiang, Q. Yang, and X. Gui, "A fair incentive mechanism for crowdsourcing in crowd sensing," *IEEE Internet of Things Journal*, vol. 3, no. 6, pp. 1364-1372, 2016.

[32] P. P. Jayaraman, J. B. Gomes, H. Nguyen, Z. S. Abdallah, S. Krishnaswamy, and A. Zaslavsky, "Scalable energy-efficient distributed data analytics for crowdsensing applications in mobile environments," *IEEE Transactions on Computational Social Systems*, vol. 2, no. 3, pp. 109-123, 2015.

[33] D. Yang, G. Xue, X. Fang, and J. Tang, "Incentive mechanisms for crowdsensing: crowdsourcing with smartphones," *IEEE/ACM Transactions on Networking*, vol. 24, pp. 1732-1744, May. 2015.

[34] S. He, D. Shin, J. Zhang, J. Chen, and P. Lin, "An exchange market approach to mobile crowdsensing: pricing, task allocation, and walrasian equilibrium," *IEEE Journal on Selected Areas in Communications*, vol. 35, pp. 921-934, Apr. 2017.

[35] B. Song, H. Mansouri, and V. Wong, "Quality of sensing aware budget feasible mechanism for mobile crowdsensing," *IEEE Transactions on Wireless Communications*, vol. 16, pp. 3619-3631, Jun. 2017.

[36] H. Li, K. Ota, M. Dong, and M. Guo, "Mobile crowdsensing in software defined opportunistic networks," *IEEE Communications Magazine*, vol. 55, pp. 140-145, 2017.

[37] E. Wang, Y. Yang, J, Wu, W. Liu, and X. Wang, "An efficient prediction-based user recruitment for mobile crowdsensing," *IEEE Transactions on Mobile Computing*, pp. 1-1, 2017.

[38] Y. Sei, and A. Ohsuga, "Differential private data collection and analysis based on randomized multiple dummies for untrusted mobile crowdsensing," *IEEE Transactions on Information Forensics and Security*, vol. 12, pp. 926-939, Apr. 2017.

[39] Q. Xu, and Z. Su, "Epidemic information spreading over mobile social networks with multiple social relationships," *2015 IEEE Global Communications Conference*, pp. 1-5, Dec. 2015.

[40] C. Li, Q. Xu, Z. Su, and Q. Qi, "A game theoretic scheme for relay service in heterogeneous content centric networks," *IEEE International Conference on Communications*, Jul. 2016.

[41] Q. Xu, Z. Su, and S. Guo, "A game theoretical incentive scheme for relay selection services in mobile social networks," *IEEE Transactions on Vehicular Technology*, vol. 65, pp. 6692-6702, Aug. 2016.

[42] M. Mahmoud, K. Rabieh, A. Sherif, E. Oriero, M. Ismail, K. Qaraqe, and E. Serpedin, "Privacy-preserving fine-grained data retrieval schemes for mobile social networks," *IEEE Transactions on Dependable and Secure Computing*, pp. 1-1, 2017.

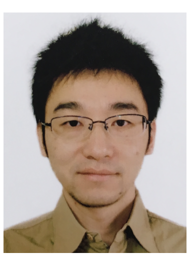
[43] W. Wang, and Y. Jiang, "Multiagent-based allocation of complex tasks in social networks," *IEEE Transactions on Emerging Topics in Computing*, vol. 3, pp. 571-584, Dec. 2015.

[44] F. Hao, G. Min, M. Lin, C. Luo, and L. Yang, "MobiFuzzyTrust: An efficient fuzzy trust inference mechanism in mobile social networks," *IEEE Transactions on Parallel and Distributed Systems*, vol. 25, pp. 2944-2955, Nov. 2014.

[45] V. Sharma, I. You, R. Kumar, and P. Kim, "Computational offloading for efficient trust management in pervasive online social networks using osmotic computing," *IEEE Access*, vol. 5, pp. 5084-5103, 2017.

[46] Q. Xu, Z. Su, and K. Zhang, "Epidemic information dissemination in mobile social networks with opportunistic links," *IEEE Transactions on Emerging Topics in Computing*, vol. 3, no. 3, pp. 399-409, Sep. 2015.

[47] M. Xiao, J. Wu, L. Huang, Y. Wang, and C. Liu, "Multi-task assignment for crowdsensing in mobile social networks," *2015 IEEE Conference on Computer Communications (INFOCOM)*, pp. 2227-2235, 2015.



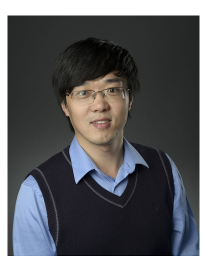
Zhou Su received the Ph.D. degree from Waseda University, Tokyo, Japan, in 2003. He is an Associate Editor of IET Communications, and Associate Editor of IEICE Transactions on Communications. He is the Chair of the Multimedia Services and Applications over Emerging Networks Interest Group (MENIG) of the IEEE Comsoc Society, the Multimedia Communications Technical Committee. He also served as the Co-Chair of several international conferences including IEEE VTC Spring 2016, IEEE CCNC2011, etc. He is a TPC Member of some flagship conferences including IEEE INFOCOM, IEEE ICC, IEEE GLOBECOM, etc. His research interests include multimedia communication, wireless communication and network traffic. He received the best paper award of International Conference CHINACOM2008, and Funai Information Technology Award for Young Researchers in 2009.

Minghui Dai is working on his master degree with the school of Mechatronic Engineering and Automation of Shanghai University, Shanghai, P. R. China. His research interests are in the general area of wireless network architecture and vehicular networks.

Qifan Qi is working on his master degree with the school of Mechatronic Engineering and Automation of Shanghai University, Shanghai, P. R. China. His research interests are in the general area of wireless network architecture and vehicular networks.

Yuntao Wang is working on his master degree with the school of Mechatronic Engineering and Automation of Shanghai University, Shanghai, P. R. China. His research interests are in the general area of smart grid and vehicular networks.

Qichao Xu is working on his Ph.D. degree with the school of Mechatronic Engineering and Automation of Shanghai University, Shanghai, P. R. China. His research interests are in the general area of wireless network architecture and vehicular networks.



Qing Yang is an assistant professor in the Department of Computer Science and Engineering at University of North Texas. He received B.S. and M.S. degrees in Computer Science from Nankai University and Harbin Institute of Technology, China, in 2003 and 2005, respectively. He received his Ph.D. degree in Computer Science from Auburn University in 2011. He worked as an assistant professor in the Gianforte School of Computing at Montana State University from 2011. His research interests include trust model, Internet of Things, network security and privacy.