RTRC: A Reputation-Based Incentive Game Model for Trustworthy Crowdsourcing Service

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Abstract: The ubiquity of mobile devices have promoted the prosperity of mobile crowd systems, which recruit crowds to contribute their resources for performing tasks. Yet, due to the various resource consumption, the crowds may be reluctant to join and contribute information. Thus, the low participation level of crowds will be a hurdle that prevents the adoption of crowdsourcing. A critical challenge for these systems is how to design a proper mechanism such that the crowds spontaneously act as suppliers to contribute accurate information. Most of existing mechanisms ignore either the honesty of crowds or requesters respectively. In this paper, considering the honesty of both, we propose a game-based incentive mechanism, namely RTRC, to stimulate the crowds to contribute accurate information and to motivate the requesters to return accurate feedbacks. In addition, an evolutionary game is designed to model the dynamic of user-strategy selection. Specially, the replicator dynamic is applied to model the adaptation of strategy interactions taking into account the dynamic nature in time dependence and we also derive the evolutionarily stable strategies (ESSs) for users. Finally, empirical results over the simulations show that all the requesters and suppliers will select honest strategy to maximize their profit.

Keywords: crowdsourcing system; evolutionary game theory; evolutionarily stable strategy; incentive mechanism

I. INTRODUCTION

The widespread use of mobile devices has made crowdsourcing a promising computing paradigm [1]. Generally, the crowdsourcing can be thought as a system where small tasks, generated by requesters, are performed in exchange for rewards awarded to the crowds who perform them, such as Answers [2] and Zee[3]. As a multi-modal sensor, the smartphone can be carried by human users locating in different places to collect and share ubiquitous data with a large number of potential crowds, such as the location-aware crowdsourcing which is usually to collect the information from the crowds currently available at the location under consideration to enrich the information for requesters [4][5][6].

In the crowdsourcing system, we classify the users which participate in the crowdsourcing into two different types: *requesters* and *suppliers*. The users who generate and post tasks are called *requesters*, and those who perform the posted tasks and return results are called *suppliers*. In addition, requesters and suppliers register with a centralized crowdsourcing server which acts as a "brain" to distribute the tasks and rewards.

However, although the emerging of crowdsourcing has brought a new way for users to collect information, the low participation level of crowds remains a hurdle that prevents the development of crowdsourcing. As is known to all, it costs some resources (e.g., power and communication) for crowds to collect and upload the information. And the sharing of personal information may also bring the exposure of privacy for crowds (e.g., identity privacy, content privacy, location privacy [7-10]). As a result, the crowds would be unwilling to contribute information or upload random erroneous information for the crowdsourcing. If there is not a compensation mechanism to encourage the crowds, none of them will contribute the accurate information solely for altruistic motivations [11][12]. Hence, it is crucial to design incentive mechanisms to encourage the crowds' contributions such that the performance of crowdsourcing system can be guaranteed.

For the above reasons, many researchers have devoted themselves to develop incentive mechanisms for crowdsourcing systems [13-18]. For example, both [14] and [15] designed two incentive mechanisms based on the auction policy to maximized the social welfare with a guaranteed approximation ratio. However, the honesty of requesters and suppliers have been hardly considered simultaneously. Most of the existing mechanisms only stimulate the suppliers to join the crowdsourcing, but cannot solve the social dilemma exist between suppliers and requesters: if the payments for tasks are ex-ante, which means that the requesters pay the tasks before suppliers return the results, the suppliers always have the motivation to take the payments and do nothing for the tasks, a behavior commonly known as "free-riding" [19]; whereas if the payments are ex-post, which means that the requesters pay the tasks after suppliers return the results, the requesters always have the motivation to refuse the payments to suppliers by lying about the results of the tasks, a behavior commonly known as "false-reporting" [20]. If such a dilemma cannot be solved, the dishonest behaviors of requesters or suppliers will bring some loss for the opponent players and also decline the participation level for the crowdsourcing.

In this paper, to address the aforementioned dilemma, we propose a **R**eputation-based incentive game model for **T**rustworthy c**R**owdsourcing servi**C**e(RTRC). In RTRC, we adopt reputation mechanism as a criteria to compensate the cheated users and punish the malicious ones. Then, an efficient incentive mechanism is established through correcting the penalty function of the game. To model the dynamic of interaction of users, we also introduce an evolutionary game to model the evolution of user-strategy selection and analyze the evolutionarily stable strategies (ESSs) for users. The simulation results show that all the requesters and suppliers will select the honest strategy finally to maximize their welfare. In conclusion, the main contributions of this paper are as follows:

- In order to solve the social dilemma, we propose an incentive game model, namely RTRC. In RTRC, the reputation model is adopted as a criteria to stimulate the users to upload accurate information. With the game-based incentive mechanism, the users which have higher reputations in crowdsourcing can obtain more earnings when they upload accurate information and loss less fines when they cheat the system occasionally. And others which have lower reputations will obtain less earnings when uploading accurate information and loss more fines when cheating the system again.
- We model the dynamic user-strategy selection as an evolutionary game and use the replicator dynamic to model and analyze the trajectory of the distribution of strategies in the population. In the game model, all the players have the same set of strategies: honesty and dishonesty. When users select honest strategy, they will get some payments and their reputations will also in-

In this paper, we have proposed RTRC, which adopts a reputation based incentive game model to motivate the suppliers to contribute accurate results for the tasks and encourage the requesters to return truthful feedbacks for the results.

crease. Driven by the incentive mechanism, more and more users will select the honest strategy to get more earnings. Then, we analyze the evolutionary game model and derive the ESSs for requesters and suppliers, respectively.

- Finally, we present series of simulation results of RTRC justifying that it can motivate all requesters and suppliers to select honest strategy and all of them will be honest at last.

The rest of this paper is organized as follows. Section II presents some related works. In Section III, we give the overview of crowdsourcing system and problem formulation. Afterwards, we model and analyze the dynamic of user-strategy selection by the evolutionary game in Section IV. In Section V, we conduct experiments by simulating the dynamic evolutionary process of the selections of strategy for requesters and suppliers. Finally, we conclude this paper and present the future work in Section VI.

II. RELATED WORK

From the earlier discussion, we can discover that the crowds will be unwilling to contribute information unless they receive enough compensation for their cost of resource. So many researchers have devoted themselves to design the incentive mechanisms to motivate the crowds to contribute accurate information. In this section, we will review the state-of-art in the designing of incentive mechanisms for crowdsourcing system and the evolutionary game theory which is used to model the dynamic user-strategy selection in this paper.

Incentive Mechanisms for Crowdsourcing: In recent years, we have seen the bloom of crowdsourcing systems and many incentive mechanisms have been designed for them. Zhang et al. [21] surveyed the diverse incentive strategies which stimulated users to participate in mobile crowd sensing applications and divided them into three categories: entertainment, service, and money. In order to improve the performance of crowdsourcing system, Zhang et al. [12] proposed a novel class of incentive protocols based on social norms which integrated reputation mechanisms into the existing pricing schemes currently. Zhang et al. [17] also designed three online incentive mechanisms which were based on online reverse auction to pursue platform utility maximization and truthfulness, respectively. Zhang et al. [13] focused on incentivizing crowds to label a set of binary tasks under strict budget constraint. Ji et al. [22] designed the incentive mechanism for discrete crowdsourcing in which each user had a uniform sensing subtask length. Wen et al. [23] proposed an incentive mechanism based on a quality-driven auction instead of the working time. And Peng et al. [24] also incorporated the consideration of data quality into the design of incentive mechanism and proposed to pay the participants as how well they do, which was similar to us at this point. However, all the works above did not consider the honesty of suppliers and requesters simultaneously. All of them only considered that how to motivate the suppliers to contribute information. But as the real, the requesters might also refuse the payment to suppliers by lying about the results of the tasks.

Evolutionary game theory: The last few decades have witnessed the increasing application of evolutionary game theory (EGT) [25]. As a general theoretical framework to model group interactions, EGT focuses on modeling the behavior of players that have a dynamic interactive neighborhood. It assumes that the survival of a strategy depends on the benefits achieved in comparison with other strategies, in contradiction to players that make rational choices as in classical game theory. In general, an evolutionary game includes two significant concepts. The first one is the evolutionarily stable strategy (ESS). As a strong concept of equilibria, it ensures stability and identifies robustness against mutations. The second is the replicator dynamics, which is a model to characterize the observed mutations in a population size. Importantly, it is useful for investigating the trajectory of the strategies of players while adapting their behaviors to reach the solution. Although evolutionary game theory was originally developed for biology, many exiting works had used EGT to model networking problems [26-31]. For example, in order to prevent the fake nodes, prevent misuse, and to protect users's privacy, Kamhoua et al. [32] used the mathematical framework of EGT to model trust, privacy, and security in a multi-hop network. In this paper, we also use the EGT to model the user-strategy selection in crowdsourcing system and find the ESSs for users.

III. SYSTEM OVERVIEW AND PROBLEM FORMULATION

In this section, we first present a generalized model which is usually used in crowdsourcing system, and then describe that how the system works in detail. Finally, we present the problems of dishonesty in crowdsourcing system, which we focus on in this paper. For your convenience, the notations used in the sequel are listed in Table I.

3.1 System model

Nowadays, the generalized model of crowdsourcing system usually contains a crowdsourcing server and some users $P = \{p_1, p_2, ..., p_n\}$ to generate or perform the tasks. These users can request the crowdsourcing service and can also contribute the results of tasks through the crowdsourcing server. At a certain time, the role of each user is "Requester" (ask for service) or "Supplier" (provide the results of tasks). In this manner, we can derive the system model as follows (see in Fig.1).

- *Suppliers. Suppliers* play the role of workers. They can accept the tasks distributed by *Task Server* and also return their available results to it.
- *Crowdsourcing Server. Crowdsourcing Server* primarily consists of two components: *Task Server* and *Payment Server*. *Task Server* is responsible for the distribution of tasks, which receives the tasks from requesters and distributes them to suppliers. *Payment Server* is responsible for the task

Table *I Definitions and notations*

Symbol	Definition
p_i, p_j	users in crowdsourcing system, including requesters and suppliers
γ	the payment sharing ratio
$R_{i,t}$	user p_i's reputation score at time t
I	the amount of earning received by requesters from the accurate results
D	the amount of payment to suppliers
C	the cost of contributing accurate information by suppliers
C'	the cost of contributing erroneous information by suppliers
F	the radix of fine and compensation
$u_{i,t}(x, y)$	the expected utility for player p_i at time t when requester takes action x and supplier takes action y
$U_{s,t}$	the expected utility for crowdsourcing server at time t
x_t, y_t	the proportion of users choosing the honest strategy at time t

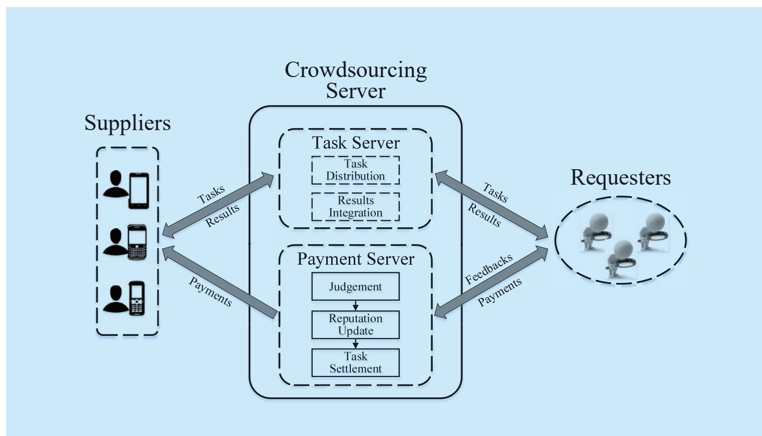

Fig.1 *The system model of crowdsourcing*

settlement, which judges the honesty of *Suppliers* and *Requesters* and pays their earnings for them.
- *Requesters. Requesters* will send their tasks to *Task Server* when they ask for the crowdsourcing service and send the feedbacks to *Payment Server* after receiving the results from *Task Server*.

Given these parties, they work as follows:
- When requesting a crowdsourcing service, a requester p_i generates a task and sends it to *Task Server* with the price D paid for completing it.
- After receiving the request, *Task Server* distributes the task to *Suppliers* and sends the payments D to *Payment Server*.

- *Suppliers* accept the task and return their available results to *Task Server*.
- *Task Server* integrates the results received from *Suppliers* and sends the integrated results to requester p_i.
- p_i receives the results and sends the feedback to *Payment Server*. If p_i is honest, he will give the truthful feedback of the accurate results, and vise versa.
- *Payment Server* receives the feedback and judges the honesty of p_i and *Suppliers*. After that, *Payment Server* will update their reputations according to their performance in this interaction and pay for their earnings.

However, as many participators, including requesters and suppliers, may be malicious or lazy, the judgement of *Payment Server* is nowadays a common problem in crowdsourcing systems. For some reasons, they may deliberately upload erroneous information to *Task Server*. As time passes, these malicious behavior will affect the performance of crowdsourcing system and bring a grave loss for the opposite players. Then, we shall explicitly list the problems of cheating in crowdsourcing system we are solving in this paper.

3.2 Problem statement

As a first line of defense, authentication may be deployed to verifies the identity of participants [33-35]. However, many suppliers may deliberately contribute erroneous information to crowdsourcing server. These suppliers may be malicious competitors or lazy workers. In light of business competition, the competitors may upload erroneous information of other merchants. In this way, the requesters will think that those merchants cannot supply available services or do not have well reputations and select the service which is supplied by the malicious competitors. In this way, the malicious competitors can earn much more through cheating requesters. Another category of malicious suppliers are known as “vampire”. These are lazy suppliers who simply upload random information to crowdsourcing server. These lazy suppliers do not want to contribute information but eager to earn the rewards. However, we also acknowledge the dishonesty of requesters. These requesters may receive the accurate results but deny the fact for a refund. These dishonest behaviors may bring a refund for the requesters but a severe punishment for the honest suppliers. To solve the problems of dishonest for both “Suppliers” and “Requesters” in crowdsourcing system, we propose RTRC to stimulate users to upload accurate information.

IV. Modeling and Analysis for User-Strategy-Selection Evolutionary Game

As discussed above, the crowdsourcing system usually suffers from unreliable crowds who are lazy or even malicious, which is a key bottleneck for its development and widespread usage. To this end, we propose RTRC to motivate participators upload accurate information and employ an evolutionary game to model the interaction process between suppliers and requesters. In order to ensure fairness, we also adopt the reputation mechanism as a criteria to compensate the cheated users and punish the malicious ones. In this section, we first present the reputation model which is used to evaluate the credibility of the users. Then, we model the dynamic competition of requesters and suppliers as an evolutionary game and use replicator dynamics to model and analyze the adaptation of interactive strategies of users while considering the dynamic nature in time dependence in the presented game. Finally, we derive the ESSs for requesters and suppliers to characterize the solution of the adopted game.

4.1 Reputation model

The Gompertz function [36] is introduced to construct the reputation model, which is used to calculate the reputation scores. There are three phases in Gompertz function, namely the reputation doubting phase (beginning), the reputation growing phase (middle) and, lastly, the reputation stable phase (end). Recall that, we select Gompertz function to compute reputation scores, because it is more appropriate to model the concept of trust in human interactions. Gompertz function is formally defined as follows and is plotted in Fig.2.

$$R_{i,t}(\alpha_{i,t}) = a * e^{b * e^{c * \alpha_{i,t}}} \tag{1}$$

where a, b and c are function parameters. In particular, a specifies the upper asymptote, b controls the displacement along the x axis and c adjusts the growth rate of the function. The output of the function (which is also the output of the reputation model), denoted by $R_{i,t}$, is a number in the range of 0 and 1 and represents the reputation score for participator p_i at time t. In this paper, we design $R_{i,t}$ as the accumulation of the historical honesty. It can be used as an indication for the probability that the user is trustworthy at this time and future. The input of Gompertz function needs to reflect the fact that reputation is the result of aggregating historical pre-time information. That means, we need to process the input ahead of time. Further, the aggregating process must account for the fact that the most recent information is more relevant than the past.

In the crowdsourcing system, we denote by $\beta_{i,t}$ as whether user p_i is honest or dishonest at time t. In order to punish the dishonest users, we set $\beta_{i,t}$ as follows in our scheme:

$$\beta_{i,t} = \begin{cases} 1, & p_i \text{ is honest} \\ -2, & p_i \text{ is dishonest} \end{cases} \tag{2}$$

Then, the input of Gompertz function is as following [37]:

$$\alpha_{i,t} = \sum_{t'=1}^{t} \lambda^{(t-t')} \beta_{i,t'} \tag{3}$$

where the summation is used to facilitate the aggregation of historical information while the exponential term, $\lambda^{(t-t')}$ with $0 \le \lambda \le 1$, reduces the impact of historical data. In this sense, λ is equivalent to the ageing weight introduced in [38].

4.2 Formulation of user-strategy-selection evolutionary game

For the user-strategy-selection evolutionary game, the players refer to the requesters and suppliers in crowdsourcing system. And they constitute the population in the context

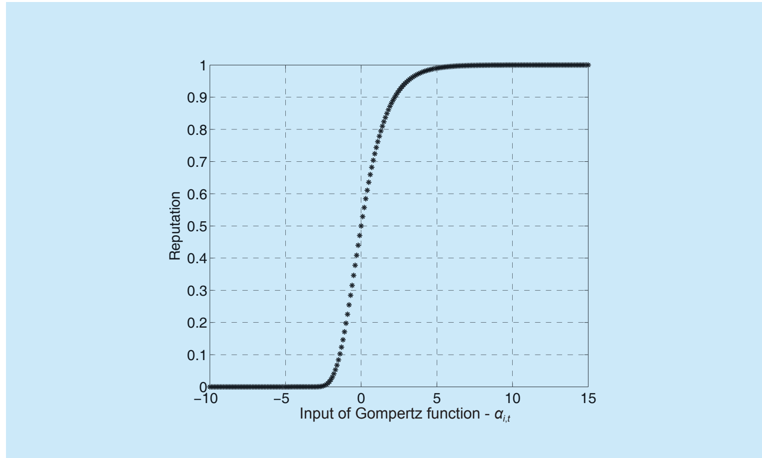

Fig.2 *Gompertz function*

of evolutionary game. The strategy of each players corresponds to honesty or dishonesty during the interaction. That is, each user has the same set of strategies, denoted as $S = \{honesty, dishonesty\}$.

At the beginning of the game, the crowdsourcing server will initialize the reputation scores for all users. Then the requesters generate some tasks and upload them to *Task Server*. The tasks may be location-aware crowdsourcing or other spatial crowdsourcing. After that, the suppliers accept the tasks which are distributed by *Task Server* and return the available results to crowdsourcing server. The *Task Server* binds the results to their providers' credential and sends the integrated results to requesters. Then requesters receive the results and return the feedbacks to *Payment Server*. After confirming the authenticity of results and feedbacks, the *Payment Server* will pay their deserved payments to suppliers and requesters. It should be noted that the judging mechanism is application dependent and out of the scope of this article, so it will not be described in detail here. The payments for tasks from requesters are shared by the suppliers and the crowdsourcing server. Particularly, the suppliers receive γD where $\gamma < 1$ as their rewards, and the crowdsourcing server charges an amount $(1 - \gamma)D$, which can be regarded as the maintenance cost or the usage fee of the system. In addition, we assume that the *Task Server* always select K

suppliers for each task. Hence, every supplier will receive $\gamma D/K$ payments for each task when its reputation score is 1.

In RTRC, we use the reputation scores as an indispensable reference to compensate the cheated users and punish the dishonest ones. If one user has a high reputation score after the last interaction, it will be considered that it is always honest and will get more compensation (resp., less punishment) when cheated (resp., dishonest occasionally). If it has a low reputation score, it will be thought as malicious and get less compensation (resp., more punishment) when cheated (resp., dishonest again). Since the users which have low reputation scores cheat others frequently, we need to punish them by giving less rewards and heavier punishment.

In the evolutionary game, we consider two players, requester p_i and supplier p_j, and neither of them is completely rational. When p_i receives the result which is contributed by p_j, it will accept the result and confirm the authenticity of that. Nevertheless, p_i and p_j may be honest or dishonest. If p_i and p_j are both honest, p_i will get the accurate result and pay some awards to p_j. So p_i receives the benefit of the accurate result, given by I, minus the amount of payment to p_j, D. Since supplier p_j's reputation may not be 1, it only receives the payment $R_{j,t-1} * \gamma D/K$, where $R_{j,t-1}$ is p_j's reputation score after the last interaction, minus the cost of contributing result, C. We assume that $I \geq D$ and $R_{j,t-1} * \gamma D/K \geq C$. If this were not the case, then the game would not be individually rational without some outside subsidies (that is, some players' expected payments would be less than zero). In essence, we want to ensure that p_i want to pay D to receive the accurate result, and p_j would accept $R_{j,t-1} * \gamma D/K$ for contributing the information. To do this, we make sure that the value that p_i places on the requesting is at least the expected payment, and the cost to p_j is no more than the amount they would be paid. No one takes a loss on the transaction. So the expected payments to each player in this strategy profile at time t can be defined as following:

$$\begin{cases} u_{i,t}(h,h) = I - D \\ u_{j,t}(h,h) = R_{j,t-1} * \gamma D/K - C \end{cases} \tag{4}$$

When all the K suppliers are honest, the earning of crowdsourcing server is revised as following:

$$u_{s,t} = (1 - \sum_{h=1}^{K} R_{h,t-1}\gamma/K) * D \tag{5}$$

On one hand, if p_i is dishonest and p_j is honest, p_i will deny the fact that it has got the accurate result. In this manner, though p_i do not want to pay for the accurate information which is contributed by honest p_j, it will be punished and lose the fine $(1 - R_{i,t-1}) * F$, where $R_{i,t-1}$ is p_i's reputation score after the last interaction and F is the radix of fine and compensation. So p_i can receive the benefit of accurate result, I, minus the fine, $(1 - R_{i,t-1}) * F$. However, although p_j does not receive the payment from p_i, it will get some compensation, $R_{j,t-1} * \gamma(1 - R_{i,t-1})F/K$, from crowdsourcing server for encouraging. In all, p_j receives the compensation, $R_{j,t-1} * \gamma(1 - R_{i,t-1})F/K$, minus the cost of contributing the accurate information, C. Therefore, the expected payment to each player in this strategy profile at time t can be defined as following:

$$\begin{cases} u_{i,t}(c,h) = I - (1 - R_{i,t-1}) * F \\ u_{j,t}(c,h) = R_{j,t-1} * \gamma(1 - R_{i,t-1})F/K - C \end{cases} \tag{6}$$

In this strategy profile, the earning of crowdsourcing server is revised as following:

$$u_{s,t} = (1 - \sum_{h=1}^{K} R_{h,t-1}\gamma/K) * (1 - R_{i,t-1}) * F \tag{7}$$

On the other hand, if p_i is honest and p_j is dishonest, p_i will tell *Payment Server* the truth that p_j is cheating. In this manner, since p_j contributes erroneous information, p_i will receive nothing from the information which is uploaded by p_j. But crowdsourcing server will pay p_i some compensation, $R_{i,t-1} * F$, for making up the loss. So the total received revenues of p_i are compensation, $R_{i,t-1} * F$, minus the amount paid to p_j, D. Because of p_j simply upload erroneous information to crowdsourcing server randomly, it will take another cost C' to contribute the information, where C' is less than C, since a player will not cheat if they do not gain anything from it.

As punishment, the dishonest p_j will lose the fine, $(1-R_{j,t-1})*R_{i,t-1}*F/\sum_{j=1}^{K}R_{j,t-1}$. So the total received revenues of p_j are the payment $R_{j,t-1}*\gamma D/K$ minus the cost of contributing erroneous information, C', and the fine, $(1-R_{j,t-1})*R_{i,t-1}*F/\sum_{j=1}^{K}R_{j,t-1}$. So the expected payments to each player in this strategy profile at time t can be defined as following:

$$\begin{cases} u_{i,t}(h,c)=R_{i,t-1}*F-D \\ u_{j,t}(h,c)=R_{j,t-1}*\gamma D/K-C'-(1-R_{j,t-1})*F \end{cases} \tag{8}$$

In this strategy profile, the earning of crowdsourcing server is revised as following:

$$u_{s,t}=(1-\frac{\sum_{h=1}^{K}R_{h,t-1}\gamma}{K})*D+(\sum_{h=1}^{K}(1-R_{h,t-1})-R_{i,t-1})*F \tag{9}$$

Finally, if p_i and p_j are both dishonest, they will tell crowdsourcing server the incorrect information randomly. Since p_i and p_j do not want to contribute any valuable information, both of them will be punished. Hence, p_i will loss the fine $(1-R_{i,t-1})*F$ and p_j will loss the fine and the cost for upload erroneous information, $C'+(1-R_{j,t-1})*F$. So the expected payments to them in this strategy profile at time t can be shown as following:

$$\begin{cases} u_{i,t}(c,c)=-(1-R_{i,t-1})*F \\ u_{j,t}(c,c)=-C'-(1-R_{j,t-1})*F \end{cases} \tag{10}$$

In this strategy profile, the earning of crowdsourcing server is revised as following:

$$u_{s,t}=(1-R_{i,t-1})*F+\sum_{h=1}^{K}(1-R_{h,t-1})*F \tag{11}$$

Therefore, the pay-off matrixes are shown in Table II and Table III. In order to guarantee the performance of crowdsourcing system, we must encourage the users to be honest. So we define the following constraints:

$$\begin{cases} u_{i,t}(h,h)>u_{i,t}(c,h) \\ u_{i,t}(h,c)>u_{i,t}(c,c) \end{cases} \tag{12}$$

and

$$\begin{cases} u_{j,t}(h,h)>u_{j,t}(h,c) \\ u_{j,t}(c,h)>u_{j,t}(c,c) \end{cases} \tag{13}$$

Then, after processed, the constraints are shown in follows:

$$\begin{cases} D+(R_{i,t-1}-1)*F<0 \\ D-F<0 \end{cases} \tag{14}$$

and

$$\begin{cases} C-C'-(1-R_{j,t-1})*F<0 \\ ((\frac{1-R_{i,t-1}}{K}\gamma-1)R_{j,t-1}+1)*F-C+C'>0 \end{cases} \tag{15}$$

Since $0\le R_{i,t-1},R_{j,t-1}\le 1$, we can simplify the constrains as following:

$$\begin{cases} D+(R_{i,t-1}-1)*F<0 \\ C-C'-(1-R_{j,t-1})*F<0 \end{cases} \tag{16}$$

In addition, we also need to guarantee the earning of crowdsourcing server to maintain the performance of crowdsourcing system. From the utility of crowdsourcing server described above, it is easy to see that the system server can get at least an amount $(1-\gamma)*D$ when all users are honest and all the suppliers' reputation scores are 1. Hence, the crowdsourcing server can obtain the rewards from every interaction and maintain the system working well.

After each play of the evolutionary game, the users' reputation scores will be updated according to the strategies which they selected during this iteration. For example, if requester p_i selects honest, its $\beta_{i,t}$ will be set to 1 and its reputation score will be increased. If p_i selects dishonest, its $\beta_{i,t}$ will be set to -2 and its reputation score will de declined. So the matrix of β in each iteration is shown in Table IV. The operating algorithm of crowdsourcing system is listed in Algorithm 1.

4.3 Replicator dynamics

When the users in an evolutionary game are up against the dynamic environment and un-

Table *II Pay-off matrix of requesters*

		Suppliers	
		Honest	Dishonest
Requester p_i	Honest	$u_{i,t}(h,h)$	$u_{i,t}(h,c)$
	Dishonest	$u_{i,t}(c,h)$	$u_{i,t}(c,c)$

Table *III Pay-off matrix of suppliers*

		Supplier p_j	
		Honest	Dishonest
Requesters	Honest	$u_{j,t}(h,h)$	$u_{j,t}(h,c)$
	Dishonest	$u_{j,t}(c,h)$	$u_{j,t}(c,c)$

certain results by other's strategies, they will try different strategies in each play and learn from the strategic interactions. As a stable equilibrium strategy concept, the ESS is also widely adopted in evolutionary game theory. It refers to "a strategy such that, if all members of the population adopt it, then no mutant strategy could invade the population under the influence of natural selection" [39]. To study the evolution of users' strategies, we employ replicator-dynamic equations to model the trajectory of the distribution of strategies in the population itself. Then, we export the feasible ESSs according to the conditions which they meet. In crowdsourcing system, the users can be divided into two categories: requesters and suppliers. Since the requesters may convert to suppliers in the next interaction, we assume that they have the same proportion to select honest strategy. In the following, we first model the strategy-selection dynamics of the requesters using p_i's utility function. Afterwards, the evolution processes of users which play as suppliers is described using p_j's utility function.

1)Replicator Dynamics for Requesters: We define x_t as the proportion of users choosing the honest strategy at time *t*; then the proportion of them following the dishonest strategy at time *t* is $1 - x_t$.

According to the game matrix, the payments of requesters choosing the honest strategy are as following:

$$\begin{aligned} E_R^h &= x_t * u_{i,t}(h,h) + (1-x_t) * u_{i,t}(h,c) \\ &= x_t * I + F * R_{i,t-1} - D - x_t * F * R_{i,t-1} \end{aligned} \tag{17}$$

The payments of choosing dishonest strategy are as following:

$$\begin{aligned} E_R^c &= x_t * u_{i,t}(c,h) + (1-x_t) * u_{i,t}(c,c) \\ &= x_t * I + F * R_{i,t-1} - F \end{aligned} \tag{18}$$

So the average payments are:

$$\begin{aligned} E_R &= x_t * E_R^h + (1-x_t) * E_R^c \\ &= x_t * I - x_t * D - x_t^2 * F * R_{i,t-1} \\ &\quad - F + F * R_{i,t-1} + x_t * F \end{aligned} \tag{19}$$

After that, the replicator-dynamic equation of the proposed game for requesters can be formulated as:

$$\begin{aligned} \frac{dx_t}{dt} &= x_t * (E_R^h - E_R) \\ &= x_t * (x_t * I + F * R_{i,t-1} - D \\ &\quad - x_t * F * R_{i,t-1} - x_t * I + x_t * D \\ &\quad + x_t^2 * F * R_{i,t-1} + F - F * R_{i,t-1} + x_t * F) \\ &= x_t * (1-x_t) * (F - D - x_t * F * R_{i,t-1}) \end{aligned} \tag{20}$$

According to the first condition ESS meets, we make $dx_t/dt = 0$, that is:

$$x_t * (1-x_t) * (F - D - x_t * F * R_{i,t-1}) = 0. \tag{21}$$

The solutions are $x_{t_1} = (F-D)/(F * R_{i,t-1})$, $x_{t_2} = 0, x_{t_3} = 1$.

Table *IV Matrix of* β

		Supplier p_j	
		Honest	Dishonest
Requester p_i	Honest	(1,1)	(1,-2)
	Dishonest	(-2,1)	(-2,-2)

Algorithm 1 The processing algorithm of crowdsourcing system

Input: Users' initialized reputation scores.
Output: The payments for requesters and suppliers.

for $t \in [1, \infty)$
  if requester p_i requests a crowdsourcing service **then**
    Accept and distribute the task.
    Receive the result from supplier p_j.
    Send the result to p_i and receive its feedback.
    Judge the honesty of p_i and p_j.
    if p_i is honest and p_j is honest **then**
      Set $\beta_{i,t} = 1$ and $\beta_{j,t} = 1$.
      Calculate the earnings:
      $u_i = u_{i,t}(h,h), u_j = u_{j,t}(h,h)$.
    else if p_i is dishonest and p_j is honest **then**
      Set $\beta_{i,t} = -2$ and $\beta_{j,t} = 1$.
      Calculate the earnings:
      $u_i = u_{i,t}(c,h), u_j = u_{j,t}(c,h)$.
    else if p_i is honest and p_j is dishonest **then**
      Set $\beta_{i,t} = 1$ and $\beta_{j,t} = -2$.
      Calculate the earnings:
      $u_i = u_{i,t}(h,c), u_j = u_{j,t}(h,c)$.
    else if p_i is dishonest and p_j is dishonest **then**
      Set $\beta_{i,t} = -2$ and $\beta_{j,t} = -2$.
      Calculate the earnings:
      $u_i = u_{i,t}(c,c), u_j = u_{j,t}(c,c)$.
    end if
    Update reputation scores: $R_{i,t}$ and $R_{j,t}$.
  end if
  return u_i and u_j to users.
end for

2) Replicator Dynamics for Suppliers: During this process of evolution, we set y_t as the proportion of the users following the honest strategy, then the proportion of ones following the dishonest strategy is $1-y_t$.

According to the game matrix, the payments of suppliers choosing the honest strategy are as following:

$$\begin{aligned} E_S^h &= y_t * u_{j,t}(h,h) + (1-y_t) * u_{j,t}(c,h) \\ &= \frac{\gamma R_{j,t-1}}{K}(y_t D + (1-y_t)(1-R_{i,t-1})F) - C \end{aligned} \tag{22}$$

The payments of choosing dishonest strategy are as following:

$$\begin{aligned} E_S^c &= y_t * u_{j,t}(h,c) + (1-y_t) * u_{j,t}(c,c) \\ &= \frac{y_t R_{j,t-1}\gamma D}{K} - (1-R_{j,t-1})F - C' \end{aligned} \tag{23}$$

So the average payments are:

$$\begin{aligned} E_S &= y_t * E_S^h + (1-y_t) * E_S^c \\ &= \frac{y_t R_{j,t-1}\gamma D}{K} + (1-y_t)F(\frac{y_t R_{j,t-1}\gamma}{K}(1-R_{i,t-1}) - \\ &(1-R_{j,t-1})) - y_t C - (1-y_t)C' \end{aligned} \tag{24}$$

After that, the replicator-dynamic equation of the proposed game for suppliers can be formulated as:

$$\begin{aligned} \frac{dy_t}{dt} &= y_t * (E_S^h - E_S) \\ &= y_t * (1-y_t) * (\frac{R_{j,t-1}\gamma F}{K}(1-R_{i,t-1})(1-y_t) \\ &\quad + F(1-R_{j,t-1}) - C + C') \end{aligned} \tag{25}$$

According to the first condition ESS meets, we make $dy_t/dt = 0$. Then, we can get $y_{t_1} = 1 - \dfrac{K(C - C' - F(1-R_{j,t-1}))}{R_{j,t-1}\gamma F(1-R_{i,t-1})}$, $y_{t_2} = 0, y_{t_3} = 1$.

4.4 Evolutionarily stable strategy

In this section, we shall analyze the ESSs for requesters and suppliers through the aforementioned evolutionary game model.

1) Stability Analysis for Requesters: Obviously, the three solutions in (21) are not all ESSs for the evolutionary game of requesters. So we need to study the stability according to the conditions which ESS meets.

Theorem 1: In the evolutionary game model of RTRC, there is only an evolutionarily stable strategy for requesters.

Proof: Firstly, we set $H(x_t) = dx_t/dt$. According to the results in [40], the ESS can be defined as the set of fixed points of the system of differential equations that are stable. In other words, a strategy x_t is the ESS, if and only if it satisfies two conditions, namely, equilibrium condition and stability condition. Accordingly, $H(x_t)$ should satisfy the following conditions:

$$\begin{cases} H(x_t) = 0 \\ H'(x_t) < 0 \end{cases} \tag{26}$$

Since $x_{t_1} = (F-D)/(F * R_{i,t-1}), x_{t_2} = 0$ and $x_{t_3} = 1$ all satisfy the first condition $H(x_t) = 0$, we will eliminate the solutions, which are not satisfy the second condition, to get the unique ESS. From equation (20), we can get $H(x_t) = x_t * (1-x_t) * (F - D - x_t * F * R_{i,t-1})$. So $H'(x_t)$ can be calculated as following:

$$\begin{aligned} H'(x_t) &= (1-x_t) * (F - D - x_t * F * R_{i,t-1}) \\ &\quad - x_t * (F - D - x_t * F * R_{i,t-1}) \\ &\quad - x_t * (1-x_t) * F * R_{i,t-1} \end{aligned} \tag{27}$$

When $x_t = 0$,

$$H'(x_t = 0) = F - D. \tag{28}$$

When $x_t = 1$,

$$H'(x_t = 1) = D + F * R_{i,t-1} - F. \tag{29}$$

When $x_t = (F-D)/(F * R_{i,t-1})$,

$$\begin{aligned} H'(x_t &= \frac{F-D}{F * R_{i,t-1}}) \\ &= \frac{(D-F) * (F * R_{i,t-1} - F + D)}{F * R_{i,t-1}}. \end{aligned} \tag{30}$$

To guarantee the performance of crowdsourcing system, we define the constrains in (16). In this regard, we can get $H'(x_t = 0) > 0, H'(x_t = 1) < 0$, and $H'(x_t = (F-D)/(F * R_{i,t-1})) > 0$. Thus, only $x_t = 1$ satisfies the second condition and is the only ESS in evolutionary game for requesters. That is, all requesters will select honest strategy at the end of the evolutionary game and reach the evolutionary stable state finally.

The proof is over.

The above analysis of stability shows that no matter whether the population of requesters choose “honest” or “dishonest” at the beginning, after a period of evolution, all the requesters will choose the pure strategy - “honest”. Therefore, RTRC can ensure the purity of requesters in crowdsourcing system.

2) Stability Analysis for Suppliers: As the same of the stability analysis for requesters, not all the solutions in (25) are ESSs for the evolutionary game of suppliers. So we also study the stability according to the conditions which ESS meets.

Theorem 2: In the evolutionary game model of RTRC, there is only an evolutionarily stable strategy for suppliers.

Proof: The proof is similar to that for requesters. We first set $H(y_t) = dy_t/dt$. Then, according to the conditions which ESS meets, $H(y_t)$ should also satisfy the following conditions:

$$\begin{cases} H(y_t) = 0 \\ H'(y_t) < 0 \end{cases} \tag{31}$$

Since $y_{t_1} = 1 - \dfrac{K(C - C' - F(1 - R_{j,t-1}))}{R_{j,t-1}\gamma F(1 - R_{i,t-1})}$, $y_{t_2} = 0$ and $y_{t_3} = 1$ all satisfy the first condition $H(y_t) = 0$, we only need to consider the results which satisfy the second condition. From equation (25), we get

$$H(y_t) = y_t * (1 - y_t) * (\frac{R_{j,t-1}\gamma F}{K}(1 - R_{i,t-1}) (1 - y_t) + F(1 - R_{j,t-1}) - C + C').$$

So $H'(y_t)$ can be expressed as following:

$$\begin{aligned} H(y_t) =&(1 - y_t)(\frac{R_{j,t-1}\gamma F}{K}(1 - R_{i,t-1})(1 - y_t) \\ &+ F(1 - R_{j,t-1}) - C + C') - y_t(\frac{R_{j,t-1}\gamma F}{K} \\ &(1 - R_{i,t-1})(1 - y_t) + F(1 - R_{j,t-1}) - C + C') \\ &- y_t(1 - y_t)\frac{R_{j,t-1}\gamma F}{K}(1 - R_{i,t-1}) \end{aligned} \tag{32}$$

When $y_t = 0$,

$$\begin{aligned} H'(y_t = 0) = &\frac{R_{j,t-1}\gamma F}{K}(1 - R_{i,t-1}) \\ &+ F(1 - R_{j,t-1}) - C + C'. \end{aligned} \tag{33}$$

When $y_t = 1$,

$$H'(y_t = 1) = C - C' - F(1 - R_{j,t-1}). \tag{34}$$

When $y_t = 1 - \dfrac{K(C - C' - F(1 - R_{j,t-1}))}{R_{j,t-1}\gamma F(1 - R_{i,t-1})}$,

$$\begin{aligned} H(y_t =&1 - \frac{K(C - C' - F(1 - R_{j,t-1}))}{R_{j,t-1}\gamma F(1 - R_{i,t-1})}) \\ =&(\frac{K(C - C' - F(1 - R_{j,t-1}))}{R_{j,t-1}\gamma F(1 - R_{i,t-1})} - 1) \\ &(C - C' - F(1 - R_{j,t-1})). \end{aligned} \tag{35}$$

Considering the constrains in (16), when $0 \le R_{j,t-1} \le 1$, we can get $H'(y_t = 0) > 0$ and $H'(y_t = 1 - \dfrac{K(C - C' - F(1 - R_{j,t-1}))}{R_{j,t-1}\gamma F(1 - R_{i,t-1})}) > 0$, and only $H'(y_t = 1) < 0$. Thus, there is only one solution, $y_t = 1$, that satisfies both conditions in (\ref{equ_26}). Hence, there is only one ESS in the evolutionary game model for suppliers.

The proof is over.

The above stability analysis for crowds shows that no matter whether the population of crowds choose "honest" or "dishonest" at the beginning of the game, after a period of evolution, all the crowds will choose the honest strategy. Therefore, the adopted incentive mechanism can ensure crowds contribute accurate results honestly to guarantee the performance of crowdsourcing system.

Notably, the above described ESSs are obtained under the constrains in (16). From the constrains, we can find that $R_{i,t-1}$ and $R_{j,t-1}$ must satisfy the following conditions:

$$\begin{cases} R_{i,t-1} < \dfrac{F - D}{F} < 1 \\ R_{j,t-1} < \dfrac{F + C' - C}{F} < 1 \end{cases}. \tag{36}$$

With the users selecting the honest strategy to reach the ESSs, their reputation scores will also increase accordingly. As time passes, their reputation scores may no longer satisfy the conditions in (36). Then, the ESSs $x_t = 1$ and $y_t = 1$ are replaced by $x_t = (F - D)/(F * R_{i,t-1})$ and $y_t = 1 - \dfrac{K(C - C' - F(1 - R_{j,t-1}))}{R_{j,t-1}\gamma F(1 - R_{i,t-1})}$. Thus, some users may choose dishonest strategy to obtain more earnings. But their reputation scores will also decline along with the betrayal from "honest" strategy. Finally, the reputation of users will also reach a dynamic equilibrium.

V. SIMULATION AND ANALYSIS

In this section, we present series of experimental results of our presented game with simulations and the results justify that the adopted incentive mechanism can motivate users to select honest strategy. If users select dishonest strategy, they will be punished immediately and select honesty again. The simulation setup is as follows: if we set the initialized reputation scores $R_{*,0}$ of users to 0.5, the parameters

a, b in reputation model should be set to 1 and $-\ln(2)$, respectively. Then, in order to achieve a satisfiable performance of the adopted incentive game model, we set the parameters c and λ to -0.35 and 0.7, respectively. Simultaneously, in order to satisfy the constrains in (16), other parameters in the evolutionary game are set to the values in Table V.

In the following, we will present the dynamic of the proportion of honesty (x_t and y_t) and reputation scores ($R_{i,t}$ and $R_{j,t}$) for requesters and suppliers, respectively. Then, we present their average payments (E_R and E_S) varied with the iterations of interactions. We also analyze the effect of initialized values of the honest proportion (x_0 and y_0) on the time to reach ESSs. Finally, we present a practical scenario of RTRC and evaluate the accuracy of the integrated results from suppliers.

5.1 The dynamics evolution for requesters

When $x_0 = 0.7$, the dynamic evolutions of x_t and $R_{i,t}$ for requesters are shown in Fig.3. And in Fig.4, we also plot the average payments of requesters varied with t. The simulation results in Fig.3 show that x_t will increase until reaching a steady state. At the beginning, requesters select honest strategy to get more earnings and their reputations increase with their selections. However, when the growing reputations do not meet the conditions in (36), requesters will select dishonest strategy to obtain more payments. But these requesters will be punished immediately by declining their reputations (e.g., $t = 5, 11, 17$, etc. in Fig.3). Then, the punished requesters find that their reputations are declined and others which select honest strategy can also get more payments. Therefore, they will select honest strategy to obtain more payments again. Finally, the requesters will only select dishonest strategy occasionally and the proportion of honesty will reach a steady state. With the increasing of $R_{i,t}$ and x_t, the average payments E_R also grows rapidly and reaches a steady state finally (see in Fig. 4). However, it should be noted that the decline of $R_{i,t}$ (e.g., $t = 5$ in Fig.3) will also cause

Table V *Parameters in evolutionary game model*

Parameter	Value
The value received from accurate information: I	6
The amount paid to crowds: D	2
The radix of fine and compensation: F	8
The amount of suppliers: K	1
The payment sharing ratio: γ	0.8
The cost of contributing accurate information: C	1
The cost of contributing inaccurate information: C'	0.1

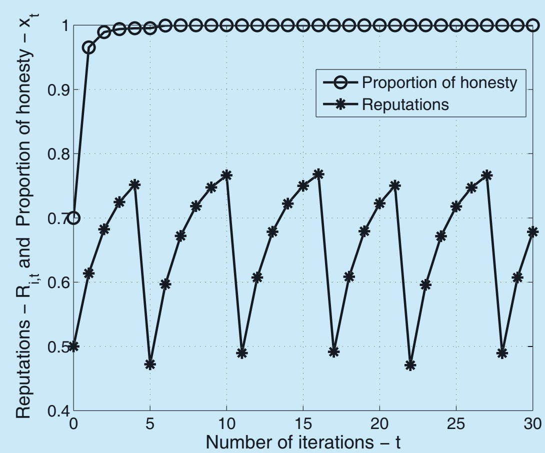

Fig.3 *The evolution of x_t and $R_{i,t}$ for initialized state $x_0 = 0.7$*

the reduction of E_R in next iteration (e.g., $t = 6$ in Fig.4) before x_t reaches the steady state.

In Fig.5, we plot the impact of initialized values of honest proportion x_0 for requesters. As shown in Fig.5, the larger the proportion of honesty is at the beginning of the presented game, the faster group ESS reaches. The reason is that if more requesters select honest strategy in populations, the requesters which select dishonest strategy have a larger probability to select a honest one as game opponent. So the dishonest requesters will have a larger probability to switch to honesty to get more earnings. Therefore, the requesters will quickly change their strategies and reach the steady state faster.

5.2 The dynamics evolution for suppliers

In Fig.6 and 7, we plot the dynamic evolutions

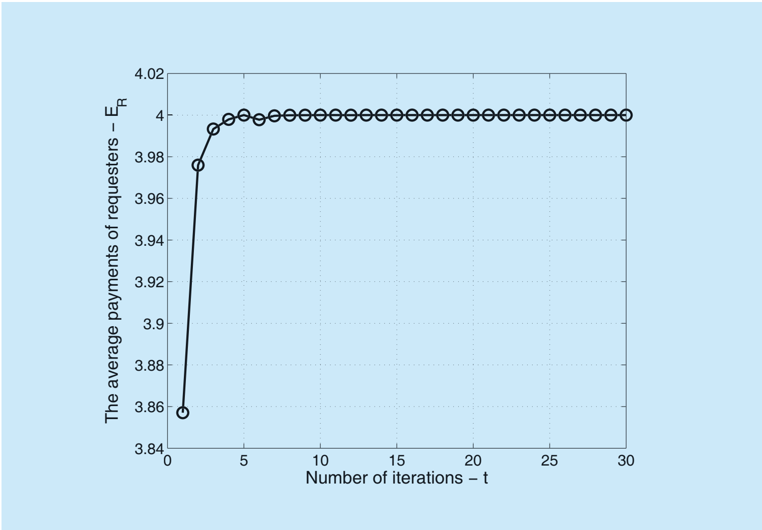

Fig.4 *The evolution of E_R for initialized state $x_0 = 0.7$*

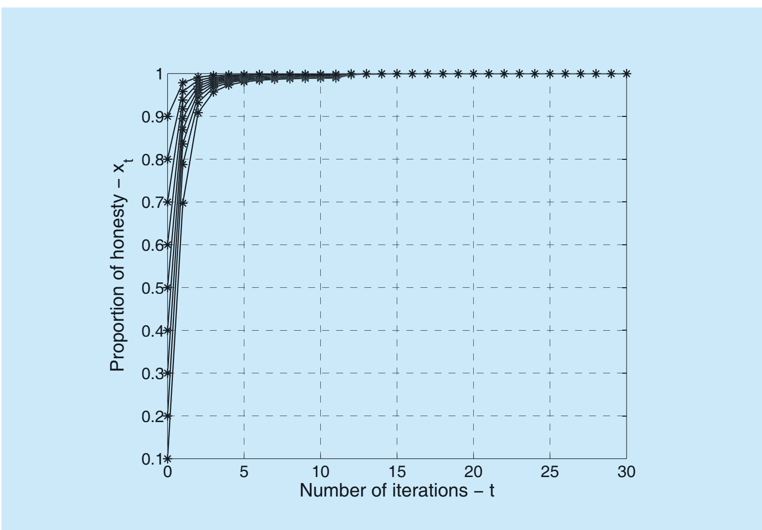

Fig.5 *The impact of initialized value x_0 on requesters*

of y_t, $R_{j,t}$ and E_S varied with t when $y_0 = 0.7$. As the same with the evolution of x_t, y_t also increases rapidly at the beginning and reaches a steady state finally, which is shown in Fig.6. When their reputation scores satisfy the conditions in (36), the suppliers will select the honest strategy to get more payments. As time goes by, all the suppliers select honest strategy and the proportion of honesty y_t reaches the steady state finally. Given the values of parameters in Table IV, none of the suppliers' reputations can dissatisfy the conditions in (36) during the evolution. Hence, they will select honesty all the time and their reputations and average payments will reach the upper bound, as shown in Fig.6 and 7.

In Fig.8, we also plot the impact of initialized values of honest proportion y_0 for suppliers. As shown in Fig.8, the suppliers which have a larger initial value of honest proportion will reach the steady state faster than the ones with smaller y_0. From that we can see the proportion of honesty for suppliers has the similar characteristic with x_t. This is because that they have the same purpose to maximize profit. When the suppliers which select dishonest strategy play the game with honest ones, they will change their strategies to select honest strategy in next iteration to get more payments. So the unique dishonest-strategy suppliers will select honest strategy quickly and the steady state will be reached faster.

5.3 A practical scenario of RTRC

As a practical scenario of RTRC, a real-time traffic querying system which is based on crowdsourcing is introduced, just as the application of Waze. In this scenario, we consider a requester p_i queries the traffic congestion of a certain road. After receiving the request, the crowdsourcing server distributes the task to the online suppliers. Then, the suppliers accept the task and send their available results to the server. However, the server has no knowledge of the ground truth and has to resort to some form of approximation to integrate the results. A common approach is to use consensus-based outlier detection. After that, the server sends the integrated results to p_i and receives the feedback of the real traffic states from him. Since there may be many requesters requesting the same service at the same road, the server can also use the same outlier detection method and combine their travelling speeds and current traffic flow to judge the honesty of them.

During the simulation, we assume that there are 100 requesters querying the traffic states at the same time and the server selects 100 suppliers to collect the information. We also assume most of the requesters are honest, which is indeed established in the real scenario. In the following, we will evaluate the accuracy of the integrated results from suppliers. The accuracy of the requesters' feedbacks are also similar with that of suppliers. So we only evaluate the accuracy of collected results.

As shown in Fig.9, we plot the accuracy of integrated results by varying the proportion of honest suppliers. In our scenario, we assume there are only 60% suppliers selecting honest strategy at the beginning. In such a situation, we evaluate the accuracy of the collected results are only 0.55. That means the crowdsourcing server only has the proportion of 0.55 to send the correct result to requesters. As time goes on, due to the incentive mechanism, more and more suppliers will select the honest strategy, which is shown in Fig.6. With the increasing of honest suppliers, the server can get a higher probability to send the accurate results to requesters. While all the suppliers are honest, the proportion of honest suppliers is 1, the collected results are consistent and reflect the real traffic state. So the server can get the accurate result with the highest probability 1.

The accuracy of the feedbacks of requesters is similar with that of the collected results from suppliers. As time goes on, more and more requesters select honest strategy and the server can get a higher probability to obtain the accurate feedbacks. After judging the honesty of requesters and suppliers, the crowdsourcing server will update their reputations and pay their earnings.

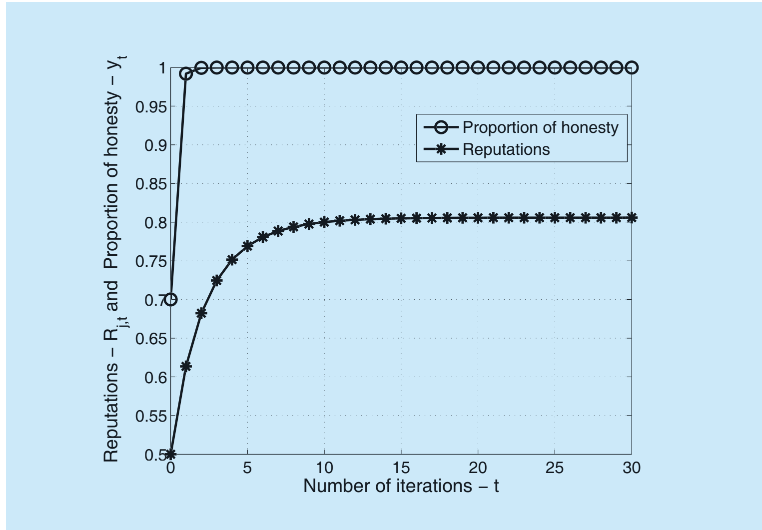

Fig.6 *The evolution of y_t and $R_{j,t}$ for initialized state $y_0 = 0.7$*

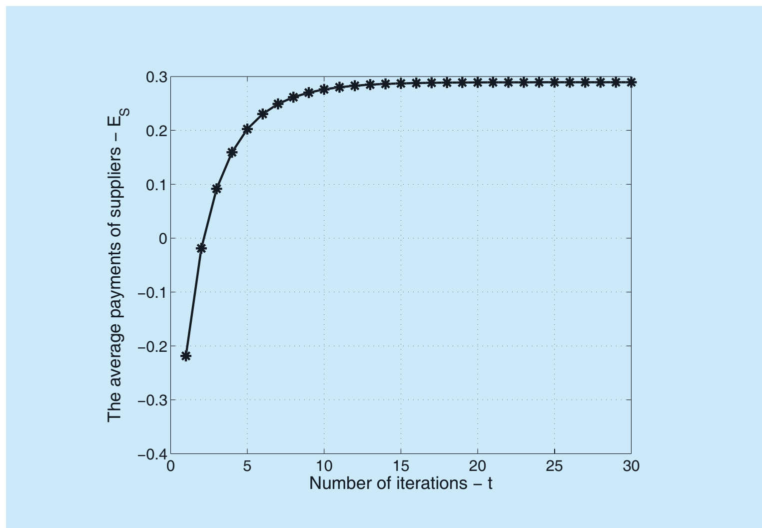

Fig.7 *The evolution of E_S for initialized state $y_0 = 0.7$*

5.4 Comparison with other schemes

To future evidence the superiority of our mechanism, we compare our RTRC with some existed works in the following two aspects.

- Comparing with [14] and [15], we solve the existed social dilemma between suppliers and requesters. Our RTRC can solve the behaviors which are known as "free-riding" and "false-reporting" perfectly. Through our incentive mechanism, the suppliers and requesters will finally select the honest strategy to obtain the maximized welfare.
- Comparing with the works which do not consider the reputation, our mechanism is more flexibility when distributing the rewards. To ensure the fairness, we introduce the reputation model as a criteria to compensate the cheated users and punish the malicious ones. If one user has a high reputation score after the last interaction, it will be considered that it is always honest and will get more compensation (resp. less punishment) when cheated (resp. dishonest occasionally).

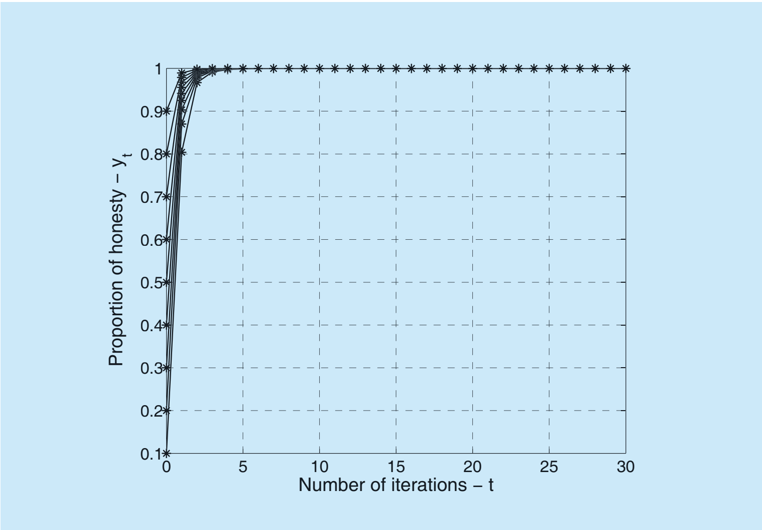

Fig.8 *The impact of initialized value y_0 on suppliers*

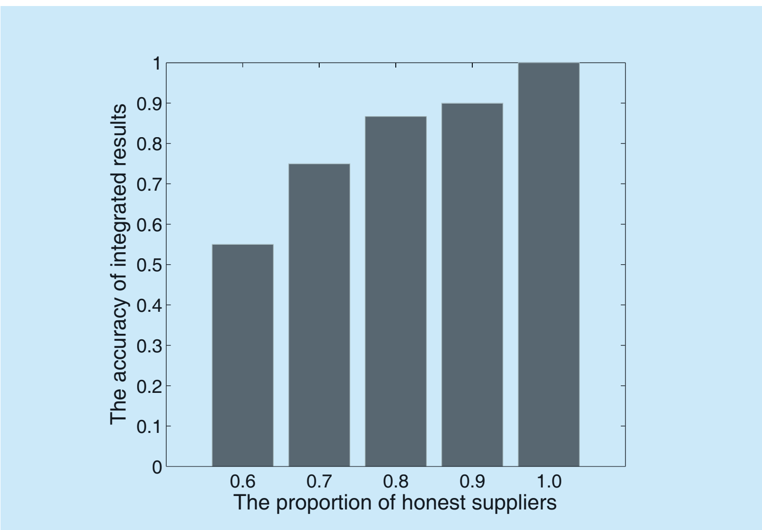

Fig.9 *The accuracy of integrated results from suppliers*

VI. CONCLUSION

The erroneous information which is uploaded by users seriously threats the performance of crowdsourcing system. In this paper, we have proposed RTRC, which adopts a reputation-based incentive game model to motivate the suppliers to contribute accurate results for the tasks and encourage the requesters to return truthful feedbacks for the results. Specifically, we present an evolutionary game to model the evolution and dynamic of user-strategy selection. And then, we analyze the strategy-adaptation process based on the replicator dynamics and derive and study the conditions of ESSs meeting for requesters and suppliers. Moreover, we simulate the evolution processes of requesters and suppliers, and the results justify that the proposed RTRC can motivate users to select honest strategy and contribute accurate information for crowdsourcing system. For the future work, we will study the evolutionary game in more complicated scenario of crowdsourcing and design a common incentive mechanism for crowdsourcing system.

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