Advances in Complex Systems
Vol. 15, Suppl. No. 1 (2012) 1250056 (17 pages)

DOI: 10.1142/S0219525912500567

EFFECTS OF ENVIRONMENT KNOWLEDGE ON AGGLOMERATION AND COOPERATION IN SPATIAL PUBLIC GOODS GAMES

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Received 17 January 2012
Accepted 16 April 2012
Published 1 June 2012

Nowadays, our society is characterized by high levels of social cohesion and cooperation that are in contrast with the selfish nature of human beings. One of the principal challenges for the social sciences is to explain the emergence of agglomeration and cooperative behavior in an environment characterized by egoistic individuals. In this paper we address this long standing problem with the tools given by evolutionary game theory. Specifically, we explore a model in which selfish individuals interact in a public goods creation environment. As a further ingredient each agent is characterized by an individual expectation and, if unsatisfied, can change its location. In this scenario we study the effects of the knowledge of other players' performances on both cooperation and agglomeration and discuss the results in the context of previous and related works. Our results show that cooperation and agglomeration are generally robust against the inclusion of different information on other player performances and, in some cases, it can produce an enhancement of the cooperative behavior. Moreover, our results demonstrate that only in extreme and very competitive environments cooperation and agglomeration are lost.

Keywords: Evolutionary dynamics; public goods games; spatial games.

1. Introduction

Cooperation between unrelated agents (from bacteria to human societies) is ubiquitous in nature even when cooperative behaviors are clearly unfavorable and selfishness seems the best choice. This unexpected observation is one of the most fascinating challenges of Evolutionary Theory [1–4]. However, the recent financial crisis has highlighted that this cooperative behavior can be undermined by several factors i.e. an excessive complexity [5] and extremely aggressive behavior [6].

Recently, Evolutionary Game Theory [7–9] has firmly established as one of the most powerful tools for the study of the emergence and sustainability of cooperation and to analyze model societies in which individuals are driven by performance and selfishness. In particular, public goods games [10] is a classic paradigm for the study of social dilemmas that naturally arises in societies when group and individual interests differ and can result in the so-called "tragedy of the commons" [11, 12]. In the past years several enhancements to the classical public goods game in well-mixed populations have been proposed in the literature. Besides direct strategies like individual punishment for free-riding [13–16], the inclusion of a spatial structure in the contacts between individuals has proved to better reproduce real world scenarios. Specifically,taken into account the structure of the population from a simple grid [17, 18] to complex and heterogenous interactions, has proved to highly favor the emergence of cooperation and to sustain it also in adverse conditions [19–27]. Another important ingredient in our rapidly changing society is related to the mobility of individuals and the variability of the environment in which they act. These features have been recently incorporated to evolutionary models [28, 29], showing that in such scenarios, cooperation is also able to survive.

Here we exploit the public goods games formalism and spatial networks to study the evolution of cooperation and agglomeration under different environmental conditions including knowledge of other players' performances. Our purpose is to investigate the effect of different kinds of information about competing and neighboring players on the formation and stability of a cooperative and cohesive society. Specifically, we take as a starting point a model for spatial public goods games recently presented in the literature [30]. This model assumes a zero knowledge about other players' strategies and performances, and their behavioral rules are only based on actual and previous individual payoffs. In addition, unsatisfied players can change their location in the network trying to reach a more favorable neighborhood. In this setting two different social dilemmas arise: One represented by the game itself, and another one posed by the possibility of formation of strongly cohesive groups in which cooperation gives higher benefits but, due to larger group sizes, also defection is particularly favored.

We modify the model in [30] to include an increasing pressure by other players' performances to change individuals perceptions and decisions. To this end, we introduce the accomplishments of neighboring players in three different aspects of individuals behavior and decision process: The aspiration of each individual about future payoffs, the way in which persons define their satisfaction and, finally, the response to a dissatisfying environment/strategy. Our results show a substantial stability of cooperative behavior and, in some cases, a little knowledge of other players earnings and strategies, results in an increase in both cooperation and agglomeration of individuals. On the other hand our study highlights that an extremely competitive setting can strongly affect cooperation and a minimum cooperative level can only be achieved at the cost of higher levels of social instability. Finally, we think that the present results can shed some light on the formation of cohesive societies and also give some hints on how changes in individual behavior can lead to catastrophic social and economical events.

The work is organized as follows. In Sec. 2 we present the original model and the different modifications to include the effect of information about neighboring players. Section 3 is devoted to the presentation of the numerical models employed and, in Sec. 4 we discuss and analyze the results of the extensive numerical simulations. Finally, in Sec. 5 we draw our conclusions and future directions.

2. The Model

In the model firstly presented in [30] a population of N mobile agents is randomly distributed on a $L \times L$ square lattice with periodic boundary conditions. Assuring that $N < L^2$ the population density is $\rho = \frac{N}{L^2}$ and surely lower than one, allowing individuals to move from one site to another and occupy free sites within a certain range R. Each site in the lattice is connected with its Moore neighborhood $k = 8$ and so, depending on the number of occupied sites, each individual i can interact with $0 \leq N_i \leq k$ other players. In each neighborhood a round of a public goods game (PGG) is played, and each player participates in $N_i + 1$ different games: The one in which she is the focal player and the other N_i games from her neighbors. In a PGG round players can decide to contribute a fixed quantity c (that for simplicity we can set to 1) and thus cooperate (C) or act as free-riders and defect (D). Once the contributions of the cooperators are collected they are multiplied by an amplification factor r and then divided equally between all the participants independently of their strategy. In this scenario each player from each PGG round earns a payoff of $\pi_c = r\frac{n_c}{N_i} - 1$ if she is a cooperator or $\pi_d = r\frac{n_c}{N_i}$ if she defects, where n_c is the number of cooperators in the neighborhood and N_i the total size of i's neighborhood. For r greater than 1 we are in presence of a social dilemma because full cooperation is more convenient than full defection, although a defector in a group of all cooperators can exploit the maximum benefit. It is also important to notice that as mobility can change the size of the neighborhoods a second dilemma arises. In fact, in larger groups the obtained benefit depends more on other players strategies but, a larger neighborhood also means to get involved in more PGG rounds and thus potential higher benefits. In this framework the best possible society is constituted by highly dense groups that cooperate for the common wellbeing but, in this case, the temptation and the benefits of behaving as free-rider are the highest possible.

In the original model [30] the behavioral update rules (the changes in the strategy, cooperate or defect, and also in the position) are intended to take into account only the single individual wellbeing without considering her neighbors number and acquired benefits. Thus, the update rule is based on a measure of the satisfaction level of each individual and her aspirations for the future. Specifically, each player i calculates its own satisfaction $s_i(t)$ at time t as:

$$s_i(t) = \pi_i(t) - a_i(t) + \eta_i(t), \tag{1}$$

where $\pi_i(t)$ represents the total payoff earned by node i in the last round of PGGs, $\eta_i(t)$ denotes a Gaussian noise with zero mean value, and $a_i(t)$ stands for i's current aspiration level. If $s_i(t)$ is positive then the player is considered satisfied and she will maintain her previous strategy and position. On the other hand, when $s_i(t) < 0$ the player is dissatisfied and she will change her strategy and her position with a probability proportional to the amplitude of $s_i(t)$. In particular, to change the strategy or position of individuals two independent random numbers are drawn (one for the strategy and one for the position) and a change is made with probability:

$$\tanh(|s_i(t)|/k_{\max}), \tag{2}$$

where $|s_i(t)|$ is the absolute value of the satisfaction and $k_{\max}$ is the maximum possible size of the neighborhood. If a player decides to change her location she will move to a randomly chosen empty site in the network within a certain range R. In the satisfaction level of an individual an important role is played by her aspiration that represents a measure of how much a player is hoping to earn based on the knowledge of her previous payoffs and greediness. The aspiration $a_i(t)$ of player i is defined as:

$$a_i(t) = \alpha_i \pi_{i,\max}(t) + (1 - \alpha_i)\pi_{i,\min}(t), \tag{3}$$

where $\pi_{i,\max}(t)$ and $\pi_{i,\min}(t)$ denote the maximum and minimum payoffs perceived by each player in the previous games and incorporate a memory effect. α_i stands for the individual greediness level which lies between 0 and 1 allowing the aspiration level to vary between $\pi_{i,\max}(t)$ and $\pi_{i,\min}(t)$. To include a finite memory effect for the values of $\pi_{i,\min}(t)$ and $\pi_{i,\max}(t)$ a memory decay is introduced, so that at each time interval their values are updated according to:

$$\pi_{i,\max}(t+1) = \begin{cases} \pi_i(t) & \text{if } \pi_i(t) > \pi_{i,\max}(t) \\ \pi_{i,\max}(t) + \mu(\pi_i(t) - \pi_{i,\max}(t)) & \text{if } \pi_i(t) \leq \pi_{i,\max}(t), \end{cases} \tag{4}$$

and

$$\pi_{i,\min}(t+1) = \begin{cases} \pi_i(t) & \text{if } \pi_i(t) < \pi_{i,\min}(t) \\ \pi_{i,\min}(t) + \mu(\pi_i(t) - \pi_{i,\min}(t)) & \text{if } \pi_i(t) \geq \pi_{i,\min}(t), \end{cases} \tag{5}$$

where μ determines the memory effect of individuals and can be between 0 and 1. Initial values for $\pi_{i,\min}(0)$ and $\pi_{i,\max}(0)$ are chosen as the first payoff earned by player i.

It is worth noting that the present model only relies on individual's history and current satisfaction without considering the environment (the number and performances of neighboring agents) that surrounds each player and can influence her decisions. In particular, players behavioral rules, both the satisfaction and the aspiration, are entirely based on three factors: The actual, minimum and maximum payoffs of individuals and no external information is used to determine agents' strategy. This model has the advantage to count only on individuals situation but in most real cases it is unrealistic to think that individuals behavior is not influenced by the environment and the neighborhood that surround them. For these reasons in this paper we consider a series of modifications to the original model that incorporate in different ways the influence of neighborhood size and other player strategies in individuals behavioral rules. Our aim is to study the effects of environmental factors on the aspiration and satisfaction levels of the players and to analyze how these changes can affect the cooperation and agglomeration between greedy individuals. To do so here we introduce three different classes of modifications that impact the three principal components of the behavioral rules: The aspiration, the satisfaction and the rules governing the strategy's selection of each player.

2.1. *Class I*

In class I models we modify the evaluation of individuals aspiration levels to take into account the wealth of other players in the surroundings since the perception of the state of the neighborhood can alter individuals expectations. The main idea in this case is that not only the memory of previous earnings can define the aspiration of a player but also the previous payoffs of its neighbors. That is, an individual that always earned a low payoff but is located in a wealthy environment will have higher aspirations, and more likely will be unsatisfied, with respect to other individuals with the same minimum and maximum payoffs but located in a very poor neighborhood.

To implement the effects of the environment on the aspiration level of a player we define two strategies. In the first one we take as a reference the maximum and the minimum values of the payoff in the entire neighborhood. In the second one we consider the average payoff of the entire group. We named the first strategy model Ia and modify Eq. (3) as follows:

$$a_i(t) = \alpha_i \max_{j\in\mathcal{N}_i}[\pi_{j,\max}(t)] + (1-\alpha_i) \min_{j\in\mathcal{N}_i}[\pi_{j,\min}(t)], \tag{6}$$

where $\mathcal{N}_i$ is the set of all the players in the neighborhood of player i including i itself, that is, all the players that participate in the PGG round centered at node i. In this case, to calculate the aspiration level of each player, we consider the maximum and minimum payoffs in the entire neighborhood as reference.

In the second strategy, defined as Ib, we consider a not so extreme scenario in which, instead of taking into account the best and worst payoffs in the surroundings, each player calculates her aspiration using the average maximum and minimum payoffs in the neighborhood

$$a_i(t) = \alpha_i\langle\pi_{j,\max}(t)\rangle + (1-\alpha_i)\langle\pi_{j,\min}(t)\rangle, \tag{7}$$

where, also in this case, $j \in \mathcal{N}_i$, so j is one of all possible nearest neighbors of i, including i.

2.2. *Class II*

In the second class of models we not only consider the effects of other players as a pressure on the aspiration of the individuals, but we also take into account neighborhood effects on the satisfaction level of each player adopting Eq. (1) to include nearest neighbors' performances. This choice is the natural extension of class I models and also in this case we introduce two different implementations, namely: Models IIa and IIb. In both models we use Eq. (7) as our starting point for the calculation of the aspiration level but assuming that individuals' aspirations are influenced by the average value of the payoffs of their neighbors. In model IIa we introduce the perturbation in the satisfaction levels as the average earnings of the players in the neighborhood. Thus we substitute Eq. (1) by:

$$s_i(t) = [\pi_i(t) - \langle\pi_j(t)\rangle_{j\in\mathcal{N}_i}] - a_i(t) + \eta_i(t), \tag{8}$$

where $\langle\pi_j(t)\rangle_{j\in\mathcal{N}_i}$ denotes the average current payoff of all the nearest neighbors of player i. It is important to remark that such modification is much more restrictive than the original model since Eq. (8) implies that every player that in the last round of the PGG perceived a lower payoff with respect to the average of her neighbors very likely will be unsatisfied and thus she will change her strategy and/or location. Model IIa represents a very dynamic and competitive world in which individuals are not only driven by their personal greediness and aspirations but also by the not so noble intent of prevailing over other players.

As a further modification we also introduce model IIb in which not only the difference between individual and average neighbors payoffs is used but also the magnitude of aspiration is rescaled by the average aspiration level of the group. We modify Eq. (1) as follows:

$$s_i(t) = [\pi_i(t) - \langle \pi_j(t) \rangle_{j\in\mathcal{N}_i}] - |a_i(t) - \langle a_j(t) \rangle_{j\in\mathcal{N}_i}| + \eta_i(t), \tag{9}$$

where as in Eq. (8) $\langle \pi_j(t) \rangle_{j\in\mathcal{N}_i}$ is the average current payoff of the group, and $\langle a_j(t) \rangle_{j\in\mathcal{N}_i}$ is the mean aspiration value in the neighborhood centered at player i. Note that for the aspiration level we choose the absolute value of the difference introducing a *conforming* effect in which higher or lower aspirations are discouraged as they will end in a higher probability to be unsatisfied. With this latter change we are trying to reproduce an effect also observed in real societies in which individuals with very different aspirations with respect to the rest of persons in the same group are usually isolated.

2.3. *Class III*

In classes *I* and *II* models we acted on the two quantities that regulate the satisfaction of an individual and thus her willingness to change strategy or location. In the third class of models, named class *III*, we do not focus on the factors that can lead a player to modify her behavior but on the response that individuals have in front of dissatisfaction. In the original model once an individual judges her condition as unsatisfactory she decides to move or change her strategy with two independent random selection processes, one for the movement and one for the strategy, both based on the same probability $p = \tanh(|s|/k_{\max})$. In class *III* models we modify this random selection rule with two different implementations creating models $IIIa$ and IIb respectively.

In model $IIIa$ the aspiration and satisfaction levels are calculated according to Eqs. (1) and (3) as in the original model, but if $s_i < 0$ only one random selection is made regarding the location change to a new random location within a given movement radius R. In this case the random selection is conditional to the original probability $p = \tanh(|s|/k_{\max})$. Once a decision has been made about the site change, if the player did not change her location she will change strategy with probability $p_c = 1$ otherwise as she arrived in a new environment she will choose a strategy C or D with equal probability. Note that this strategy can be defined more *rational* than two different selection procedures. Admittedly if a player is unsatisfied and decide to stay at her place the only thing she can do to change her situation is to move to the opposite strategy, otherwise, if a player reaches a new environment, without a previous knowledge about other players, the two strategies have *a priori* the same probability of success.

In model $IIIb$ we adopt the same principles as model $IIIa$ but we suppose that, once a player enters a new neighborhood, she has the opportunity to know the wealth status of each individual at the new location and also their strategies. Thus, in model $IIIb$ we evaluate the aspiration and satisfaction of each player using Eqs. (1) and (3) and we calculate the probability of moving in the same way as model $IIIa$ but, if a player decides to change her location she has the opportunity to copy the best performing neighbor strategy, using the so-called "imitate the best" imitation rule.

3. Numerical Simulations

To assess the effectiveness of our assumptions about how players behavior is modified by external stimuli (neighbors performances and aspirations) we conduct extensive numerical simulations of the three classes of models. Our main purpose is to explore the stability of cooperative and aggregative behavior under the different modifications we introduced in the systems. To measure how the system responds to the two dilemmas, the one related with the PGG and the other related with the groups cohesion, we define three observables: (i) cooperation: Defined as the fraction of cooperators in the system at the steady state, (ii) agglomeration: Measured as the average number of neighbors of each player divided by the maximum possible number of neighbors, and finally (iii) social instability, that represents how often individuals change their positions, measured as the fraction of players that changed position in the last time-step.

To study the emergence of cooperation and its stability we start each numerical simulation with a population totally composed by defectors allowing the appearance of cooperation only by the effect of the noise η in Eqs. (1), (8) and (9). In the majority of our simulations we set the lattice side $L = 100$ creating an environment with $L \times L = 10^4$ possible positions and we set the number of individuals to $N = 5000$ resulting in a density of $\rho = 0.5$ and as mobility range we employ $R = 10$ although, as for the basic model, results are almost insensitive to changes in R. At each time-step simulations run as follows. Firstly, each player plays a PGG round in which she is the focal player and for all the rounds she earns a payoff. Then, according to the different models, each player evaluates her aspiration and satisfaction levels. Finally the update process starts. For the update process we choose an asynchronous method in which we select each player randomly, assuring that every individual is chosen exactly one time. Then, according to her satisfaction level, she decides to change game strategy and/or position. At the end of each time-step the payoff, satisfaction and aspiration are set to zero and the maximum and minimum payoffs at time t are updated following Eqs. (4) and (5).

4. Discussion

Figure 1 shows the typical time evolution of the three variables: Cooperation, agglomeration and social instability, for our implementation of the basic system in [30]. The main result of Fig. 1 is that, although in a moderate greedy setting ($\alpha = 0.3$), cooperation arises in a whole defectors' system and ends up colonizing around the 70% of the entire population; determining also an enhancement in the agglomeration. It is also important to notice the low social instability suggesting that most of the individuals are satisfied and did not change their positions.

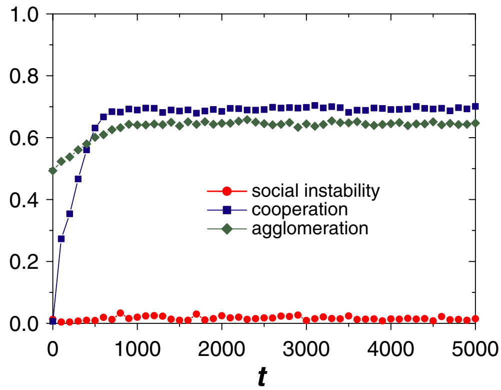

Fig. 1. Time evolution of social instability, cooperation and agglomeration for our implementation of the basic model in [30]. The model parameters are $L = 100$, $N = 5000$ leading to $\rho = 0.5$, $\alpha = 0.3$ the same for all individuals, $\eta = 0.1$, $\mu = 0.01$, $R = 10$ and the synergy factor $r = 5$.

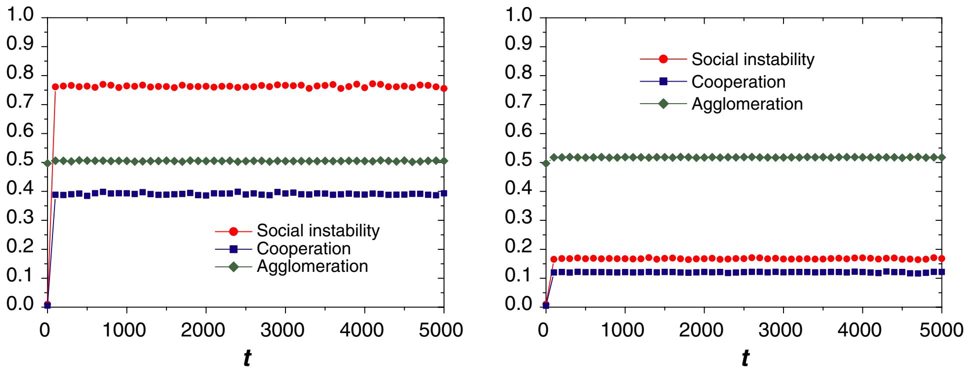

Fig. 2. **(models Ia and Ib)** Time evolution of social instability, cooperation and agglomeration for models Ia (left panel) and Ib (right panel). The model parameters are $L = 100$, $N = 5000$ leading to $\rho = 0.5$, $\alpha = 0.3$ the same for all individuals, $\eta = 0.1$, $\mu = 0.01$, $R = 10$ and the synergy factor $r = 5$.

In Fig. 2 the time evolution of the first class of models is showed. Results show that the inclusion of neighbors' performances in the aspiration level does not significantly alter the evolution of cooperation, demonstrating the stability of the cooperative behavior against external perturbations and, also in this case, the low levels of social instability remark the high satisfaction levels reached by the entire population. To have a detailed view of the effects of neighborhood influence on the aspiration levels Fig. 3 presents the results for the stationary state of the three quantities: Social instability, cooperation and agglomeration while varying the two parameters of model Ib: The individual greediness α and the PGG synergy factor r (similar results, not showed here, are obtained for model Ia). The results in Fig. 3 again demonstrate the extreme stability of cooperative behavior for model Ib and

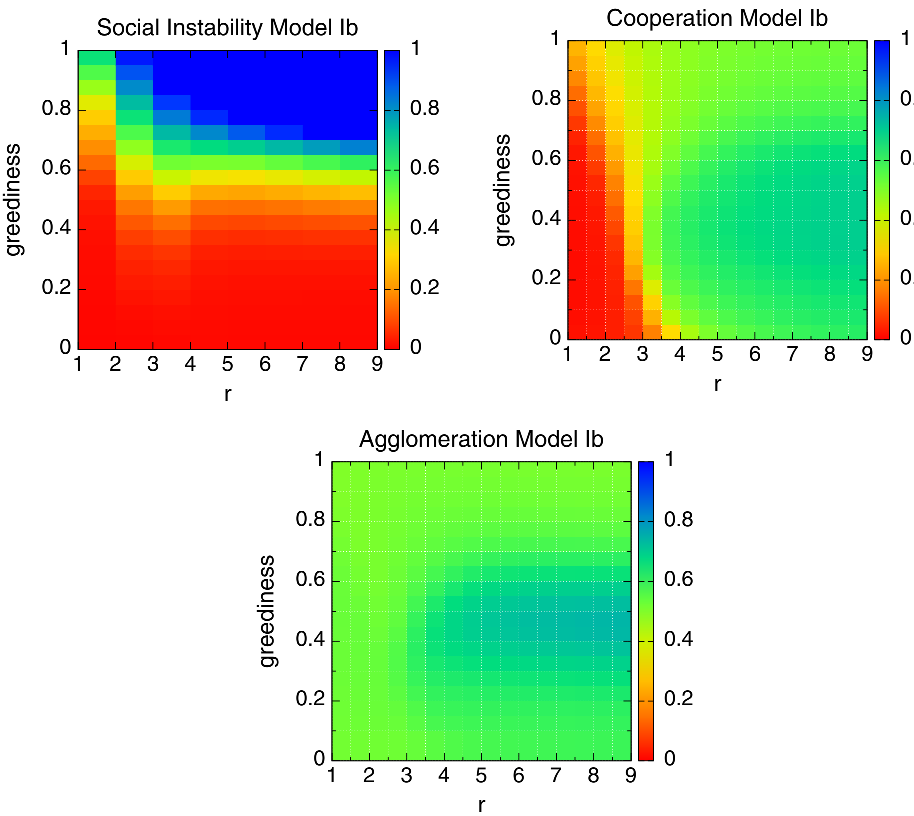

Fig. 3. Color map representing social instability (left), cooperation (right) and agglomeration (down) at the stationary state for model Ib as function of α and r. All other parameters are the same as in Fig. 2. Each point is an average over 10^2 realizations.

the low social instability also in settings where cooperation is highly discouraged like low r values and very high greediness. The strong similarities between the results obtained for the basic model and the ones of models Ia and Ib suggest that in the basic model an indirect evolutionary pressure is at work favoring the formation of dense clusters, mainly formed by cooperators, with similar aspirations and satisfaction. To test this hypothesis, it could be helpful to have a more detailed look of the system organization at the stationary state. Figure 4 presents a snapshot of the final state reached by the system in models Ia and Ib in which cooperators are depicted in blue and defectors in red. Also at the microscopic level the basic system (Fig. 1 in [30]) and models Ia and Ib show a high level of similarity corroborating the hypothesis that in both cases agents tend to form clusters with similar features reducing the effects of the modifications of class I that explicitly introduce a mechanism that is in some sense already present in the basic model. It is important to stress that similar effects are present also in real world societies where individuals of the same social class and with similar backgrounds form highly cohesive groups.

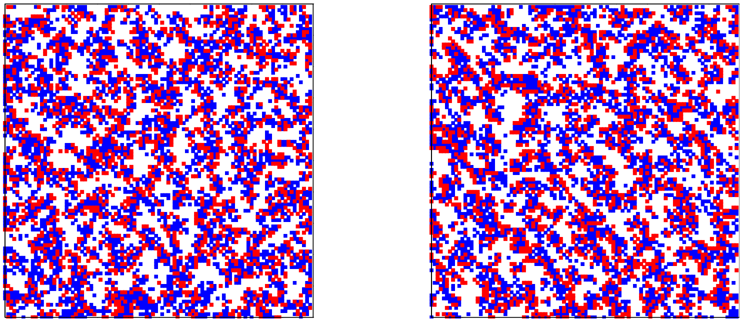

Fig. 4. (Color online) **(models Ia and Ib)** Snapshot of the stationary state (cooperators are in blue and defectors are in red) for models Ia (left panel) and Ib (right panel). The model parameters are $L = 100$, $N = 5000$ leading to $\rho = 0.5$, $\alpha = 0.3$ the same for all individuals, $\eta = 0.1$, $\mu = 0.01$, $R = 10$ and the synergy factor $r = 5$.

Once we have demonstrated the stability of the cooperative behavior when individuals' aspiration is affected by neighboring players we move to an extreme and very competitive environment in which besides the aspiration levels also the satisfaction is altered by other player earnings. Specifically in model IIa an individual probably will be unsatisfied if her payoff is lower than the average payoff of the neighborhood introducing a competition between individuals. In model IIb also the mean aspiration level comes in the evaluation resulting in a standardization effect. Results presented in Fig. 5 show how an extremely aggressive behavior can be detrimental for cooperation levels leading to a substantial decrease of cooperative behavior in both cases. Another striking result is represented by the effect of the so-called *standardization* strategy. In fact in model IIa although individuals

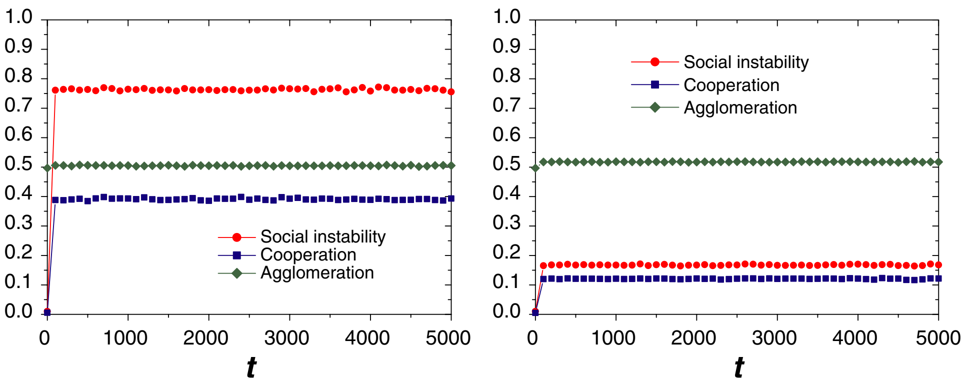

Fig. 5. **(models IIa and IIb)** Time evolution of social instability, cooperation and agglomeration for models IIa (left panel) and IIb (right panel). The model parameters are $L = 100$, $N = 5000$ leading to $\rho = 0.5$, $\alpha = 0.3$ the same for all the individuals, $\eta = 0.1$, $\mu = 0.01$, $R = 10$ and the synergy factor $r = 5$.

are often unsatisfied (i.e., high levels of social instability) they still can maintain a minimum of cooperation rapidly changing their position. In model *IIb* instead, the addition of a conformation effect leads to a reduction of individuals movement (and thus to a general satisfaction) and a drastic decrease of cooperation levels causing the appearance of a society of opportunistic individuals that are, in general, satisfied. Results of Fig. 5 are confirmed in general in all the parameter space α and r (Fig. 6) in which minimal levels of cooperation are observed only for higher values of the synergy factor r and the minimum possible level of agglomeration is reached for the parameters' combinations.

Other interesting insights came from the microscopic organization of the agents at the steady state. Figure 7 shows that for both models agents distribute to occupy the entire environment and reach very sparse configurations (the minimum possible value for agglomeration is 0.5) in which large cohesive groups disappear and cooperation can only survive in small clusters usually surrounded by free-riders. This effect is even amplified in model *IIb* in which, in addition to a very competitive

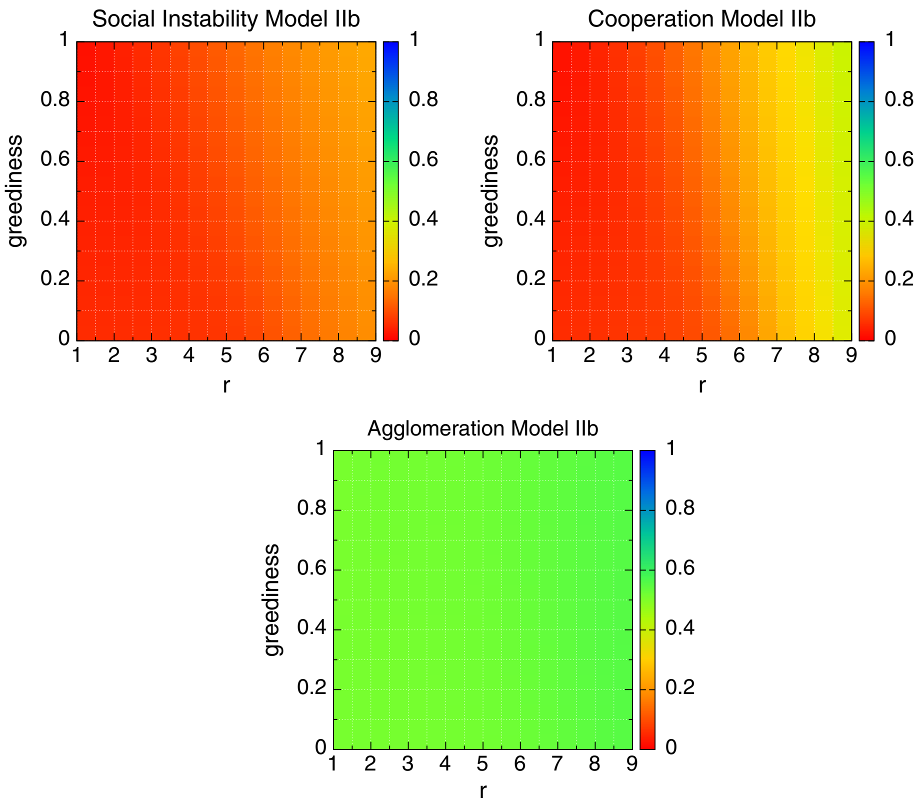

Fig. 6. Color map representing social instability (left), cooperation (right) and agglomeration (down) at the stationary state for model *IIb* as function of α and r. All other parameters are the same as in Fig. 5. Each point is an average over 10^2 realizations.

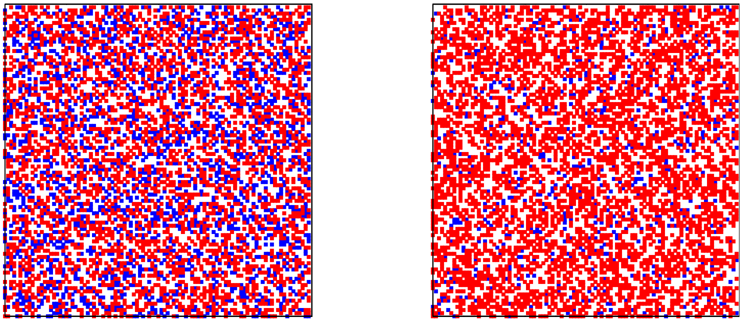

Fig. 7. (Color online) **(models** IIa **and** IIb**)** Snapshot of the stationary state (cooperators are in blue and defectors are in red) for models IIa (left panel) and IIb (right panel). The model parameters are $L = 100$, $N = 5000$ leading to $\rho = 0.5$, $\alpha = 0.3$ the same for all the individuals, $\eta = 0.1$, $\mu = 0.01$, $R = 10$ and the synergy factor $r = 5$.

behavior, a conformation effect is included. On a global perspective results for class II suggest that one of the possible causes for the end of large societies is an excessive competition between its individuals that can lead to the tear of large groups that favor the emergence of cooperation.

We conclude our analysis with the third class of models in which instead of modifying the conditions for individual satisfaction and aspirations we revise the behavior of unsatisfied players. Figure 8 presents the time evolution of three observables: Social instability, cooperation and agglomeration for models $IIIa$ and $IIIb$ respectively. In this case, as for class I models we observe a substantial stability of cooperation and, especially for model $IIIb$, in which the knowledge of other players' performances is used to copy the best strategy, a sensible growth in cooperation and agglomeration is observed with a minimum level of social instability. As in the

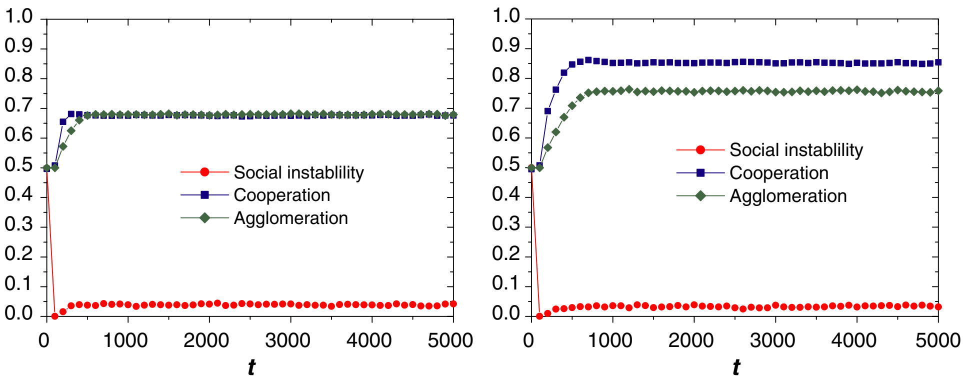

Fig. 8. **(models** $IIIa$ **and** $IIIb$**)** Time evolution of social instability, cooperation and agglomeration for models $IIIa$ (left panel) and $IIIb$ (right panel). The model parameters are $L = 100$, $N = 5000$ leading to $\rho = 0.5$, $\alpha = 0.3$ the same for all the individuals, $\eta = 0.1$, $\mu = 0.01$, $R = 10$ and the synergy factor $r = 5$.

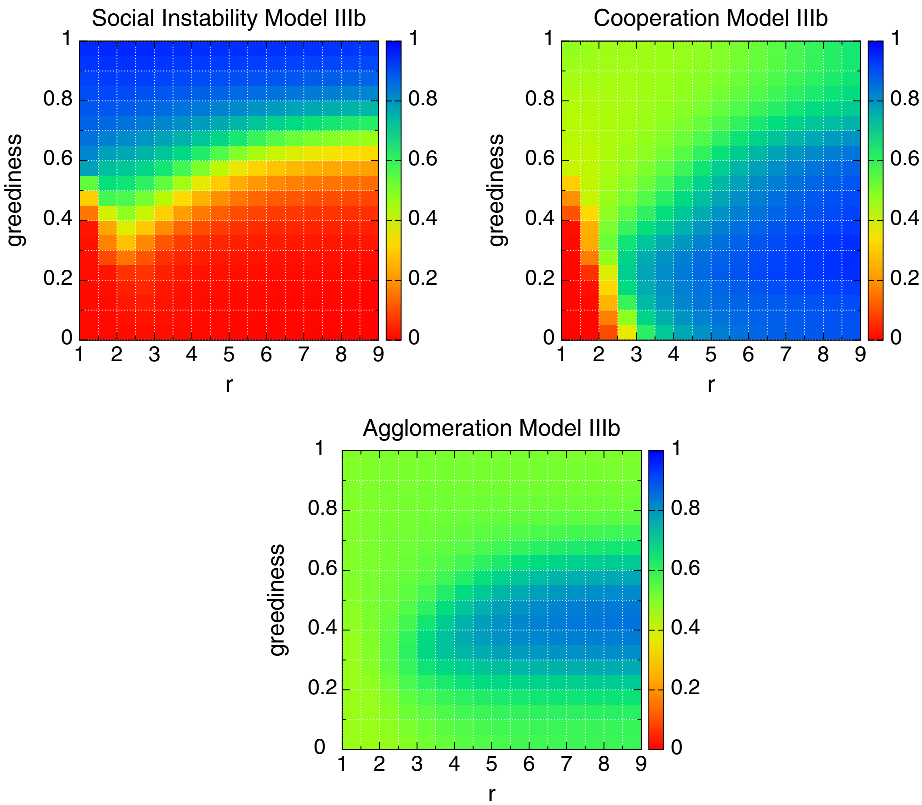

Fig. 9. (Color online) Color map representing social instability (left), cooperation (right) and agglomeration (down) at the stationary state for model *IIIb* as function of α and r. All other parameters are the same as in Fig. 8. Each point is an average over 10^2 realizations.

previous cases, Fig. 9 shows the stationary behavior of model *IIIb* for parameters α and r. The general enhancement of cooperation is confirmed with respect to the basic version in [30] and model *Ib*. Another important result highlighted in this figure is the fact that also in the presence of higher social instability, i.e., low r and high greediness α, cooperation reaches a considerable level. It is also worth noticing that changes in model *IIIb* only affect the strategy of an individual when she modifies her location and does not act in other points in the satisfaction evaluation process, highlighting that once a certain level of cooperation has been reached the system is able to maintain it. The higher cooperation and agglomeration levels are also reflected in agents' spatial organization as showed in Fig. 10 where, especially for model *IIIb*, very large groups of cooperators appear leading to the creation of an almost connected single giant component. These latter results highlight once more that agglomeration and cooperation are strictly related and agglomeration is a fundamental ingredient for the emergence of cooperative behavior.

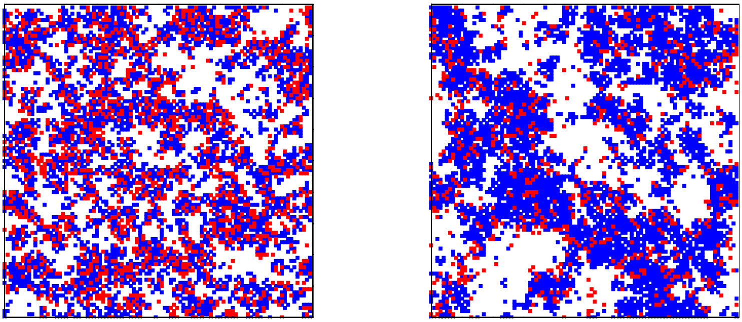

Fig. 10. (Color online) **(models $IIIa$ and $IIIb$)** Snapshot of the stationary state (cooperators are in blue and defectors are in red) for models $IIIa$ (left panel) and $IIIb$ (right panel). The model parameters are $L = 100$, $N = 5000$ leading to $\rho = 0.5$, $\alpha = 0.3$ the same for all the individuals, $\eta = 0.1$, $\mu = 0.01$, $R = 10$ and the synergy factor $r = 5$.

5. Conclusions

In summary, in this paper we have studied how the knowledge of other players' earnings and strategies can affect the evolution and stability of cooperation on a minimal society model in which individuals interact via PGG and are free to change their locations when they are unsatisfied. We took as a reference a model for the creation of public goods in a minimum information scenario in which players can only percept their aspiration and satisfaction ignoring other players performances and behavior. In this context we modify individuals' behavioral rules to include the payoffs and aspirations of neighboring agents. To do so we create three different classes of modifications to the original model in which we address the three main characteristics of the behavioral rules: The evaluation of individuals' aspiration and satisfaction levels and how players react once they are dissatisfied.

We studied the behavior of the three classes of models by means of extensive numerical simulations. In particular, we focused on the two social dilemmas that arose in the models: The emergence of cooperation and the agglomeration of individuals in large neighborhoods. Our results demonstrate that the inclusion of different types of knowledge on other players in many cases does not alter the stability of the cooperative behavior and sometimes can produce an enhancement of cooperation and agglomeration. Specifically, model $IIIb$ demonstrated that a little knowledge of new neighbors' conditions can produce an increase in the cooperation levels. Of interest also are the results of model IIa in which players are designed to be very competitive. Although a sensible decrease in the cooperation is observed, the system is able to maintain a reasonable level of cooperation at the cost of a higher social instability. In addition the proposed model and its variations have demonstrated to be able to reproduce some of the features typical of human societies like the formation of groups of individuals with similar aspirations or the collapse of such groups due to excessive competition between their components.

Concluding, our results indicate that the interplay between self-learning rules and environmental factors can be one of the primary ingredients for the emergence and stability of cooperative behavior and they can explain the rise and the fall of complex human societies.

Acknowledgments

C-Y. Xia is partially supported by the National Natural Science Foundation of China under Grant No. 60904063, Tianjin Municipal Natural Science Foundation under Grant No. 11JCYBJC06600 and the 7th Overseas Training Project for the Young and Middle Teachers in Tianjin Municipal Universities. S.M. is supported by the Spanish Ministry of Science and Innovation (MICINN) through project FIS2009-13364-C02-01. Y. M. is supported by the Spanish MICINN through projects FIS2008-01240 and FIS2009-13364-C02-01 and by the Government of Aragón (DGA) through a grant to FENOL.

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