A Memetic Framework for Describing and Simulating Spatial Prisoner's Dilemma with Coalition Formation

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ABSTRACT

This paper presents a framework for describing the spatial distribution and the global frequency of agents who play the spatial prisoner's dilemma with coalition formation. The agent interaction is described by a non-iterated game, where each agent only locally interacts with its neighbours. Every agent may behave as a defector or a cooperator when playing isolated, but they can join or lead coalitions (group of agents) where a leader decides the coalition strategy. Isolated agents' strategies or groups' strategies are public and therefore can be memetically imitated by neighbours. The agent strategy is selected between two possibilities: probabilistic Tit-for-Tat (pTFT) or learning automata (LA). Coalition dynamics are organized around two axes. On the one hand, agents get a percentage of compromise when cooperating with other agents. On the other hand, leaders impose taxes to the other agents belonging to its coalition. These two rules and their related parameters guide the coalition formation and the game evolution. The main contribution of the paper is the framework for memetic analysis of coalition formation in spatial prisoner's dilemma. This work also includes simulation results on a lattice showing that the pTFT memetic approach becomes more effective than an isolated learning policy.

Categories and Subject Descriptors

J.4 Social and Behavioral Sciences. I.2.11 Distributed Artificial Intelligence. K.6.0 Economics

General Terms

Economics, Experimentation

Keywords

Evolutionary Game Theory, Spatial Prisoner's Dilemma, Memetics, Coalition Formation

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1. INTRODUCTION

Game theory [1] provides useful mathematical tools to understand the possible strategies that self-interested agents may follow when choosing a course of action. The context of cooperative games and cooperation evolution has been extensively studied seeking general theoretical frameworks like the Prisoner's Dilemma (PD) [2]. In his seminal work, Axelrod has shown that cooperation can emerge in a society of individuals with selfish motivations. Since that, Game Theory and the Generalized Prisoner's Dilemma have been applied in biological, social, economical and ecological contexts [3, 4]. An interesting spatial version of the PD had been suggested and deeply analyzed by Nowak and other authors [7, 20, 21] trying to understand the role of local interactions in the maintenance of cooperation.

Among the areas for applying game theory and PD models we may cite Peer-to-Peer (P2P) systems [5, 13], for instance BitTorrent [6] considers the popular Tit-for-Tat strategy [2]. In P2P, and many other complex systems, appears one of the main problems concerning sustainability denoted by the Tragedy of Commons [8]. This problem arises when people, villages, states or P2P nodes generally defect and the system suffers a collapse since there is no mechanism to enforce collective rewards, and every member shows an exclusively selfish behaviour and general defection. As a result we may notice a reduction of biodiversity, overpopulation, war, and many other social problems. Following [8], a major route to prevent the tragedy of commons is the emergence of leaders from a set of previous independent elements.

This paper focuses on the spatial interaction along generations of cooperators and defectors by means of computer simulations and Evolutionary Game Theory [14]. We agree with Axelrod [8] in that although the topic being investigated may be complicated, the assumptions underlying the agent-based model should be simple when our goal is to understand fundamental processes. This approach is followed all along this paper.

We consider an agent population placed on a square lattice and simulate the dynamics of the population by means of agent cells. The interaction between the agents is modelled as an n-person game, i.e. n agents interacting simultaneously. Every agent may behave as a defector or a cooperator when playing isolated, but they also can join or lead coalitions (group of agents) where a leader agent decides the group strategy. Isolated agents' or groups' strategies are public and therefore can be memetically imitated by neighbours. Coalition dynamics are organized around compromise among agents and the tax that the leader imposes to the agents that belong to its coalition.

Increasing the organization level concerns multiple complex and natural systems [8], for instance, how biological systems made the transition from single-celled organisms to multiple-celled organism [9] or how brains organize individual neurons into meaningful structures [10].

The remainder of the article is structured as follows. Section 2 introduces the concepts or Evolutionary Game Theory and Memetics, related with the proposed model. Section 3 presents the multi-agent scenario considered in this work. Section 4 describes the agent strategies considered for the game. Section 5 shows the simulation results obtained. Finally, section 6 points out the conclusions.

2. EVOLUTIONARY GAME THEORY AND MEMETICS

This section introduces two important concepts related with the work discussed in the rest of the paper. The first is Evolutionary Game Theory that describes the interaction of strategies in populations along generations. The second is Memetics which describes imitation strategies in populations and games.

2.1 Evolutionary Game Theory

Evolutionary game theory (EGT) [14] models the application of interaction dependent strategies in populations along generations. EGT differs from classical game theory by focusing on the dynamics of strategy change more than the properties of strategy equilibrium. EGT has become of increased interest to economists, sociologists, anthropologists, and philosophers [1].

In game theory and behavioural ecology, an evolutionarily stable strategy (ESS) [14] is a strategy which, if adopted by a population of players, cannot be invaded by any alternative strategy. An ESS is a Nash equilibrium which is "evolutionarily" stable meaning that once it is fixed in a population, natural selection alone is sufficient to prevent alternative (mutant) strategies from successfully invading.

In evolutionary games, participants do not posses unfailing Bayesian rationality. Instead they play with limited computing and memory resources. All the requirement is that the players learn by trial and error, incorporate what they learn in future behaviour, and die or somehow “change” if they do not.

2.2 Memetics

In The Selfish Gene [11], Dawkins proposes that social ideas, what he calls “memes,” are a non-organic replicator form. His examples of memes include tunes, catch-phrases, taboos, and fashions among others. In Dawkins’ view, the fundamental characteristics of life are replication and evolution. In biological life, genes serve as the fundamental replicators; while in human culture, memes are the fundamental ones. Both genes and memes evolve by mutation-coated replication and natural selection of the fittest. The memetic theme has found popularity in several fields [12, 15, 16]. Especially interesting have been the approach denoted by Memetic Algorithms (MA) which represent one of the recent growing areas of research in evolutionary computation. The term MA is now widely used as a synergy of evolutionary or any population-based approach with separate individual learning or local improvement procedures in Optimization Methods (Global Search, Pareto Search, etc.). The tutorial [17] provides an introduction and [18] recent results.

In the memetics model, less successful individuals and groups within a population imitate the behaviour of the more successful peers in order to improve their competence for resources. Accordingly, the more above average an individual is, the more others copy his behaviour. As a result, the population establishes and self-enforces over time standards of normal behaviour. Normal behaviour may either be time-independent or it may cycle through a range of behaviours. Memetics belong to evolutionary games because the evolutionary process is essentially a scenario of replication dynamics based on survival of the fittest [14].

3. MULTI-AGENT SYSTEM

The approach we follow in this paper is a composite spatial game where actions are effectively simultaneous but every agent may interact with several neighbours at a time. We consider a spatial structure of the population, i.e. if the interaction between agents is locally restricted to their neighbours; then, a stable spatial coexistence between cooperators and defectors becomes possible under certain conditions. The approach presented here is based and extends the works in [7, 8, 20].

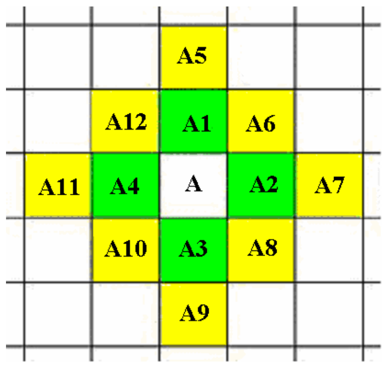

Figure 1. Cell agent (A) and two neighbourhoods (first with 4 cells {A1,…,A4} and second with 12 cells {A1,…,A12}

3.1 Spatial Distribution

For the spatial distribution of the cells we consider a two-dimensional square lattice consisting of N nodes (see figure 1). Each cell is ruled by an agent and it will follow one of the two basic strategies: defection (D) or cooperation (C). Figure 1 shows cell agent A and two possible neighbourhoods. Thus, there are both local and spatial interactions between neighbour cells. If we let every node in the system to interact with the remaining $(N-1)$ nodes, we have a panmictic population. But, in many real contexts like politics, biology or user networks [13]; each node interacts mainly with its neighbours. Thus, we consider that each cell agent Ai only interact with the cells in its neighbourhood, whose size may be increased or reduced depending on the neighbourhood radio (NR).

3.2 Basic Game Rules

The game rules assume that each agent Ai has two options to act in a given situation: to cooperate (C) or to defect (D). Playing against agent Aj, the outcome of this interaction depends on the action chosen by agent Ai, without knowing the action chosen by the other agent participating in a particular interaction of the game. This game can be described by a payoff matrix, which for the 2-person game has the form that appears in figure 2 (left).

Ai \ Aj	C	D
C	R, R	S, T
D	T, S	P, P

Ai \ Aj	C	D
C	**3, 3**	**0, 5**
D	**5, 0**	**1, 1**

Figure 2. 2-person game matrix (left) and Prisoner's Dilemma classical game matrix (right)

Suppose, agent Ai has chosen to cooperate, then its payoff is R if the other agent Aj has also chosen to cooperate (without knowing about the decision of agent Ai), but S if agent Aj defects. On the other hand, if agent Ai has chosen not to cooperate, then it will receive the payoff T if agent Aj cooperates, but P if agent Aj defects too.

Depending on the values of T, R, P, and S we have several types of 2-person games. In the famous Prisoner's Dilemma (PD), the payoffs have to fulfil the following two inequalities:

$$T > R > P > S \quad (1)$$

$$2R > S + T \quad (2)$$

The known standard values are T = 5, R = 3, P = 1, S = 0 (see figure 2, right). This means in a cooperating environment, a defector will get the highest payoff. From this, the abbreviations for the different payoffs become clearer:

- T means *Temptation* payoff for defecting in a cooperative environment,
- S means *Sucker'* payoff for cooperating in a defecting environment,
- R means *Reward* payoff for cooperating in a likewise environment, and
- P means *Punishment* payoff for defecting in a likewise environment.

In any one round (or "one-shot") game, choosing action D is a Nash equilibrium [1], because it rewards the higher payoff for agent Ai whether the opponent chooses C or D. At the same time, the combined payoff for both agents Ai and Aj is maximized if both cooperate.

A simple analysis shows that defection is a so-called evolutionary stable strategy (ESS) in a one-shot PD (see [1,14]). This conclusion holds for a so called panmictic population where each agent interacts with all other (N – 1) agents. But in this paper, we are mainly interested in the spatial effects of the PD game [20]. Therefore, let us assume that each agent Ai interacts only with the m agents of its neighbourhood. In evolutionary game theory this is called a m-person game, where n = m + 1 in the given case. Each game is played between n players simultaneously, and the payoff for each player depends on the number of cooperators in its neighbourhood. At the beginning of every new round the payoff of every cell of the lattice is reset to zero.

3.3 Agent Roles

In [7, 20] every agent may behave as a defector or a cooperator playing isolated, but in the work presented here agents can join to create coalitions (group of agents) leaded by only one agent cell (agent leader) that decides the group strategy. Isolated agents strategies and coalition strategy are public and therefore can be memetically imitated by its neighbour cells.

This approach has some common points with Holonic MAS [19], where an agent is the holon head of the cluster, while the rest of agent cells become its holon parts. Nevertheless, in this work we only have a two level hierarchy and there are no sub-holons within a holon; so from now on the terminology will be the coalition leader (for an agent cell leading a group) and the coalition part (for an agent cell belonging to a group).

Therefore, there are three possible roles in our MAS:

1. *Independent cells*: ruled by its own agent that may behave as a cooperator or a defector with its neighbours depending on its own decisions and imitation. They can join to a group in their neighbourhood or remain independent (see section 4).
2. *Coalition part cells*: these are the cells that belong to a coalition and let all the decisions about their strategy to its coalition leader. They can become independent whenever their agents desire.
3. *Coalition leader cells*: a cell leading a coalition (group of cells) decides the common strategy for the next turn. Leaders impose that all the cells within a coalition must cooperate among themselves. A leader can not decide its on independence but can apply a tax percentage to the income of its coalition part cells.

3.4 Coalition Formation

The model for coalition formation comes from [8] and, in this paper, it is adapted to a spatial PD game, and it works as follows. Any cell agent Ai increases its percentage of compromise with a neighbour agent Aj in 10% whenever Aj behaves as a cooperator, or reduces its compromise in 10% whenever Aj behaves as a defector.

When a cell belongs to a coalition, then it behaves cooperative with the other cells of the coalition, and as its leader decides (cooperative or defective) with the cells outside the coalition.

The rules governing coalition formation appear in table 1 for any cell agent Ai which is not a leader, i.e., Ai is independent or belongs to a coalition. In table 1 Am is the neighbour agent with the maximum payoff (income).

Table 1. Agent rules for coalition formation and independence

```
1   IF ( HasLeader (Ai) )
2    {
3    IF ( IsIsolated (Ai) )
4        GetIndependence (Ai);
5    ELSE IF ((PayOff (Ai) >= PayOff (Am)) AND (PayOff (Ai) > 0))
6        ChangeCompromiseWithLeader (+10);
7    ELSE IF ((PayOff(Ai) < PayOff(Am)) AND (Leader(Ai) != Am))
8        {
9        ChangeCompromiseWithLeader (-10);
10       IF ( WorstPayOff (Ai) OR (CompromiseWith (Am) > 75) )
11            JoinCoalition (Am);
12       ELSE IF ( (NOT HasLeader (Am)) AND
13                 (CompromiseWithLeader (Ai) < 25) )
14            GetIndependence (Ai);
15       }
16   }
17  ELSE IF (IsIndependent (Ai))
18    IF (  WorstPayOff (Ai) OR
19       ( (PayOff(Ai) < PayOff(Am) ) AND CompromiseWith (Am) > 75 ) )
20           JoinCoalition (Am);
```

Table 1 algorithm may be explained as follows. There are two alternatives, either agent Ai has a leader (line 1) or agent Ai is independent (line 17).

If agent Ai has a leader (i.e., belongs to a coalition) then three possibilities are checked. First, if agent Ai is isolated (line 3) then it becomes independent. This situation models when there is no other cell belonging to its coalition in its neighbourhood. Of course, this rule supports the existence of cell groups (islands or colonies) isolated from a bigger coalition.

Second, if agent Ai is not isolated (line 5), and the Ai's payoff is the best in its neighbourhood and greater than zero, then Ai increases its compromise with its leader by 10%. Third, if Ai's payoff is not the best (line 7) and its leader is not Am, then Ai may take several decisions. First, Ai reduces its compromise with its leader by 10% (line 9). If Ai's payoff is the worst in its neighbourhood, or its compromise with Am is greater than 75% (line 10); then it joins the coalition of Am (note that Am may or may not be the leader). Otherwise, if Am is an independent cell and the Ai's compromise with its leader is lower than 25% (lines 12-13) then it declares independence (line 14).

Finally, if Ai is independent (line 17) and either, it has the worst payoff or it is not the best but its compromise with Am is greater than 75%, then it joins the coalition of Am.

3.5 Leader's Tax

As stated before, a leader can apply a tax percentage to the income of its coalition part cells. This means that becoming a leader means increasing the own income in an amount, which depends on: the tax percentage, the number of cells leaded in the coalition, and the income of the leaded cells.

A higher leader's tax means more revenues in the short term, but this may causes bankrupt for the leaded cells that may chose independence.

3.6 Game Matrix

Axelrod in [8] describes a game named "*pay or else*" where a random chosen actor A may ask for a tribute of 250 wealth units to another actor B. Then actor B may pay the tribute or fight, if B chooses to fight, then each actor loses the 25% of the *other* side's wealth. In case of fighting, "… both sides suffer, but the stronger side imposes more damage than the weaker side does".

In the simulation presented here, we consider this interesting approach, but adapting it to the spatial PD game with coalition formation. Thus we keep the matrix shown in figure 1, but in the case of the Sukers'(S) and Punishment (P) payoffs; they are influenced by the natural logarithm of the number of cells in the opponent coalition as:

$$Si = S - \ln (size\ (coalition\ (Aj)\ )\ ); \qquad (3)$$

$$Sj = S - \ln (size\ (coalition\ (Ai)\ )\ ); \qquad (4)$$

$$Pi = P - \ln (size\ (coalition\ (Aj)\ )\ ); \qquad (5)$$

$$Pj = P - \ln (size\ (coalition\ (Ai)\ )\ ); \qquad (6)$$

Where Si and Sj are respectively: the sukers' payoff for agent Ai and agent Aj. The same stands for the punishment payoffs Pi and Pj. This means that we can have negative values in the matrix and that the bigger the group, the higher the lost it causes in an opponent when defecting. On the other hand, having a higher group does not enhance the benefit of cooperation.

4. MANAGING STRATEGIES

The agent strategy describes how the cell behaves in every turn, i.e., when it plays a round of the spatial PD game with its neighbours. There are three cell situations: the cell is independent, the cell belongs to a coalition or the cell leads a coalition.

1. *Independent cell*: if the cell is independent, then its agent decides its next turn strategy depending on the strategy type it has (see next subsections).
2. *Coalition cell*: if the cell belongs to a coalition then it behaves cooperatively with the coalition members and follows the coalition leader strategy with the outside cells.
3. *Leading cell*: if the cell leads a coalition then it imposes to all the cells in its coalition to be cooperative among them, and decides the foreign policy of the coalition against other independent cells or coalitions.

For managing the agent strategies we explore two possibilities: probabilistic Tit-for-Tat (pTFT) and learning automata (LA). They are described in the next subsections.

4.1 Probabilistic Tit-for-Tat (pTFT)

This is a probabilistic extension of the Tit-for-Tat (TFT) strategy and used only by independent cells. Classical TFT [1] initially behaves cooperative, then selects the same action that the opponent chose in the previous round. Thus, TFT is a pure memetic strategy as it imitates the behaviour of the opponent in the last round. In probabilistic Tit-for-Tat (pTFT), the agent considers the actions chosen by its set of neighbours in the previous round and imitates the majority with the probabilistic approach that appears in table 2.

Table 2. Probabilistic TFT strategy

```
IF (random () < (NumDefectNeighbours (t-1) / NumNeighbours) )
   NewAction (D);        // Defect
ELSE
   NewAction (C);        // Cooperate
```

In the special case that the agent is a leader, then it always defects other cells which do not belong to its coalition, and the same is exactly done by its coalition cells.

This strategy management is imitative, i.e., memetic; as the agent imitates the most popular strategy in its neighbourhood.

4.2 Learning Automata (LA)

In the case of learning automata, the agent just considers its history defecting or cooperating and selects his next strategy depending on its experience and payoffs. We use the next two very simple rules [22]:

$$\text{ProbStrategy}[A] = \text{ProbStrategy}[A] + \alpha \,.\, (1.0 - \text{ProbStrategy}[A]); \quad (7)$$

$$\text{ProbStrategy}[B] = (1 - \alpha) \,.\, \text{ProbStrategy}[B]; \quad (8)$$

In these equations (α) is a small learning factor. Rule (7) is used to reinforce the best average strategy over the past (h) rounds. Therefore (A) is supposed to be such better strategy (either defect (D) or cooperate (C)). At the same time, we apply rule (8) to the other strategy, decreasing its probability. In the next round, the agent will chose its new strategy using the updated probabilities.

Note that here, a coalition may collaborate with other outside cells or coalitions. This situation does not happen in the pTFT case, as the leader may be surrounded by its own coalition cells, and therefore can not imitate outside cells.

5. SIMULATION RESULTS

This section presents the results of an extensive set of simulations done with the multi-agent system and the strategy management introduced in the two previous sections, attending to the variation of several simulation parameters.

In all simulations we consider a square lattice of 40 x 40 = 1600 square cells. When starting, every agent cell selects randomly its strategy and tax (to be applied to others if sometime it rules a coalition). This tax only changes randomly when a cell gets independence (assuming it has not been very useful in the past). The game matrix used in all these simulations is the standard PD matrix that appears in figure 2 (right). Every new round, the income of every cell in the lattice is reset to zero (no accumulation of payoffs).

All simulations have been done in Java, running on a PC (Pentium VI dual-core with a memory of 3 GB) and usually taking less than 1 minute per execution (from a hundred to a thousand rounds to achieve stability). Every simulation has been performed several times; in the next subsections the figures correspond to an average result.

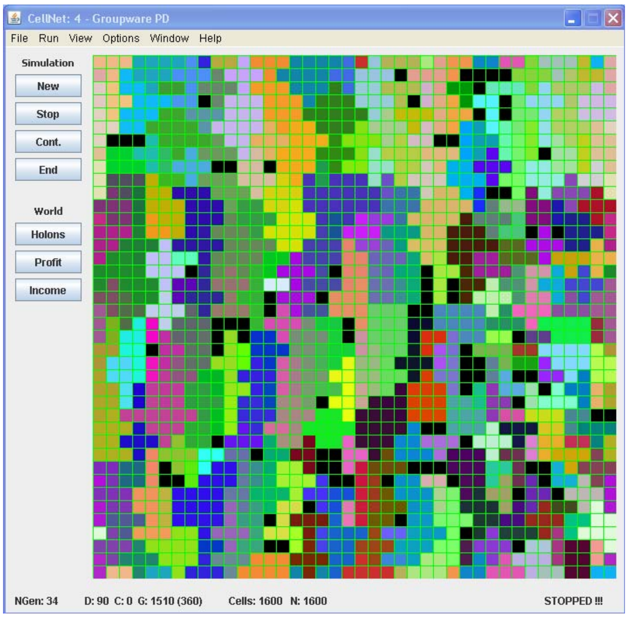

Figure 3. Snapshot of the Java simulator

First, we consider a pure memetic scenario where all cell agents use the pTFT strategy. Under such framework, we can see the influence of the neighbourhood radio and mutation parameters. Then we describe the results for the isolated scenario (LA strategy). Finally, we consider a more complex scenario, where the two management strategies (pTFT and LA) coexist, and the agents may choose among them; depending on which one has been chosen by their neighbours.

5.1 Imitation Scenario (pTFT)

The imitation scenario corresponds to the Probabilistic Tit-for-Tat strategy described in section 4.1.

5.1.1 Neighbourhood Radio Parameter

The neighbourhood radio (NR) parameter determines the number of neighbours a cell has. For instance, in figure 1, a radio of 1 unit determines a neighbourhood of four cells; a radio of 1.5 units sets eight cells and a radio of 2 units provides 12 cells.

A snapshot of the Java simulator appears in figure 3, using the pTFT strategy, and showing a typical run stopped after 34 rounds with 90 defectors (D), zero cooperators (C) and 1510 cells in 360 coalitions. There are groups of several cells with the same colour meaning they belong to the same coalition. Isolated cells are independent cells behaving as cooperators (no one survived) or defectors (in black colour).

In all next figures, horizontal axis represents discrete time measured as number of generations (NG), i.e., game rounds.

Figure 4 shows the evolution of the frequency of cells per action corresponding to the simulation displayed in figure 3. Cooperators quickly disappear, but they are important for the initial coalition construction.

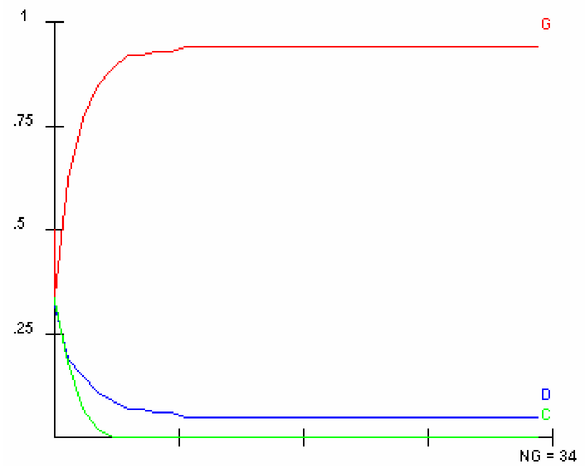

Figure 4. Frequency of cells per action: C, D or (G)roup

Figure 5 depicts the average profit for leaders and non-leader cells. In this particular context, it is clearly an advantage to join a group, and even more to become the leader.

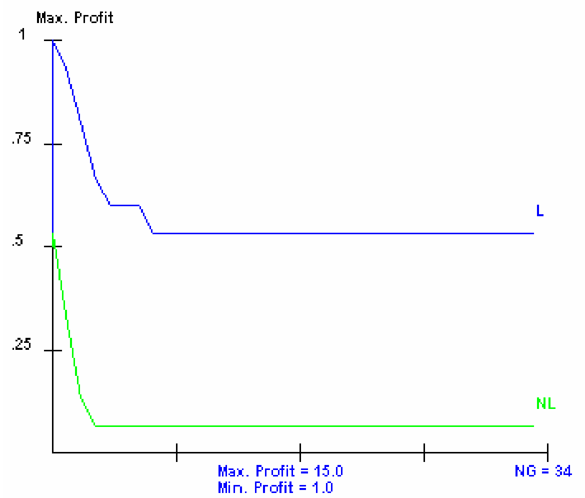

Figure 5. Average profit of leaders (L) vs. non-leaders (NL)

Figure 6 shows the global profit of the lattice, i.e., all cell incomes are summed up. As we see, at the beginning it is higher and then it decreases and kept almost constant. The reason is that at the beginning the agents behave more cooperatively, but as soon as more coalitions emerge; they defect to the cells outside their own coalition causing a decrease in the global profit.

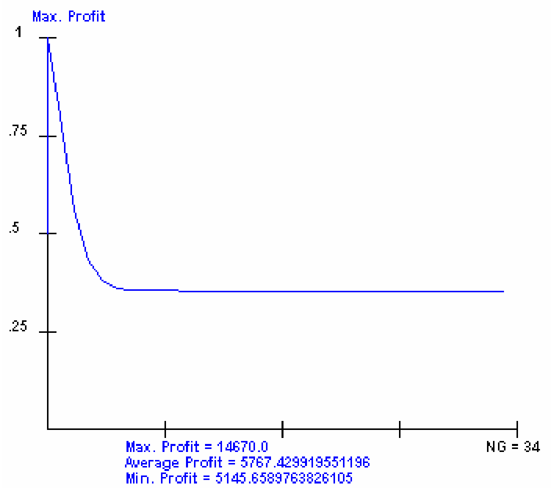

Figure 6. Global profit per round (summing up all cell payoffs)

Table 3 shows the effects of increasing the neighbourhood radio (NR) in the number of cooperators (C), defectors (D), coalition cells (G), number of coalitions (NC) and, finally, average size per coalition. The data correspond to average values after 10 executions until they reach stability. When NR increases, independent defector cells may *attack* more cells and it is more difficult for groups to appear. Remember that inside a coalition every cell must cooperate with its cellmates. Greater values of the NR parameter cause more difficulties for groups to appear but bigger sizes, and at the same time the number of defectors also grows. At the end, the number of cooperators is zero in all cases, but (as commented for figure 4) they participate at the birth of the initial coalitions.

Table 3. Cooperator, Defectors, Groups and average size

NR	C	D	G	NC	Av. Size
1.0	0	124.2	1475.8	364.8	4.04
1.5	0	410,2	1189,8	162	7,34
2.0	0	636,2	963,8	143,6	6,71
3.0	0	938,4	661,6	55	12,03
4.0	0	988,8	611,2	27	22,63
5.0	0	1086,4	513,6	13	39,50

5.1.2 Mutation Parameter

Now we consider the effect of mutation in non-leader cells. Mutation causes a random change of strategy (C or D), and in case the cell belongs to a coalition its independence. We apply a mutation factor of 5% in the previous scenario with (NR= 1.0). The results after 1000 rounds appear in figure 7, where white cells represent leaders, black cells defectors and isolated green cells cooperators. In this case, there are a few coalitions but with greater size than in figure 3.

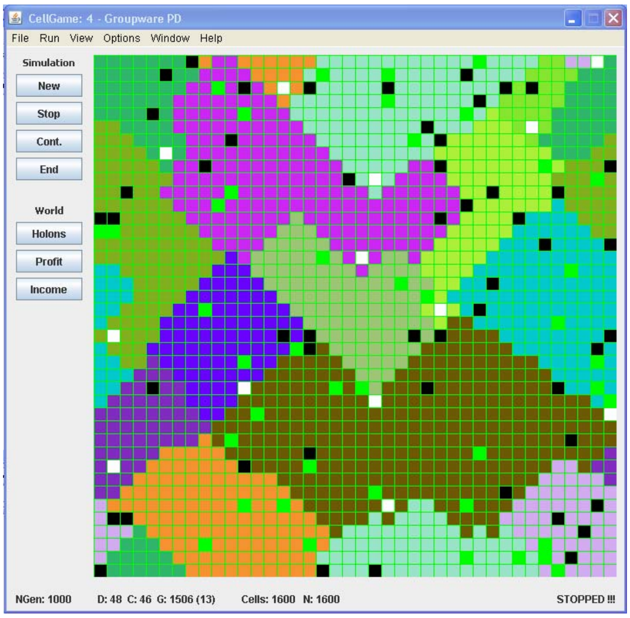

Figure 7. Snapshot with (NR=1.0) and a mutation of 5%

With mutation, coalitions compete among them for capturing new independent cells, and the ones with higher taxes tend to disappear with time. As a result (figure 8) the average tax paid per cell decreases with time. The simulation ends when only one coalition dominates (thousands of rounds). As the number of coalitions is getting lower; their size grows and, as their inner cells cooperate, it causes a growing in the global profit (figure 9).

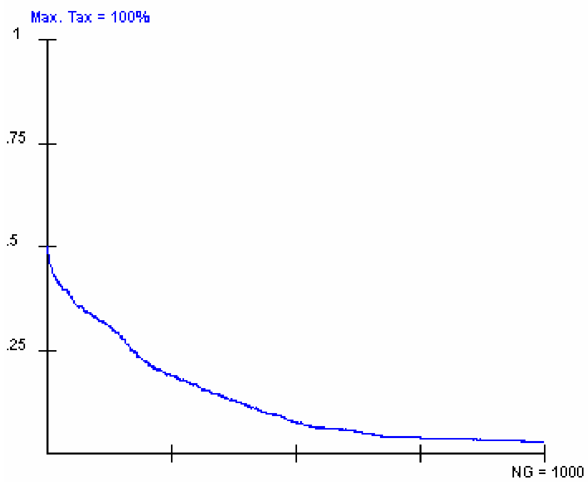

Figure 8. Average tax paid by coalition cells

5.2 Learning Automata Scenario

The previous pTFT scenario is very interesting but deterministic for leader strategies, as they always defect outside their own coalition. A more dynamic scenario appears if we allow each leader and independent cell to decide their strategy depending on its experience along their history; in our case, in the last five rounds (h=5, α=0.1). At the beginning we get a similar scenario to the imitation one, with many coalitions, but with time and without the need for mutations, stronger coalitions with lower taxes expand until only one or a few big coalitions survive. Therefore, the results are very similar to the imitation scenario (pTFT) with mutation described in figures 7, 8 and 9.

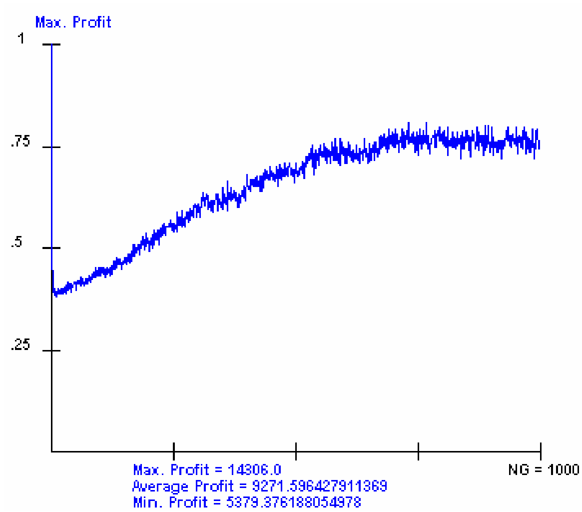

Figure 9. Global profit per round for the LA scenario

5.3 Complex Memetic Scenarios

Finally, we consider a more complex scenario, where the two management strategies (pTFT and LA) coexist, and any agent memetically choose among them; depending on the most successful one used by its neighbours.

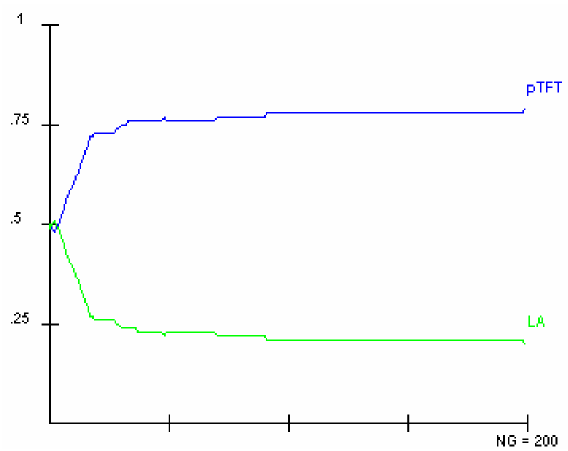

Figure 11. Freq. of cells with strategies (pTFT, LA)

The lattice distribution of the coalitions and the main numbers are similar to the other graphics shown before. The interesting point here is what we see in figure 11; where the simple memetic pTFT strategy is three times more popular than the self-contained LA strategy. This means that a simple pTFT memetic approach can be more effective than an isolated learning policy.

6. CONCLUSIONS

This paper presents a framework for describing the spatial distribution and the global frequency of agents who play the spatial prisoner's dilemma with coalition formation. Agent cells may play isolated or join a coalition (group of cells) ruled by a leader who decides the coalition strategy. Strategies are public and can be memetically imitated by neighbours.

Two management strategies have been presented: probabilistic Tit-for-Tat (pTFT) and learning automata (LA). In the pTFT case, the agent follows a variation of the classic TFT strategy but adapted to a coalition game. In the learning automata case, the agent just considers its history defecting or cooperating and selects his next action depending on its better experiences. Coalition dynamics are organized around two axes. On the one hand, agents increase a percentage in the compromise when other agents cooperate and reduce it when the others defect. On the other hand, coalition leaders impose taxes to the other agents belonging to its coalition. These two rules and their related parameters guide the coalition formation and the game evolution.

Even the model assumptions are simple; the simulations provide interesting paths to obtain complex results. The model hypothesis allowed the emergence of coalitions depending on the neighbourhood radio, mutation and strategy management. Besides, the results show that a simple pTFT memetic approach becomes more effective than an isolated learning policy. We can conclude that, in this model; frameworks with information sharing, which is a basic condition for memetics, are more useful than those ones where agents work isolated.

Multiple research work derives from the model discussed here. We can consider leaders adapting their taxes and decisions to their particular neighbourhood. Another natural extension to this spatial PD approach, based in local groups with leaders, could be a social network scenario. Finally, more complex decision rules for the agents can be considered.

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8. REFERENCES

[1] Binmore, K. 1994. Game Theory. Mc Graw Hill.

[2] Axelrod, R. 1984. The evolution of Cooperation. Basic Books, New York.

[3] Axelrod, R. 2000. "On Six Advances in Cooperation Theory." Analyse und Kritik 22: 130–51.

[4] Hoffmann, R. 2000. Twenty years on: The evolution of cooperation revisited. Journal of Artificial Societies and Social Simulation, 3(2).

[5] Feldman, M., Lai, K., Stoica I., and Chuang, J. 2004. Robust Incentive Techniques for Peer-to-Peer Networks. ACM E-Commerce Conference (EC'04).

[6] The official BitTorrent page, http://www.bittorrent.com

[7] Schweitzer, F., Behera, L., and Mühlenbein, H. 2002. Evolution of Cooperation in a Spatial Prisoner's Dilemma. Advances in Complex Systems, vol. 5, (2-3): 269-299.

[8] Axelrod, R. 1997. Building New Political Actors. The Complexity of Cooperation: Agent-based Models of Competition and Collaboration. Princeton University Press.

[9] Buss, L.W. 1987. The Evolution of Individuality. Princeton N.J. Princeton University Press.

[10] Minsky, M. 1985. Society of the Mind. New York: Simon and Schuster.

[11] Dawkins, R. 1976. The Selfish Gene. Oxford. Great Britain. Oxford University Press.

[12] Waldrop, M. 1992. Complexity: the emerging science at the edge of order and chaos. New York: Simon & Schuster.

[13] Costa-Montenegro, E., Burguillo-Rial, J.C., González-Castaño, F. J., and Vales-Alonso, J. 2007. Agent-Controlled Sharing of Distributed Resources in User Networks. Computational Intelligence for Agent-based Systems (Studies in Computational Intelligence). Lee, Raymond S.T.; Loia, Vincenzo (Eds.). Volume 72. Springer.

[14] Maynard Smith, J. 1982. Evolution and the Theory of Games. Cambridge University Press.

[15] Brodie, R. 1996. Virus of the Mind: The New Science of the Meme. Seattle, Wash: Integral Press.

[16] Boyd, R., and Richerson, P.J. 2005. Not by Genes Alone: How Culture Transformed Human Evolution. Chicago University Press.

[17] Krasnogor N., and Smith, J.E. 2005. A tutorial for competent memetic algorithms: model, taxonomy and design issues. IEEE Transactions on Evolutionary Computation, 9(5):474-488.

[18] Ong, Y.S., Krasnogor, N., and Ishibuchi, H. 2007. Special issue on memetic algorithms. IEEE Transactions on Systems, Man and Cybernetics, Part B, 37(1):2-5.

[19] Fischer, K., Schillo, M., and Siekmann, J. 2003. Holonic Multiagent Systems: A Foundation for the Organisation of Multiagent Systems. LNCS 2744/2004. Holonic and Multi-Agent Systems for Manufacturing, 1083-1084.

[20] Nowak, M.A., May, R.M. 1992. Evolutionary games and spatial chaos. Nature 359: 826-829.

[21] Langer, P., Nowak, M.A, Hauert, C. 2008. Spatial invasion of cooperation. Journal of Theoretical Biology 250:634-641.

[22] Narendra, K., & Thathachar, M. 1989. Learning Automata: An Introduction. Prentice-Hall, Englewood Cliffs, NJ.