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Design and evaluation of a multiagent interaction protocol generating behaviours with different levels of complexity

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ABSTRACT

The design of a multiagent system based on simple interaction rules is presented, which can generate different types of overall behaviours, from asymptotically stable to chaotic, verified by two tests for chaos. Exogenous perturbations are analysed, showing that very small changes can have a great impact on the evolution of the system. Some methods of controlling such perturbations in order to have a desirable final state are investigated. Also, endogenous perturbations and the effect of alternative decisions on the evolution of agent utilities are examined. Different methods are suggested for describing the behaviour of the multiagent system.

1. Introduction

Non-linear effects are commonly encountered in dynamic systems. They are characteristic for example of evolutionary game theory [37], which aims to enhance the concepts of classical game theory [43] with evolutionary issues, such as the possibility to adapt and learn. In general, the fitness of a certain phenotype is, in some way, proportional to its diffusion in the population. The strategies of classical game theory are substituted by genetic or cultural traits, which are inherited, possibly with mutations. The payoff of a game is interpreted as the fitness of the agents involved [3].

Many such models have been proposed, based on the different ways in which agents change their behaviours over time. Among them we can mention replicator dynamics [13,41], its replicator–mutator generalisation [26] and the quasi-species model [10], which have been used to model social and multiagent network dynamics, e.g., [12,24,8].

A review of the group interactions on structured populations, including lattices, complex networks and coevolutionary models highlights the synergic contribution of statistical physics, network science and evolutionary game theory to the analysis of their dynamics [30]. In general, group interactions cannot be reduced to the corresponding sum of pairwise interactions.

The evolution of public cooperation on complex networks is particularly important and has been studied for example in the context of public goods games [36] or the emergent behaviour of agent social networks [20].

In the context of diffusion, which allows players to move within the population, the analysis of the spatiotemporal patterns reveals the presence of chaos, which fits the complexity of solutions one is likely to encounter when studying group interactions on structured populations [44,30].

The emergence of cooperation within groups of selfish individuals, where cooperators compete with defectors, is an interesting research direction because it may seem to contradict natural selection. Recent results reveal that the evolution of strategies alone may be insufficient to fully exploit the benefits of cooperative behaviour and that coevolutionary rules can lead to a better understanding of the occurrence of cooperation [31].

Coevolutionary rules supplement evolutionary games because not only the strategies evolve over time, but also the environment and many other factors that affect the outcome of the evolution of strategies. For example, a commonly used strategy adoption rule in coevolutionary models is "richest-following" [14], where a certain player always imitates the strategy of its most successful neighbour [46].

Some coevolutionary processes have a finite duration and do not directly affect the outcome of the evolutionary games, but indirectly, due to the changes they produce in the environment. Others are permanent and introduce dynamical alterations that affect the evolution of cooperation on a continuous basis [31].

The applicability of the concept of evolutionary games can be found in many social and natural sciences, with examples such as

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the RNA virus [42], ATP-producing pathways [34] and traffic congestion [29].

On the other hand, chaos has been extensively studied in physical systems, including methods to control it for uni-, bi- and multi-dimensional systems [1]. Also, concepts such as causality and the principle of minimal change in dynamic systems have been formalized [27].

Many human-related, e.g., social or economic systems, are nonlinear even when the underlying rules of individual interactions are known to be rational and deterministic. Prediction is very difficult or impossible in these situations. However, by trying to model such phenomena, we can gain some insights regarding the fundamental nature of the system. Surprising or counterintuitive behaviours observed in reality can be sometimes explained by the results of simulations.

Therefore, the emergence of chaos out of social interactions is very important for descriptive attempts in psychology and sociology [16], and multiagent systems are a natural way of modelling such social interactions. Chaotic behaviour in multiagent systems has been investigated from many perspectives: the control of chaos in biological systems with a map depending on the growth rate [38], the use of a chaotic map by the agents for optimisation [4] and image segmentation [23], or the study of multiagent systems stability for economic applications [5]. However, in most of these approaches, chaos is explicitly injected into the system, by using a chaotic map, e.g., the well-known logistic map, in the decision function of the agents.

The main goal of the present work is the design of a set of simple interaction rules which in turn can generate, through a cascade effect, different types of overall behaviours, from stable to chaotic. We believe that these can be considered metaphors for the different kinds of everyday social or economic interactions, whose effects are sometimes entirely predictable and can lead to an equilibrium while some other times fluctuations can widely affect the system state, and even if the system appears to be stable for long periods of time, sudden changes can occur unpredictably because of subtle differences in the internal state of the system. We also aim at investigating how very small changes can non-locally ripple throughout the system with great consequences and whether it is possible to reverse these changes in a non-trivial way, i.e., by slightly adjusting the system after the initial perturbation has occurred.

The paper is organised as follows. Section 2 presents the interaction protocol of the multiagent system and its mathematical formalization. Section 3 discusses the stable and unstable (including chaotic) behaviours that emerge from the system execution. Section 4 presents an experimental study regarding the effects of small exogenous perturbations in the initial state of the system and the possibility of cancelling them through minimal external interventions. Section 5 addresses the endogenous perturbations, namely alternative decisions made by agents and provides different methods to describe the differences induced in system behaviour. The final section contains the conclusions of this work.

2. The design of the multiagent system

The main goal in designing the structure and the interactions of the multiagent system was to find a simple setting that can generate complex behaviours [21]. A delicate balance is needed in this respect. On the one hand, if the system is too simple, its behaviour will be completely deterministic. On the other hand, if the system is overly complex, it would be very difficult to assess the contribution of the individual internal elements to its observed evolution. The multiagent system presented as follows is the result of many attempts of finding this balance. The major versions are briefly described in Section 2.3.

The proposed system is comprised of n agents; let A be the set of agents. Each agent has m needs and m resources, whose values lie in their predefined domains D_n, $D_r \subset \mathbb{R}^+$. This is a simplified conceptualization of any social or economic model, where the interactions of the individuals are based on some resource exchanges, of any nature, and where individuals have different valuations of the types of resources involved.

It is assumed that the needs of an agent are fixed (although an adaptive mechanism could be easily implemented, taking into account, for example, previous results [19,18]), that its resources are variable and they change following the continuous interactions with other agents.

Also, the agents are situated in their execution environment: each agent a has a position π_a and can interact only with the other agents in its neighbourhood Λ_a. For simplicity, the environment is considered to be a bi-dimensional square lattice, but this imposes no limitation on the general interaction model – it can be applied without changes to any environment topology.

2.1. Social model

Throughout the execution of the system, each agent, in turn, chooses another agent in its local neighbourhood to interact with. Each agent a stores the number of previous interactions with any other agent b, $i_a(b)$, and the cumulative outcome of these interactions, $o_a(b)$, which is based on the profits resulted from resource exchanges, as described in the following section.

When an agent a must choose another agent to interact with, it chooses the agent in its neighbourhood with the highest estimated outcome: $b^* = \arg\max_{b \in \Lambda_a} o_a(b)$.

The parallelism of agent execution is simulated by running them sequentially and in random order. Since one of the goals of the system is to be deterministic, we define the execution order from the start. Thus, at any time, it can be known which agent will execute and which other agent it will interact with. When perturbations are introduced into the system, the same execution order is preserved. It has been shown that the order of asynchronous processes plays a role in self-organisation within many multiagent systems [6]. However, in our case this random order is not necessary to generate complex behaviours. Even if the agents are always executed in lexicographic order (first A1, then A2, then A3 etc.), sudden changes in utilities still occur, although the overall aspect of the system evolution is much smoother.

2.2. Bilateral interaction protocol

In any interaction, each agent tries to satisfy the needs of the other agent as well as possible, i.e., in decreasing order of its needs. The interaction actually represents the transfer of a resource quantum γ from an agent to the other. Ideally, each agent would satisfy the greatest need of the other.

For example, let us consider 3 needs (N) and 3 resources (R) for 2 agents a and b: $N_a = \{1, 2, 3\}$, $N_b = \{2, 3, 1\}$, $R_a = \{5, 7, 4\}$, $R_b = \{6, 6, 5\}$, and $\gamma = 1$. Since need 2 is the maximum of agent b, agent a will give b 1 unit of resource 2. Conversely, b will give a 1 unit of resource 3.

In order to add a layer of nonlinearity, we consider that an exchange is possible only if the amount of a resource exceeds a threshold level θ and if the giving agent a has a greater amount of the corresponding selected resource r_{sel} than the receiving agent b: $R_a(r_{sel}) > R_b(r_{sel})$ and $R_a(r_{sel}) > \theta$.

In the previous situation, if we impose a threshold level $\theta = 5$, agent a will still give b 1 unit of resource 2, but b will only satisfy need 1 for agent a.