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On the spatial dynamics and oscillatory behavior of a predator-prey model based on cellular automata and local particle swarm optimization

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HIGHLIGHTS

- We developed a lattice model of a predator–prey system where predators move using a Particle Swarm Optimization algorithm.
- We give a qualitative analysis of the spatial and temporal dynamics of the proposed model.
- It is found that the size of the clusters formed by predators increases as the social component of the movement is increased.
- It is found that as the mobility of predators increases the system enters into an oscillatory regime.

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ABSTRACT

A two-dimensional lattice model based on Cellular Automata theory and swarm intelligence is used to study the spatial and population dynamics of a theoretical ecosystem. It is found that the social interactions among predators provoke the formation of clusters, and that by increasing the mobility of predators the model enters into an oscillatory behavior.

1. Introduction

The study of the long term dynamics of an ecosystem has found in lattice models an excellent tool; able to describe in great detail the local interactions between the organisms that compose such systems. The analysis of these interactions has provided new insights into the underlying processes that determine the global behavior of an ecosystem, e.g., the self-organized criticality in a hierarchical food chain (Xin-She, 2003), the long term maintenance of species diversity (Molofsky and Bever, 2002), or the effects of the interspecific competition at local scale on the coexistence and diversity of multiple competing species (Vandermeer and Yitbarek, 2012). Among the most interesting phenomena that can be observed both in non-spatial explicit models (Guill et al., 2011), as well as those based on cellular automata theory (Pekalski, 2004), is the oscillatory behavior of prey–predator systems. The nature of these oscillations is diverse: time lags in the reproductive cycles of preys and predators, migration, seasonal hunting, weather conditions, behavioral patterns such as aggressiveness, etc. Some of these examples suggest that the cycles might not be caused by prey–predator interactions at all, and emphasizes the need to analyze other kind of interactions, e.g., competition, to achieve a good description of the ecosystem (Begon et al., 2006). Because of these differences the development of a general theoretical framework to study prey–predator systems is very difficult. Like in any other modeling discipline the assumptions made about the system to model (natural or purely theoretical) have a great impact on the dynamics observed.

Ecological models often need to be simple enough to be tractable and to help to determine the underlying processes that

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drive the dynamics of an ecosystem, also they need to be complex enough to reflect a realistic behavior. Indeed, lattice models were first considered because they offered a simple, yet realistic enough approach to model the interactions among the organisms that comprise an ecosystem. A lattice model that focus on the survival strategies taken by preys and predators appears in Boccara et al. (1994), the model considers a *pursuit and evasion* neighborhood where predators move to catch preys, and preys move to escape from predators. In order to catch a prey, predators move to one of their eight nearest neighbors following the direction of highest prey-density; similarly, to escape from predators, preys move in the opposite direction of highest predator density. Results obtained from simulations of the model show that for a low predator birth rate, there is a threshold, given in terms of the number of movements per individual, above which the ecosystem evolves into a non-trivial fixed point where the densities of preys and predators remain constant. An increase of the predator birth rate causes, for a large number of movements per individual, a completely different behavior: there is a long transient where noisy cycles can be observed. In Monetti et al. (2000) and Rozenfeld and Albano (1999), the analysis of the model proposed by Boccara et al. is extended: the study of the evolution of the system in terms of the birth and death rate of predators reveals an absorbing state and a stationary regime where both population coexist. Furthermore, it is stated that the oscillatory behavior of the populations of preys and predators is caused by a dynamic percolation process, i.e., alternating percolation and non-percolation events.

Another example of a lattice model where the movement of organisms is linked to a regular oscillatory behavior appears in Bascompte et al. (1997). Here, the dynamics of the snowshoe hare are studied. The model employs several rules to mimic the life cycle of the hares (dispersal, feeding, breeding and death) and their relationship with their preys (grass). Moreover, each rule takes into account several parameters that reflect the biological information available about the ecosystem, e.g., the vegetation increase rate, breeding period of the hares, number of offspring, etc. Simulations of the model show a limit cycle with a period of 9–10 years, the authors state that the local dispersion rule is linked to these cycles, since when dispersal is made at random the cycles disappear.

Models studying more complex food chains also report the presence of regular oscillations, Blasius et al. (1999) proposed a model to study the population dynamics of the Canadian lynx and the snowshoe hare. The model consists of a system of differential equations that represent a three-level food chain with predators feeding on herbivores, and herbivores consuming vegetation. Besides showing a typical limit-cycle behavior, this food chain model shows that the populations of preys and predators oscillate with an almost constant frequency. However, the amplitude at each peak of the time series is highly unpredictable, both of these features are present in the hare–lynx population data. When simulated in a regular array of patches linked by migration, all patches became synchronized to the same frequency. Nevertheless, the amplitudes of the populations observed in each individual patch were only weakly correlated. On the contrary when diffusion was eliminated, the population of each patch behaves independently with no phase synchronization.

It is common that when using a lattice model to describe prey–predator interactions only the negative effects of such interactions be considered, e.g., competition or crowding, and beneficial effects appear only as a greater chance of reproduction. This is particularly evident when the behavior of a predator is considered, most rules proposed to model predation in lattice models neglect any kind of interaction between predators, see e.g., Cattaneo et al. (2006). However, cooperation is common among animal communities: bird flocks, swarms, herds, and fish schools are good examples of the phenomena. A member of any of these animal groups is able to react based on the information it has acquired on an individual basis or by communicating with other members of its community, e.g., to flee from a predator or to keep a flight pattern. The observation and study of the social behavior of animal communities led to the development of the Swarm Intelligence algorithms, a critical event towards the development of Particle Swarm Optimization (PSO) was to recognize the fact that the social behavior among organisms represents an advantage that may outweigh the negative effects of competition (Kennedy and Eberhart, 1995), through cooperation an individual may benefit from the experience of other members of the community. Surprisingly enough, even when its inception PSO has been successfully applied to problems such as numerical optimization (Jong-Bae et al., 2005), the deployment of wireless sensor networks (Kulkarni and Venayagmoorthy, 2011) or image processing (Gorai and Ghosh, 2009), its application to ecological modeling is to the best of our knowledge non-existent.

This paper presents a prey–predator lattice model where the movement of predators is modeled through a local PSO algorithm, instead of using Swarm Intelligence to model the defense of preys against predators, we use PSO to model the search for food by the predators. To accomplish this goal, a fitness function that measures the local density of preys at each cell is proposed. We give a qualitative analysis of the spatial dynamics of the model and describe the conditions that give rise to regular oscillations in both populations.

2. Background

2.1. Cellular automata

A Cellular Automaton (CA) is a dynamical system, discrete in time and space; it consists of a regular array of cells known as lattice. The set of possible states that a cell can take is denoted by Q. The state of a cell is changed according to a local transition function that takes into account the previous state of the cell, and the state of other cells in a finite neighborhood. At each time step the state of all cells is updated synchronously.

In a two-dimensional CA a cell can be identified by a vector $\vec{n} \in \mathbb{Z}^2$, the state of cell $\vec{n}$ at time t is given by $s^t(\vec{n})$, and the neighborhood of each cell can be defined as

$$N = (\vec{n}_1, \vec{n}_2, \ldots, \vec{n}_m) \tag{1}$$

where each $\vec{n}_i \in \mathbb{Z}^2$, $\vec{n}_i \neq \vec{n}_j$ and m is the number of cells in the neighborhood. Each vector in N specifies the relative locations of the neighbors of a cell (Kari, 2005), in particular, cell $\vec{n}$ has coordinates (0, 0) and neighbors $\vec{n} + \vec{n}_i$ for $i = 1, 2, \ldots, m$. The Moore neighborhood is often used, it comprises the cell to evolve and its eight nearest neighbors. It can be generalized as the two-dimensional M_r neighborhood defined as

$$M_r = \{\vec{n}_i \in \mathbb{Z}^2 : \vec{n}_i = (n_{i_1}, n_{i_2}), n_{i_j} \leq r\} \tag{2}$$

where r is the radius of the neighborhood.

2.2. Particle swarm optimization

PSO is a bio-inspired algorithm based on the collective behavior of several groups of animals (flocks, fish schools, insect swarms, etc.) (Eberhart and Kennedy, 1995). Its main objective is the searching of an optimum in a search space that defines the set of possible solutions to a particular problem. Each point in the search space represents an specific set of features that qualify that position, it is possible then to assign a numerical value to each

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