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A framework for modeling information propagation of biological systems at critical states

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ABSTRACT

We explore the dynamics of information propagation at the critical state of a biologically inspired system by an individual-based computer model. "Quorum response", a type of social interaction which has been recognized taxonomically in animal groups, is applied as the sole interaction rule among individuals. In the model, we assume a truncated Gaussian distribution to depict the distribution of the individuals' vigilance level. Each individual can assume either a naïve state or an alarmed one and only switches from the former state to the latter one. If an individual has turned into an alarmed state, it stays in the state during the process of information propagation. Initially, each individual is set to be at the naïve state and information is tapped into the system by perturbing an individual at the boundaries (alerting it to the alarmed state). The system evolves as individuals turn into the alarmed state, according to the quorum response rules, consecutively. We find that by fine-tuning the parameters of the mean and the standard deviation of the Gaussian distribution, the system is poised at a critical state. We present the phase diagrams to exhibit that the parameter space is divided into a super-critical and a sub-critical zone, in which the dynamics of information propagation varies largely. We then investigate the effects of the individuals' mobility on the critical state, and allow a proportion of randomly chosen individuals to exchange their positions at each time step. We find that mobility breaks down criticality of the system.

1. Introduction

For a system in a critical state, long range correlations occur. That implies that perturbations caused by individual constituents can have systemic effects. The properties of criticality may benefit biological systems to process environmental perturbations efficiently (Mora and Bialek, 2011). Self-organized criticality (SOC), which was proposed by Bak et al. (1987), is now a commonly accepted underlying mechanism to phenomena such as earthquakes and brain dynamics (Bak, 1996; Sharma et al., 2016; CDR, 2010). It states that a complex system can organize itself to a critical state without tuning parameters from the outside. The "finger print" of a system entering a critical state is a power law distribution of the size of the "avalanches" which is measured by counting the number of the affected individual components in the dynamic process. This distribution indicates that, at a critical point, there is no characteristic scale in the system. The correlation length in the system can vary from a local level to a system-wide one. Recently, Cavagna et al. (2010) observed that in the airborne motion of large starling flocks, the correlation length between two individuals does not depend on the size of the flock, the so called scale-free correlation. This observation reveals that the starling flocks work at a critical state, in which one individual can effectively affect the state of any others' no matter what the group size is, and vice versa. This property confers the group an ability to share information efficiently so that the flock can optimally respond to external perturbations. Viktorovich (1973) noted that schools of fish can also transfer information rapidly in reaction to perceived risk at the front of the school. He found that the fishes at the front made a quick rotation from the risk and their local neighbors behind imitated this behavior. The consecutive rotations of the fishes resulted in a rapidly traveling disturbances, which rippled from the front to the rear at a speed much faster than individual fish's speed. However, besides these experimental studies, the underlying micro-mechanism of information propagation is left largely ignored (Herbert-Read et al., 2015; Couzin et al., 2005; Bialek et al., 2012). Other systems at different biological levels show collective behavior including cancer cells (Deisboeck and Couzin, 2009), bacterial colonies (Zhang et al., 2010), and human brains (CDR, 2010). The working efficiency of which may depend on the underlying mechanism of information propagation.

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In this paper, we studied the dynamics of information propagation at critical points in an individual-based computer model with the interaction among particles being quorum response. Each individual was assigned a "vigilance number" to quantitatively depict its vigilance level to respond to its local neighbors' commitment. We assumed the distribution of the "vigilance number" to be a truncated Gaussian distribution in the interval of (0, 1). By tapping information from boundaries into the system, we found that, by fine tuning parameters of the Gaussian distribution, the system could be poised at a critical state in the dynamics of information transfer. We presented phase diagrams to show that the parameter space is divided into a sub-critical and a super-critical zone, in which the dynamics of information propagation is quite different. We then investigated the effects of individual's mobility on the system's critical state, and found that mobility breaks down the critical state of the system.

2. Quorum response

Quorum response is a type of social interaction widely found during the process of collective decision-making in bee and ant colonies (Seeley and Visscher, 2004; Franks et al., 2015), cockroach aggregations (Amé et al., 2006), broiler chicken crowds (Collins and Sumpter, 2007) and fish schools (Ward et al., 2008). It quantitatively states that an individual's chance of making one option depends on the number of its local neighbors that committed to this option.

Lets consider the following simple example, suppose there are only two options (e.g., being at an alarmed state ("+" state) or a naïve one ("−" state)). The mathematical description of the rule of "quorum response" is as follows (Sumpter and Pratt, 2009):

$$p_+^i(t) = \frac{((n_+^i(t))/q_i)^k}{1+((n_+^i(t))/q_i)^k}, \quad p_-^i(t) = 1 - p_+^i(t), \qquad (1)$$

where $p_\pm^i(t)$ is the probability for individual i choosing to be at an alarmed or a naïve state at time step t, respectively (individual i will turn into "+" or "−" state at time step $t+1$ according to the probabilities) and $n_\pm^i(t)$ is the number of local neighbors who have committed to the alarmed or the naïve state at time t, respectively. The parameter q_i $(0 < q_i < n_0(= n_+^i(t) + n_-^i(t)))$ is the quorum value for individual i to turn into an alarmed state and n_0 is the number of its local neighbors. Quorum value is related to the individual's vigilance level. If q_i is big, compared to the number of individual i's local neighbors, it means individual i is difficult to be alerted by its alarmed local neighbors to turn into an alarmed state. Otherwise, If q_i is small, individual i is easily startled by its a few alarmed local neighbors to turn into an alarmed state. This function resembles the well-known Hill function (Sumpter and Pratt, 2009). If k is bigger, the variation of the curve becomes steeper than the linear increase at the quorum point, see Fig. 1. Thus it can be expected that $k \geq 2$ is a necessity in the framework of the interaction rule (Sumpter and Pratt, 2009). In field experiments, it is found that animals adapt k to be ~3 as a result of evolution (Amé et al., 2006; Ward et al., 2008). Quorum response is essentially a distributed positive feedback process that enables information propagation and it is believed that this type of interaction can enhance decision speed and accuracy for a group to make a collective decision (Sumpter and Pratt, 2009).

3. An individual-based model

Quorum response can be modeled in computers for quantitative investigation and to determine the parameters associated with different types of information flow. In this paper we investigated information propagation in 2D. A system is composed of a square of the dimension of 100 × 100 evenly spaced grid. Each individual is positioned in a grid, and we assign each individual a "vigilance number" $\alpha_i (i = 1, 2, \ldots)$ which measures how vigilant the individual i is responding to its local neighbor's state. The distribution of α_i is assumed to obey a truncated Gaussian distribution in the interval (0, 1), with the mean being μ and the standard deviation being δ. In this section, each individual is immobile on the grid. The effects of the individual's mobility will be considered in Section 5.

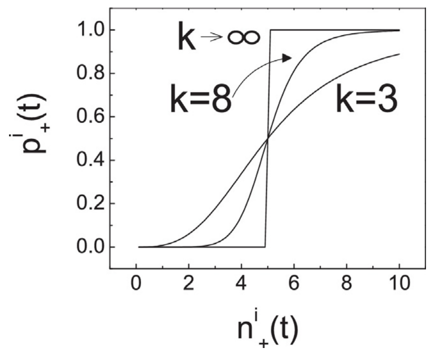

Fig. 1. Function of quorum response according to Eq. (1). The y-axis is the probability for individual i at time t to choose to be at an alarmed and the x-axis is the number of its local neighbors who have committed to this option at time t. The total number of local neighbors n_0 of particle i is set to be 10 and the threshold value is $n_0/2$ in this figure. The quorum response increase more slowly under the threshold value and more rapidly above it than a linear fit. The steepness is increasing when k is increasing, and becomes a step function in the limit $k \to \infty$.

The sole interaction rule among the individuals in the model is the quorum response according to Eq. (1), with q_i being defined as,

$$q_i \equiv n_0 * \alpha_i,$$

where $n_0 = 4$ is the local neighbors to any individual not positioned at boundaries (if a individual lies at one of the four corners, $n_0 = 2$, or else if it lies at one of the four boundary lines, $n_0 = 3$). Each individual can either be in an alarmed state ("+" state) or in a naïve state ("−" state) at the probability calculated according to Eq. (1). The probability is realized by Monte Carlo method at each time step in the dynamic process of the system, i.e. a random number which is evenly distributed in the interval of (0, 1) is sampled at the time step t and being compared to the probability $p_+^i(t)$ in Eq. (1). If the sampled random number is smaller, then the individual i will turn into the alarmed state at the next time step. Otherwise, it will stay in the naïve state.

Following the general assumption that individuals at peripheries find the approaching risks in advance (Inglis and Lazarus, 1981), we tap information in the system by randomly picking a individual lying at one of the boundary lines and turn its state to the alarmed one. The local interactions may affect the state of its local neighbors, and the affected neighbors continue to repeat the interaction which may cascade into an "information wave" eventually. If an individual turns into the alarmed state at time step t, then it will stay at the alarmed state unchanged during the dynamics of information propagation. One run of information propagation is considered completed when all the alarmed individuals are not capable to alter the state of its local neighbors anymore.

We find that if the parameters of μ and δ are fine tuned, a power law distribution of the size of the information waves is emerged. The total population of the individuals in the system is 100 × 100 and the standard deviation of the Gaussian distribution is set to $\delta = 0.15$ in Fig. 2. Each data point is averaged over 5×10^5 runs of simulation. The fine tuned parameters of μ and k are: $k = 3$, $\mu = 0.307$; $k = 8$, $\mu = 0.310$; and $k \to \infty$, $\mu = 0.316$ (when k approaches infinity, quorum response function is practically a step function). The size of the information waves is quantified by