

# A SIMPLE NONLINEAR DYNAMICS MAY RESULT IN ADAPTIVE BEHAVIORS

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## **Abstract**

Various organisms share in common certain basic rules for a searching behavior. We hypothesize that these rules may emerge from basic properties of non-linear systems as a whole, rather than being evolved from a scratch gradually. In order to support this hypothesis, we have developed a virtual agent that consists of three simple central pattern generators (CPG). These CPGs are driven by an internal noise, which results in phase transitions in their activity. External stimuli modify the activity via sensors and food consumption. The interaction among the activity of CPGs and external influences give rise to an emergence of searching rules that are similar to those shared by various organisms, thus favoring the above hypothesis. The hypothesis could be verified further by investigating various types of non-linear systems in different environments. Also, such an investigation may answer the question: how simple could be an underlying dynamic system to ensure viability of an agent in a given environment? To what extent adaptive abilities of living being are constrained and steered by dynamic laws of non-linear systems?

*Keywords:* adaptive rules, dynamic systems, artificial agents

*Running head:* Emergence of searching rules

## 1. Introduction

An adaptive behavior in living beings could be described as a set of rules for adaptive responses to stimulation. This led naturally to a designing of artificial agents provided with explicitly defined rules that control, for example, searching behavior. This approach allows for a study of holistic behavior emerging in individuals from interactions among rules. The subsumption architecture of autonomous robots (Brooks, 1986) and virtual ecosystems (Terzopoulos, Tu and Grzeszczuk, 1994) are representative examples of the approach.

However, the research in the field of artificial agents provides also an opportunity to raise fundamental problem: what is an origin of searching rules in real organisms? One answer to the problem is that the rules are developing gradually, starting from scratch, in a course of natural selection. This answer is intuitively appealing, but, in fact, provides a little insight regarding an origin of adaptive rules. An alternative answer to the problem is that basic searching rules could emerge as a whole from basic principles of non-linear dynamics that underlies the animal behavior. The same non-linear phenomena may reveal themselves in very different systems; therefore, one might expect the resulting searching rules, at least basic ones, to be principally similar in different organisms. This paper presents a simple “dynamic agent” which produces biologically plausible rules for a searching behavior of simpler types: unguided wandering, olfactory orientation using one sensor, response to food patches and obstacle avoidance.

This paper is organized as follows. In the next section, we consider what is required of the dynamic system intended to study an origin of biologically plausible behavioral rules. Specific searching tasks and searching rules used by organisms to accomplish these tasks are described in Section 3. The architecture of agent is described in Section 4, and Section 5 shows how the agent accomplish the above tasks and which rules it produces. In Section 6, we discuss to what extent the agent’s behavior conforms principles of animal behavior (6.2), how the agent produce searching rules (6.3), as well as implications for the use of artificial agents to study an origin of adaptive behavior in living beings (6.4).

## 2. General considerations and approach

The dynamic approach is well established in the field of “New Artificial Intelligence” based on biological insights (Steels, 1994; Beer, 1997). However, several basic properties of organism’s behavior should be taken into consideration when designing an agent capable of biologically plausible behavioral rules.

### 2.1. Spontaneous activity in organisms

All organisms from unicellular ones to higher animals are capable of a spontaneous behavioral activity. In bacteria *Escherichia coli*, for example, this activity stems from an interaction of metabolic cycles within a bacterial cell. This activity manifests itself at a behavioral level as an apparently spontaneous wandering: a sequence of tumbles divided by straight runs which are randomly directed and have varying duration (Berg and Brown, 1972; Müller, di Primio and Lengeler, 2001). In higher animals, a nervous system, as well as it’s components like ganglia, reveals self-organizing dynamics (Erdi, 2000), which may give rise to complex spontaneous activity. One example is short-term oscillations of activity in mice, which could be explained by a dynamic chaos in nervous activity (Guillot and Meyer, 2000). Another example is complex fractal activity pattern in *Drosophila* under constant condition (Cole, 1995; Martin, Ernst and Heisenberg, 1999a). In the last case, evidences were found that some neuronal circuits in the neural system of *Drosophila* are responsible for the pattern

(Martin, Raabe and Heisenberg, 1999b). Thus, central pattern generators (CPG) drive the spontaneous activity in organisms.

This spontaneity can be interpreted in terms of autopoietic theory. According to the theory, a living being is an operationally closed system, that is, the self-referring system which operates on its own states. The process, which takes place within this system, produces components that interact in such a way that they maintain the same process that produce these components (Maturana, 1980; Varela, 1992). Thus, the process is autopoietic (self-creating) and is aimed solely at its own maintenance, while an observable spontaneous activity is an external manifestation of this process. This implies that the activity per se is not necessarily aimed at accomplishment of any task, rather it provides a basis for generation of adaptive rules for various tasks (see Section 2.3).

## 2.2. Variability and structure of the spontaneous activity

It should be emphasized that spontaneous movements of living beings are notoriously variable, like a length and direction of runs in wandering bacteria. Many authors argued (though using different arguments) that the intrinsic behavioral variability is an essential part of behavioral adaptation (see, e.g., Stewart, 1995; Mobus and Fisher, 1999; Inglis, 2000).

This quantitative variability is typically accompanied by a qualitative structure of spontaneous activity. In bacteria *E. coli* (Berg and Brown, 1972; Müller et al., 2001) and nematode *Caenorhabditis elegans* (Pierce-Shimomura, Morse and Lockery, 1999; Shingai, 2000) this structure consists of alternation of two distinct behavioral modes. In the absence of any changes in external stimulation, they spontaneously switch between relatively straight randomly directed runs and sharp changes in movement direction: tumbles in bacteria and sharp turns in nematodes. Spontaneous fractal behavioral sequences also imply apparent temporal structure: behavioral events are clustered, while clusters are divided by wide gaps. In *Drosophila*, for example, events are stops divided by periods of motion (Cole, 1995). Similarly, the swimming of goldfish in uniform environment consists of runs divided by series of turns (Nepomnyashchikh and Gremyatchikh, 1996). Both active periods in *Drosophila* and runs in goldfish have a variable duration.

## 2.3. Generation of behavioral rules

The autopoietic theory postulates that external influences do not determine the intrinsic spontaneous process; rather they perturb it according dynamical laws that control the process. From a viewpoint of external observer, perturbations of the process are seen as responses to external stimuli according some behavioral rules (Maturana, 1980; Varela, 1992; Riegler, 2001). This does mean that any behavioral rule reflects dynamical laws of the above basic process. In other words, any behavioral rule an organism is able to produce is nothing else but a modification of the basic spontaneous process.

The postulate can be illustrated using examples from the previous section. The movement pattern of bacteria (Berg and Brown, 1972) and nematode (Pierce-Shimomura et al., 1999) modifies when they perceived a chemical stimulus. Runs directed roughly away the source of stimulus are quickly terminated by a change of movement direction, while those directed roughly toward the source last longer. As a result, both species reveal an efficient orientation in gradients of chemicals. When goldfish is presented with a visual landmark, turns became clustered around them, so that fish explores an area around the landmark (Nepomnyashchikh, 2000). Thus, the structure of spontaneous activity does not changes fundamentally in all these organisms, rather quantitative changes serves to adjust it to changed external situation.

## 2.4. General approach

The above considerations are generally not taken into account in the field of designing adaptive artificial agents. First of all, the demand for spontaneous, independent of an external signals activity is frequently neglected. For example, simulations of metabolism in unicellular organisms were used to design artificial agents capable of avoiding obstacles (Ojala, 1998) and seeking for light (Ziegler, Dittrich, and Banzhaf, 1998). However, an external sensory input is needed to maintain an activity of these agents. When deprived of such an input, agents run through a transient phase and reach an equilibrium state.

Even if CPGs capable of intrinsic activity are being developed for artificial agents, they usually lack for the variability and/or qualitative structure. For example, Clark, Anderson and Skinner (2000) developed a CPG-based agent that generates varying movements in response to a repeating stimulation, but moves along a straight line if there are no external stimuli. More recently, Di Paolo (2002) developed the agent capable of internally generated zigzag movements that serve as a part of efficient taxis. However, these movements result in a fairly predictable wavy path in the absence of orienting stimuli. To the best of our knowledge, only one CPG was developed to produce an animal-like spontaneously variable path (Mobus and Fisher, 1999).

Furthermore, agents are typically developed using genetic algorithms or other tools to achieve some pre-specified particular tasks in a pre-defined environment, e.g. taxis. As a result, an agent reveals rules needed for these tasks, but remains incapable of solving even a simplest problem that had not been foreseen by a designer. For example, a simple agent consisted of few neurons was developed purposively for orientation within a continuous odor field (Beer and Gallagher, 1992), but it remains unclear what the agent should do if the field is interrupted by gaps, or a stimulation vanishes completely, or an obstacle is encountered. An additional “evolution” and complication of agents is needed to provide them with additional rules for new tasks (see e.g., Kodjabachian and Meyer, 1998). To our knowledge, no attempt was made to start a development of an agent with a variable and structured “purposeless” spontaneous activity, and then investigate a role the activity possibly plays in a generation of rules for different tasks.

Additionally, the most widespread method for creation of agents is based on artificial neural networks (ANN) that are capable of complex dynamics (Beer, 1997; Ijspeert, 2001; Di Paolo, 2002). If a number of neurons is not too large, networks’ dynamics can be analyzed (Beer, 1997) and command “neurons” can be identified (Beker, Aharonov and Ruppin, 2001). However, ANNs developed to control an agents’ behavior are typically complex and it is hard to analyze them and see which type of dynamics account for behavioral rules revealed by an agent. On the other hand, a dynamic process, which controls an agent behavior, should be clearly specified, if we want to see how observed behavioral rules are generated. To this end, an agent should consist of few components.

Basing on the above considerations, we developed the agent that reveals a spontaneous activity within each of its few CPG. All these CPGs are identical and are represented by well-known one-dimensional logistic map (May, 1976). The activity of a CPG results from the non-linear phenomenon: noise-induced phase transitions. The phenomenon is well studied (Horsthemke and Lefever, 1984), which makes the observed agent’s behavior tractable.

## 3. Tasks for the agent

If adaptive behavioral rules really may emerge from basic properties of non-linear systems, then the same system is expected to produce rules, at least, for those tasks which are equally essential for survival of various organisms, either unicellular or multi-cellular ones.

We, therefore, adjusted parameters of agent to ensure phase transitions and provided it with different types of external stimulation, but in no case we changed parameters to improve a performance of agent when it faced different tasks. We suggest that at least some of the essential tasks and expected adaptive rules to accomplish them are as described below.

### 3.1. *Wandering*

One could suggest an ordinary Brownian walk as a simple rule for the wandering in the absence of guiding cues, but a correlated random walk is a more realistic idealization for animals' searching movements (for the sake of brevity, we refer to a walk as correlated if directions of animal's sequential movements *positively* correlate). The correlated walk was observed under uniform experimental conditions in as different beings as spermatozoa (Mortimer, Swan and Mortimer, 1996), mites (Dicke and Burrough, 1988) and fish (Coughlin, Strickler and Sanderson, 1992). The fact suggests that 1) the correlated walk reflects some basic properties of organism's behavior rather than a specific organization of any particular organism, and 2) some internal mechanism can control the correlated walk even in the absence of ambient cues that could guide animals.

Some field and experimental data suggest also the Lévy walk as another idealization for animal wandering (Viswanathan et al., 1999; Levandowsky, White and Schuster, 1997). Like the Brownian walk, the Lévy one consists of randomly oriented uncorrelated runs, but the distribution of run lengths is different: most runs are very short and keep a walker within a restricted area; series of short runs are interrupted by rare very long runs which lead a Lévy walker far away searched areas.

Whichever of these idealizations one chooses for an animal walk, in both cases a path of walker intersects itself less frequently than it can be expected of Brownian walker. As a result, animals avoid revisiting previously searched sites and finds more new sites per time unit (Zollner and Lima, 1999; Viswanathan et al., 2000), which makes a searching behavior more efficient.

Possibly, the simplest way to describe a walk quantitatively is to consider a group of non-interacting animals that spread from the same point. The spread of Brownian walkers may be described as the Gaussian diffusion. In case of non-Brownian walk, the mean squared displacement (MSD) of swarm from the point of release increases with time more rapidly as compared with Brownian walk, resulting in the "anomalous" diffusion. Real organisms indeed reveal the anomalous diffusion (Root and Kareiva, 1984; Johnson, Milne and Wiens, 1992; Nams, 1996; Levandowsky et al., 1997; Upadhyaya et al., 2001). Therefore, one can require of wandering agents to reveal the same property in order to be both efficient and biologically plausible.

On the other hand, the anomalous diffusion is not observed over all time scales in real organisms: an increase of MSD decelerates at larger scales (Johnson et al., 1992; see also Levandowsky et al., 1997, for brief review of data on leukocytes and fibroblasts). Accordingly, a realistic agent should reveal a similar deceleration.

### 3.2. *Orientation*

When an animal finds some cue to guide it, then the wandering should be replaced with another rules. One of the most primitive types of guided movements is the orientation within an odor gradient using single sensor. This orientation is based on an interaction between spontaneous turning behavior on the one hand, and increment of stimulation an organism perceives at sequential movements, on the other. If an agent moves toward a source of

stimulation, then the increment is positive and suppresses turns, thus making an agent to keep the current heading (Mason, 1975).

### 3.3. Escaping gaps in odor gradients

An odor gradient is unlikely to be smooth in natural environments. It may be disrupted because of an air turbulence, or because an odor is emitted by pulses, rather than continuously. Under these circumstances, animals may persist moving in a previously chosen direction for a while, even if an odor is not perceived. This would help to move through a narrow gap and encounter a next odor pulse. On the other hand, an animal should switch to some kind of searching movement if an odor is not perceived for a long time, because this might mean that the direction is wrong (Vickers, 2000).

### 3.4. Area-restricted search

The next rule is the thorough search within a restricted area the animals performs upon finding a single prey (Bell, 1991; Grünbaum, 1998). This rule is obviously adaptive: a food and other resources are typically clustered in natural environments. This area-restricted search (ARS) is accompanied by a significant increase in tortuosity of animals' paths, which helps to keep it within the area. Even if the path significantly differs from random before a prey capture, it may become Brownian after the capture (Winkelman and Vinyard, 1991).

### 3.5. Sampling food patches

The consequence of ARS is that animals show a general preference for more reach food patches. However, animals may leave even a rich patch to "sample" other patches. This sampling obviously results in a sub-optimal patch use in a short run, but might be adaptive in a long run, because it allows for tracking temporal changes in an environment and, potentially, discover most profitable food sources (Stephens and Krebs, 1986). The sampling can be observed even under simplified and stable experimental conditions, where a distribution and quality of few food patches is familiar to animals (Wildhaber and Crowder, 1991). This means that the sampling is not necessarily the response to a patch quality or other external influences, but can be one more manifestation of intrinsic spontaneous activity.

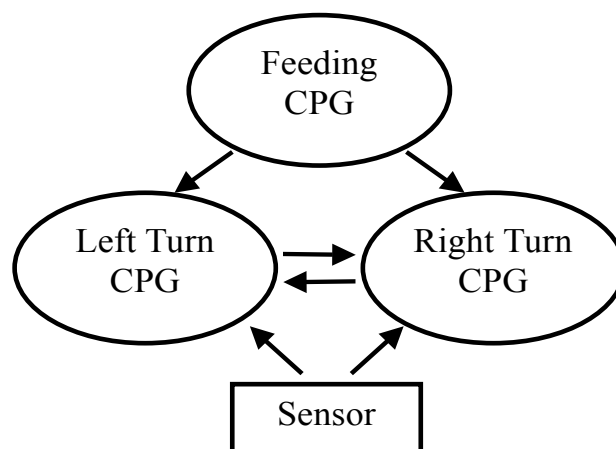


Figure 1. Architecture of the agent. See text for explanations.

## 4. Simulations

### 4.1. Agent

The agent consists of three CPGs and has a single odor sensor (figure 1). CPGs are always active, while external stimuli modify their activity via the sensor and food consumption. The first CPG controls feeding, while other two, right and left, CPGs control rightward and leftward turns. Outputs of these CPGs are feeding tendency ( $F$ ), and right ( $R$ ) and left ( $L$ ) turn tendencies respectively. The tendencies change by discrete steps ( $i$ ) and are kept within a restricted range by means of feedback:

$$\begin{aligned} F_{i+1} &= \lambda^F_i F_i (1 - F_i) \\ L_{i+1} &= \lambda^L_i L_i (1 - L_i) \\ R_{i+1} &= \lambda^R_i R_i (1 - R_i), \quad 0 < F, L, R < 1, \quad 0 < \lambda < 4 \end{aligned} \quad (1)$$

We assume that there is an internal noise in a CPG that is added to parameters  $\lambda$ . For the sake of simplicity, we assume the noise in each CPG to be white Gaussian and independent of noise in other CPGs. We assume further that the feeding CPG feeds forward both turn CPGs. Finally, turn CPGs inhibit one another and receive a sensory input  $I$ . Like the noise, all these excitatory and inhibitory inputs are added to parameters  $\lambda$ . Basing on these assumptions, the parameters are defined as follows:

$$\begin{aligned} \lambda^F_i &= \mu + \sigma \xi^F_i \\ \lambda^L_i &= \mu + \sigma \xi^L_i + F_i - R_i - I_i \\ \lambda^R_i &= \mu + \sigma \xi^R_i + F_i - L_i - I_i, \end{aligned} \quad (2)$$

where  $\mu$  is the average parameter,  $\xi$  is the Gaussian noise varying between  $-1.0$  and  $+1.0$ , and  $\sigma$  is the peak magnitude of internal noise. As it was pointed out in Section 2.4, the noise causes phase transitions in a CPG. More specifically, an accidental temporary increase in noise magnitude boosts the activity of CPG. The activity remains high long after the noise magnitude drops, because the behavior of the CPG depends on its previous states. Similarly, an accidental decrease in the noise magnitude causes a long-lasting decay of activity. Thus, noise transitions result in alternating series of high and low activity. Duration of series varies to a great extent (Nepomnyashchikh and Gremyatchikh, 1996).

The sensor does not respond to an absolute intensity of ambient stimulation  $S$ . Instead, the sensory input into CPGs represents the increment of stimulation, that is, the relative difference between stimulation intensities perceived at steps  $i$  and  $i - 1$ :  $I_i = (S_i - S_{i-1}) / S_{i-1}$ . Thus, a positive increment causes a decrease in parameters  $\lambda$  (equations 2), and vice versa. Note that sensory inputs into right and left turn CPGs are equal.

To simulate a two-dimensional walk, we assume that at any step the agent turns by angle  $T_i$  (in radians) that is simply the difference between right and left turn tendencies at the step  $i$ :

$$T_i = R_i - L_i. \quad (3)$$

Upon turning, the agent moves ahead for 1 distance unit.

## 4.2. Tasks and simulation details

The results described in the Section 5 were obtained at  $\mu = \sigma = 1.10$ , but qualitatively the same results hold when the parameters varied 1.05 to 1.20. Simulations were started with all variables set to 0.1, and initial headings of agents distributed uniformly and randomly within  $360^\circ$ . Each individual run consisted of 10,000 steps preceded by 1,000 idle steps to avoid an influence of possible transient process on agent's movements. At least 100 individual runs were performed for each task presented to the agent.

**Wandering.** In order to simulate a wandering, 100 individuals were positioned at the same point in space, and then their movements were tracked. Thus, all individual paths taken together can be viewed upon as a dispersal of group, which consists of non-interacting individuals. We assumed an ambient stimulation to be constant in the case of wandering, so that the sensor sent no input into CPGs.

**Orientation.** Each individual path within an odor gradient started with placing the agent at 1,000 distance units from the center of continuous Gaussian-shaped field of "odor", and finished after the agent has either reached a source of odor (the circle with a radius of 5 unit in the center of gradient), or traveled for the total distance of 10,000 units. Absolute intensities of stimulation at the center and start point were set 100 and 0.1 arbitrary units respectively. We also inserted no-stimulation gaps 100 to 500 units wide across the odor field.

**Response to prey.** Simulations of ARS were based on the following assumptions. When an animal actually finds a prey, a time is needed to consume it. We assume that this time is relatively short in comparison with the whole process of search. Accordingly, the feeding lasted for 5 steps only in our simulations. An arbitrary chosen constant (1.0) was added to the average parameter  $\mu$  in feeding CPG at each of these 5 steps of feeding in order to simulate an excitatory effect of food intake. We also added a negative constant ( $-1.0$ ) to the parameter, which could be interpreted as an attempt to eat some repelling prey. Finally, we assume that turn CPGs are still active during feeding and receive an input from the feeding CPG, but the agent does not actually move when it consumes a food item. We used absolute values of turn angles to characterize an after-effect of feeding on tortuosity of subsequent path. The reason is that the after-effect was not long enough to calculate MSD.

**Sampling.** Patches were simulated as parallel strips 100 units wide. The agent encountered upon a food item at every 20th step of iterations within a rich patch, and every 100th step within a poor patch. Rich and poor patches were separated by empty ones (figure 6). The regular rather than stochastic encounters with food items were simulated in order to avoid runs of bad luck that could provoke the agent to leave a patch. Each simulated run started with the agent placed at a random position within the environment.

## 5. Results

### 5.1. Wandering

The representative fragment of wandering path is shown in figure 2. Typically, paths have a noticeable structure: they consist of relatively straight runs and more or less tight loops between them. Representative log-log plot of MSD vs. time spent spreading is shown in figure 3. The plot is typical in that MSD increases with time more rapidly than it can be expected of a group of Brownian walkers. Thus, the agent really reveals anomalous diffusion and, therefore, non-Brownian walk without any external guidance.



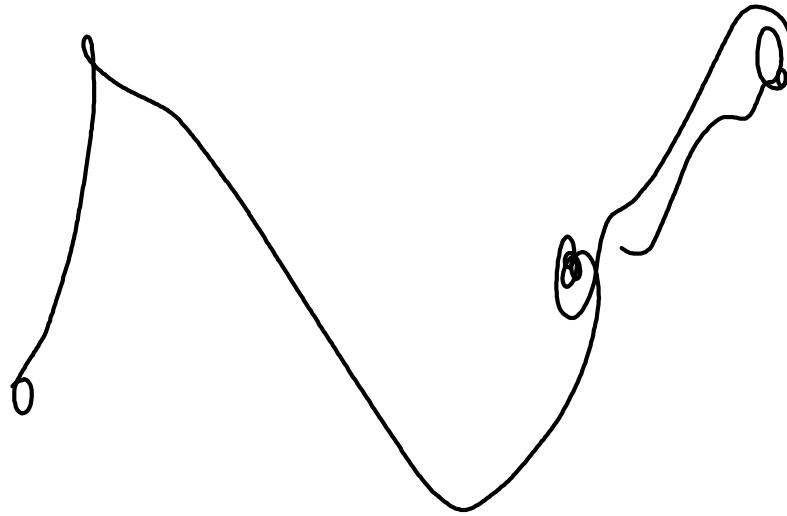


Figure 2. A fragment of simulated path, 1000 steps long.

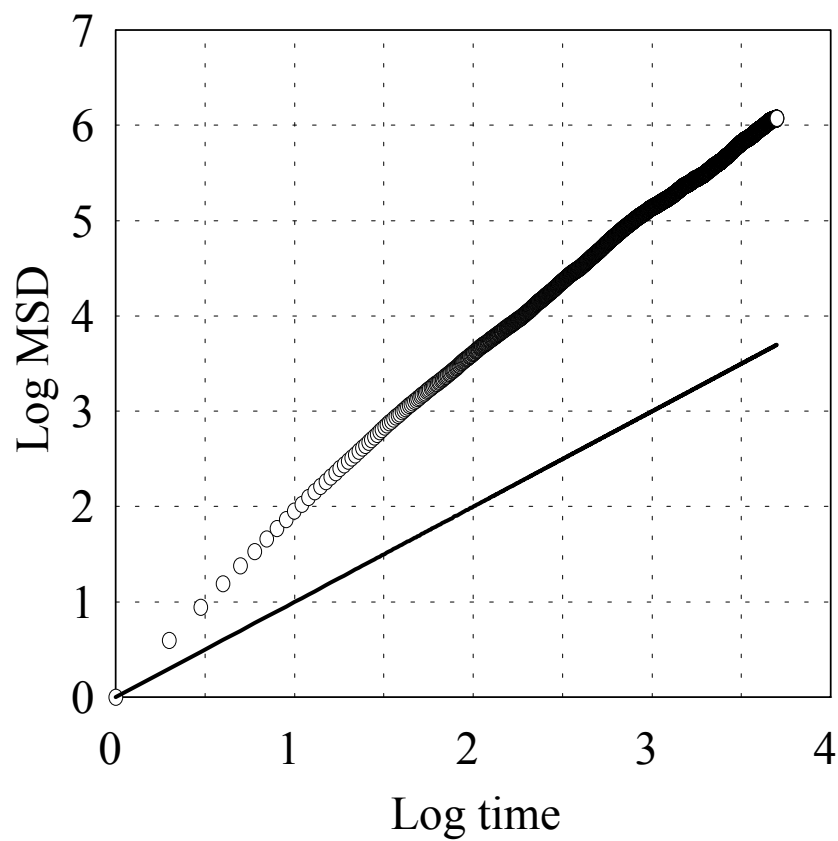


Figure 3. Plot of MSD vs. time spent spreading by the “swarm” of 100 individuals (circles). The solid line represents MSD expected of Gaussian diffusion.

On the other hand, the MSD should rise at the same rate over all time scales in case of ideal Lévy walkers, i.e. the log-log plot of MSD vs. time should fit a straight line. This is by no means a case for MSD in our simulations: agents reveal the deceleration of MSD, which is consistent with dispersal of real organisms.

The behavior of agent is explained as follows. As it was described in Section 4.1, noise-induced phase transitions result in alternating series of high and low output values in each CPG. The analysis of individual paths has shown that loops correspond to series where a difference between turn tendencies is large. Series of high feeding tendency enhances the activity of turn CPGs, which results in a higher difference between their outputs. As opposite, straight runs correspond to series of similar and low values of turn tendencies, and low values of the feeding tendency.

## 5.2. Orientation

The agent practically always reaches the odor source. Its path consists predominantly of straight runs that rarely directed exactly toward the source (figure 4a,b). This behavior is explained as follows.

Both a positive increment in ambient stimulation and occasional decrease of noise magnitude suppress turn tendencies (equations 1 and 2). If these two events occur simultaneously, this may result in series of low output of both turn CPGs and, consequently, in a straight path, even if the agent deviates from the right direction to source.

A course correction is evoked by two events that act either separately, or in combination. First, an increment of stimulation decreases or even becomes progressively negative when the agent deviates from the source. Second, an occasional burst of internal noise results in a spontaneous series of high output in one of CPGs.

Once the increment increases as a result of turning toward a right direction and/or the spontaneous series of high output in CPGs break off, the agent stop turning and follows a new course persistently, even if it also deviates from the source.

As a result of all these events, the agent generally turns more frequently if it moves away from the source and vice versa, which is consisted with orientation rules of bacteria and nematodes described in Section 2.3.

The agent does not stop at the odor source upon reaching it. Instead, it repeatedly leaves the source in various directions and returns to it again. The agent may move up to 300 units away the source during these excursions, which could be interpreted as a sort of sampling behavior. An excursion starts when series of low output occur simultaneously in both turn CPGs under the influence of internal noise.

## 5.3. Gaps in gradients

When entering a gap, the agent does respond to it immediately, but follows a previously chosen course for a while. As a result, it crosses a gap as if it does not exist at all, provided gap width does not exceed 100-200 units (figure 4a). This is explained by the fact that the agent is driven by the dynamic process which depends on a “memory” of its own previous states. Namely, if an output of both turn CPGs have been suppressed by a high stimulation increment during a movement up the gradient, then the output cannot rise quickly, even if the stimulation have ceased.

However, the memory span is limited, and the output eventually increases in wider gaps. As a result, the agent switches to the wandering. As the wandering path includes long straight

runs, the agent has good chances to escape a gap and resume it's movement toward the source (figure 4b).

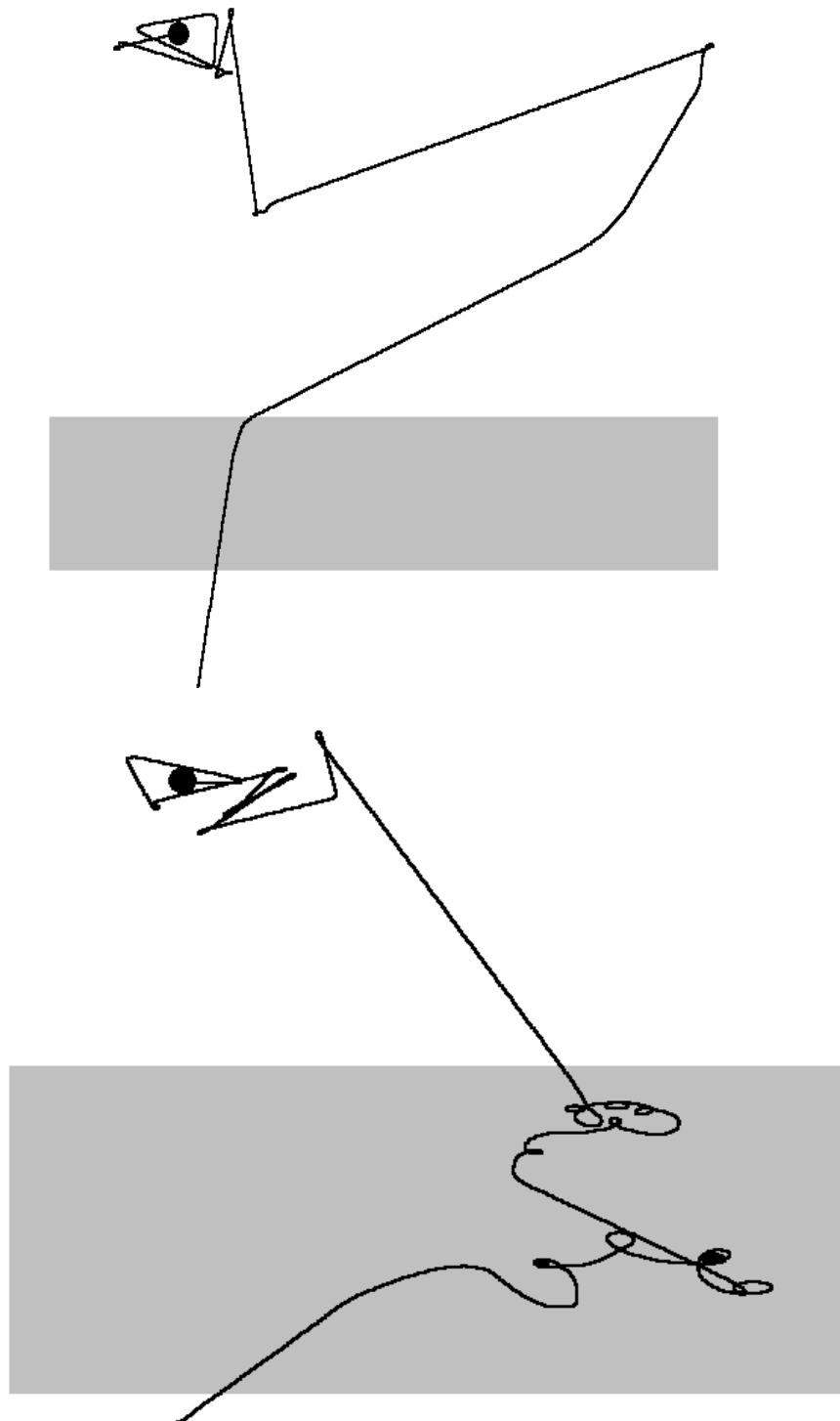


Figure 4. Agent's path in odor gradients. Sources of odor are marked with black circles. Gaps in gradients 200 (a) and 500 (b) units wide are represented by gray stripes.

#### 5.4. Area-restricted search

Figure 5 shows absolute values of turn angles before and after eating a single prey. It is seen that even the short feeding exerts a pronounced after-effect on turn angles, and therefore, path tortuosity. Turn angles still proceed to increase for a while after the feeding ceases, thus keeping the agent within a restricted area, and then gradually decrease. The duration of after-effect varies from 10 to 100 steps among individuals. This ARS results from an increase of activity in the feeding CPG caused by a feeding. The increase enhances an output of turn CPGs and, therefore, evokes an intensive turning.

Figure 5 shows also the response to an addition of negative constant to the feeding CPG. Turn angles proceed to decrease for relatively long time after the feeding, while subsequent increase is very slow. The resulting paths are straighter than before feeding and take the agent away from the spot where prey was captured, suggesting a sort of avoidance.

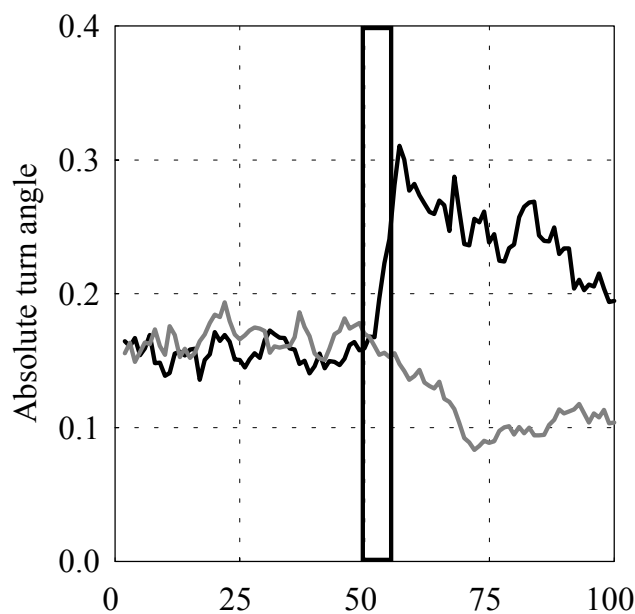


Figure 5. Area restricted search: an influence of feeding on a degree of subsequent turns (in radians). Each value is averaged over 100 individuals. Vertical bar indicates duration of feeding. Black line: positive constant (1.0) is added to feeding unit. Grey line: negative constant (-1.0) is added.

#### 5.5. Sampling

The time spent by agents within the rich patch equaled  $85 \pm 10\%$  ( $m \pm s.e.$ ), as averaged over 100 individual runs. The sample individual path is shown in figure 6. After having spent some time within the poor patch, the agent crosses the empty patch and finds the rich one. As a whole, agents left rich patches in 34 runs, in spite of the overall preference for rich patches. Like excursions to a vicinity of odor source (Section 5.2), these departures from patches are explained by spontaneous series of low CPGs' outputs.

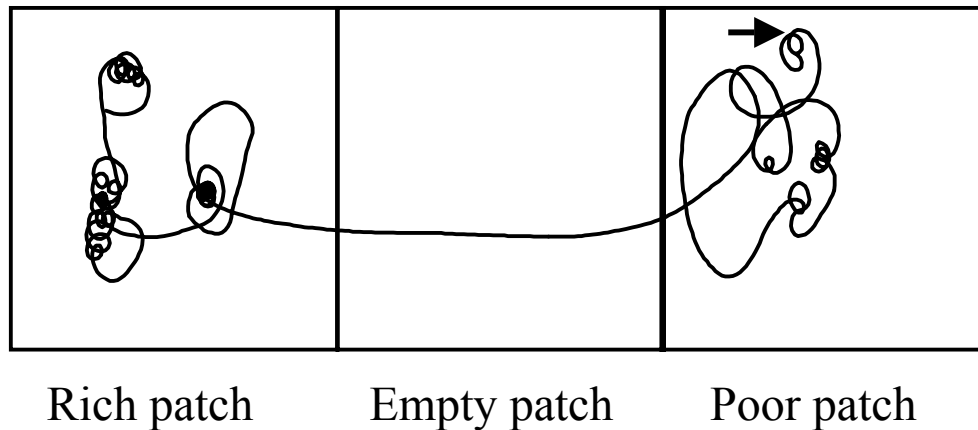


Figure 6. Patch sampling. The agent started in poor patch (the start point is marked with arrow), crossed empty patch and finished in rich one.

## 6. Discussion

### 6.1. Searching rules produced by the agent

The agent reveals searching rules, which had not been pre-programmed explicitly or evolved gradually. The rules, however, have their counterparts in real organisms, and these counterparts have obvious adaptive value:

- If deprived of guiding ambient stimuli, the agent performs a non-Brownian walk, which consists of spontaneous switches from relatively straight long runs to tight loops and vice versa. This walk results in an anomalous diffusion observed in population of agents.
- The agent switches to the oriented movement when odor gradient is found. When moving to the source of odor, it does not follow changes in stimulation continuously, but leaps roughly toward a source and corrects the chosen direction only rarely.
- If there is a gap in gradient, the agent persists with a chosen direction for a while, which helps to get through narrow gaps and doesn't lose a way to source. If a gap is wide, the agent eventually resumes non-Brownian walk, which helps to find a way out of gap more efficiently as compared to ordinary Brownian walk.
- Upon finding a food item in some area, the agent initiates a thorough search within restricted area and keeps doing so for a while, even if there are no more preys to stimulate the search. On the other hand, the agent leaves an area if captures a repulsive prey that suppresses feeding.
- The agent prefers patches with higher food density, but also reveals a sampling behavior known in foraging animals. When within a food patch, the agent may leave it and sample elsewhere, which provides an opportunity to find richer patches. Similarly, upon reaching an odor source, it makes excursions to various directions, taking a chance to find other possible sources.

## 6.2. *Are the rules biologically relevant?*

Obviously, the agent behaves in adaptive way within its simplified environment. The searching rules, which could be derived from its behavior, are strikingly similar to what is observed in many real organisms (compare Sections 3, 5 and 6.1). However, are these rules relevant to biological reality in more essential ways, besides the apparent similarity to behavior of real organisms? Many authors pointed to those principles of animal behavior, which account for their ability to solve real world problems efficiently. In this section, we compare some of these principles with those seen in the agent's behavior. To do so, we will describe the behavior of agent as it seen by an external observer, with no reference to underlying mechanisms. Also, in spite of the fact that principles defined in different ways by different authors are closely interrelated, we will consider these principles separately for the sake of clarity.

First, an adaptive behavior is autonomous. The notion of autonomy is rather broad one. As a minimum, an autonomous being selects an appropriate rule all by itself, with no instructions from outside. Our agent reveals such a minimal autonomy. However, it was argued that a real autonomy requires also an ability to create rules anew for new tasks, rather than to select them from a list prepared by designer (Smithers, 1997). Obviously, rules described here are produced anew.

Second, it is now only a commonplace to say that an adaptive behavior is a result of interaction between intrinsic dynamics of agent and dynamics of its environment (see e.g., Beer, 1997). This is the case with the agent. For example, its movements in the odor field results from the interaction between dynamics of CPG, on the one hand, and changes of external stimulation, on the other.

Third, animals typically do not respond to a momentary stimulation by a short-term single action. Instead, they produce a sequence of actions in response to a transient stimulus. This behavior is proactive in that an animal does not follow a sequence of stimuli, but completely changes an external situation. A typical example is an avoidance behavior in some juvenile organisms that performs a series of maneuvers in response to a short touch, thus avoiding more attacks. It was also shown experimentally that robots avoid obstacles and get out of corners more efficiently, if they are able to produce a rather long behavioral sequence in response to a momentary stimulation (Clark et al., 2000). Our agent reveals a proactive behavior when, for example, it leaves an area where a "repulsive" prey was found.

Forth, the agent produces rules which can be said anticipatory: the agent acts as if it expects a certain result in future even if a current stimulation does not confirms expectations. For example, the agent persists moving in a chosen direction after it has entered a gap despite the stimulation increases no more. An anticipatory behavior of this primitive type is typical for real organisms, and it had been argued (Riegler, 2001), that anticipatory rules are crucial for really adaptive behavior. Furthermore, it was argued that organisms do not track continuously the stimulation from an environment. Instead, they check for external changes and correct their behavior at some moments of time only, while relying on internal anticipations at any other time. Thus, organisms avoid an unaffordable task of tracking every minute change in an incessant flow of external stimulation (Riegler, 2001). In line with the argument, the agent corrects its movement in gradients from time to time only, and neglects external changes during lengthy time intervals.

Fifth, because an operationally closed system operates on its own states only, it had been argued also, that it does not discriminate between internal and external perturbations (Peschl and Riegler, 1999). As a result, a behavior could be generated in response to internal perturbations, with no reference to external events. This is exactly what takes place when the agent leaves the source of odor and "inspects" surrounding areas, or when it leaves a food

patch and crosses an empty area when sampling patches. These inspections are potentially adaptive, because the agent has a chance to find new odor source or richer patch. Again, this consideration returns us to the importance of spontaneity and variability for a behavioral adaptation. Agents' movements never repeat themselves, and this accounts for variability in duration of ARS or unpredictable sampling of patches. This variability is typical of animals, and could be viewed upon as a primitive form of exploratory behavior observed in the simple agent.

Thus, behavioral rules revealed by the agent do conform, at least, some of those principles that have been proposed to account for an adaptability of animal behavior.

### *6.3. Where do the rules emerge from?*

The process that control behavior of agent is driven by the internal noise, which results in phase transitions in each of CPG. In their turns, CPGs interact to produce movements of agent. The observed spontaneous wandering behavior is an external manifestation of this process. All other rules produced by the agent are externally caused modifications of the wandering. There would be no emerged rules if not for this basic spontaneous behavior.

These results favor the hypothesis that searching rules shared by a variety of organisms may be rooted in basic properties of non-linear systems. Primitive types of adaptive behavior might emerge as a whole, even from as simple system as we described here.

### *6.4. Conclusions and implications*

The current dynamical approach to adaptive behavior is based on the assumption that desirable behavioral traits can be evolved in the course of evolution gradually, by a mutation and selection of dynamic systems and their components (see e.g., Beer, 1997). This approach does not presume that a primitive adaptive behavior may, in a sense, be inherited to these systems. Our results lead to a quite different suggestion. An adaptive behavior in living being need not be evolved from a scratch in the course of evolution. Instead, the evolution needs only develop further behavioral primitives that already had existed. This suggestion could be verified by simulating an evolution of the same CPG in different environments.

The behavioral rules revealed by the agent are a small part of what could be observed even in simple organisms. However, a modification of these systems may give rise to more rules. The study may start with a variation of system's parameters: for example, the logistic map used in our simulations reveals a chaotic dynamics within certain range of parameters (May, 1976), which may result in an emergence of new rules. Besides, our preliminary results suggest that new adaptive rules may emerge even without any changes of previously set parameters if the agent is provided with additional sensors. For example, we added a sensor that is activated by contact with an obstacle and sends an inhibitory output into both turn CPGs in the same way as the odor sensor. Rather unexpectedly, this makes the agent capable of obstacle avoidance when moving in an odor gradient. The same sensor also makes the agent capable of wall following. It may "voluntarily" change a direction of wall following, or leave a wall and resume the unguided walk.

Furthermore, the searching rules described here are primitive in both meanings of the word: they are simple, and they are similar to those rules that might evolve at earlier stages of evolution. The problem is whether a basic simple system can be developed so that more advanced rules could emerge "ready-made" similar to an emergence of primitive rules, without a necessity to develop them gradually. For example, is it possible to achieve this goal by adding more CPGs to an agent? Can a complex action sequence (like, e.g., foraging trips

in bees) emerge this way? Will primitive rules still be preserved, as an agent grows more complex?

Additionally, an artificial evolution of dynamic agents similar to one described here may provide an opportunity to raise and investigate the following problems. How simple could be an underlying dynamic system to ensure viability of populations of agents in a given environment? Why rules observed in real organisms are as they are? Why a very different organisms use essentially similar behavioral rules for similar purposes, while other rules could be imagined, at least in principle? In other words, to what extent adaptive abilities of living being, as well as evolution of these abilities, are constrained and steered by laws of non-linear dynamics?

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