A Random Walker Can Optimize the Exploration without the Large Capacity Memory

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Abstract: A random walker explores an unknown field and sometimes changes its movement property using new spatial information obtained by it during its exploration. An important matter is the relation between the movement property of a random walker and the use for acquired information. I recently developed a random walk model in which a walker coordinated its directional rule based on its experiences and found that this model presented an optimal random walk, which demonstrated a so-called Lévy walk with $\mu = 2.00$. Here, I investigate the foraging efficiency for that model and verify whether a large memory capacity is required or not in order to maintain the foraging efficiency. My findings reveal that the proposed model can apply to biological processes where a random walker does not have a high memory capacity.

1 INTRODUCTION

Animals demonstrate random search in the absence of prior knowledge in order to get some information, such like spatial information (Kareiva and Shigesada, 1983; Viswanathan et al. 2001; Bartumeus et al. 2005, 2008; Bartumeus and Levin, 2008). Many random search models such like the Lévy walk or the Brownian walk model are effective for random exploration and have been very well studied (Bartumeus et al. 2005, 2008; Bartumeus and Levin, 2008). A Lévy walk, which exhibits a scale-free distribution, is defined as a process where an agent takes steps of length l at each time and the probability density function of those steps decays asymptotically as a power law:

$$P(l) \sim l^{-\mu}, \quad \text{where } 1 < \mu \leqq 3$$

Several studies of animal foraging strategies have reported that Lévy walks are efficient where resource is sparse and randomly distributed (Bartumeus et al. 2005; Humphries and Sims,2014). On the contrary, the advantage of Lévy walks will disappear in high-density environments where resource is abundant (Bartumeus et al. 2005; Humphries and Sims,2014). The Lévy and Brownian walks show similar exploration efficiencies if extremely abundant resources are available for random walkers.

The search ability for food resources is a matter of life and death for random walkers. To this end, the search ability of random walk models has been extensively investigated (Sakiyama and Gunji, 2013). Recently, I developed a random walk model named as the self-reference model (Sakiyama, 2020). A walker in that model avoids a certain direction using the past information. At the same time however, the walker modulates its directional rule if it experiences some directional inconsistencies in the recent series of its movements. The self-reference model exhibited a so-called power-law tailed movement with optimal μ value ($\mu \approx 2.0$) (Bartumeus et al. 2005). In this paper, I check the paramenter effects by examining the performance of resource search ability of this model. Here, a random walker obeying that model explores a two-dimensional field where food resources are distributed. I investigate the parameter effects in respect with the exploration ability of the walker and discuss the unnecessity of a large memory capacity.

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2 MATERIALS & METHODS

2.1 The Self-reference Walks

Each trial is run for a maximum of 1,000 time steps. Field size is set to 1,000 × 1,000. Periodic boundary is assumed. I set the simulation stage for each trial and set the agent at the origin; $(x(0), y(0)) = (0, 0)$. In this algorithm, the agent moves in two-dimensional square lattices. On each time step, the agent selects one direction among four discrete directions and updates its position like follows;

$$(x(t+1), y(t+1)) = (x(t)+1, y(t)) \text{ with Prob } (+x),$$
$$(x(t+1), y(t+1)) = (x(t)-1, y(t)) \text{ with Prob } (-x),$$
$$(x(t+1), y(t+1)) = (x(t), y(t)+1) \text{ with Prob } (+y),$$
$$(x(t+1), y(t+1)) = (x(t), y(t)-1) \text{ with Prob } (-y),$$

$$\text{Prob } (+x) + \text{Prob } (-x) + \text{Prob } (+y) + \text{Prob } (-y) = 1.00.$$

At the beginning of each trial, the agent equally selects each direction.

A directional move that consists of a series of the different move, such as $+y$, $-x$ or $+x$, $+y$ and so on, is counted as

if $(x(t+1) - x(t)) = (x(t) - x(t-1)) = \pm 1$
or $(y(t+1) - y(t)) = (y(t) - y(t-1)) = \pm 1$,

$$\text{Exp}(t+1) = \text{Exp}(t),$$

otherwise,

$$\text{Exp}(t+1) = \text{Exp}(t) + 1$$

For example, "Exp (t+1)" can be "Exp (t) + 1" when the agent moves in $+x$ direction at time t-1 and is going to move in $-x$ direction at time t.

If Exp (t) exceeds a threshold number, th, the four directional probabilities are changed as follows and the agent obeys these new rules from the next time step;

if $x(t+1) - x(t) = +1$,
Prob $(+x) = \varphi$,
Prob $(-x)$ = Prob $(+y)$ = Prob $(-y) = (1-\varphi)/3$
if $x(t+1) - x(t) = -1$,
Prob $(-x) = \varphi$,
Prob $(+x)$ = Prob $(+y)$ = Prob $(-y) = (1-\varphi)/3$
if $y(t+1) - y(t) = +1$,
Prob $(+y) = \varphi$,
Prob $(+x)$ = Prob $(-x)$ = Prob $(-y) = (1-\varphi)/3$
if $y(t+1) - y(t) = -1$,
Prob $(-y) = \varphi$,
Prob $(+x)$ = Prob $(-x)$ = Prob $(+y) = (1-\varphi)/3$

Here, φ indicates a random number that satisfies ratio is the element of a set [0.25, 1.00]. Here, the maximum random number was set to 1.00 in order to produce a straight movement toward a certain direction. Note that Exp (t) is reset to 0 at that time.

The agent obeys a biased directional rule in order to avoid moving in a certain direction. By doing so, the agent can avoid visited positions to some extent and effectively explore. At the same time however, the agent modifies its rule when the agent experiences several series of the different directional move such like $+x$, $-x$ or $-y$, $-x$ and so on.

Only at first, i.e., at time t=0, where the agent calculates $(x(1), y(1))$ by obeying a Brownian-like walk, the four directional probabilities are modified as follows independently of Exp (t):

if $x(1) - x(0) = +1$,
Prob $(+x) = \varphi$,
Prob $(-x)$ = Prob $(+y)$ = Prob $(-y) = (1-\varphi)/3$
if $x(1) - x(0) = -1$,
Prob $(-x) = \varphi$,
Prob $(+x)$ = Prob $(+y)$ = Prob $(-y) = (1-\varphi)/3$
if $y(1) - y(0) = +1$,
Prob $(+y) = \varphi$,
Prob $(+x)$ = Prob $(-x)$ = Prob $(-y) = (1-\varphi)/3$
if $y(1) - y(0) = -1$,
Prob $(-y) = \varphi$,
Prob $(+x)$ = Prob $(-x)$ = Prob $(+y) = (1-\varphi)/3$

In our simulations, th is set to 5 as a default value.

3 RESULTS

Here, food resources are randomly distributed on the field and the resource density is set to 0.001. The agent can consume food items if those items are located within 5.0 radii. Food depletion, which means that food items disappear once the agent consumes those items, does not occur. Therefore, the agent can consume each food item whenever it detects that item within 5.00 radii. Later however, I will check the effect of the resource density and the food depletion. Food depletion is an important factor for the search ability and the movement strategy of random walkers. This is because the random walker with sub-diffusive movements does not have a trouble with consuming food resources if food depletion does not occur since it can find and consume resources again and again. On the contrary, the random walker may need to change its strategy if food depletion occurs due to the fact that no items can be found by the walker once it consumes those items. Therefore, the effects of food depletion will reveal the performance of my model.

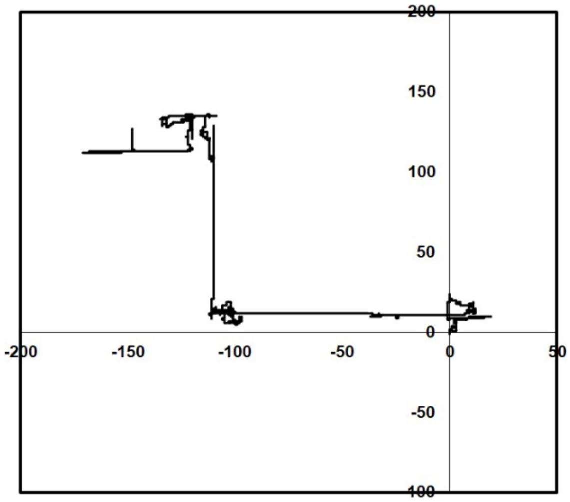

Figure 1: An example of the agent's trajectories where the resource depletion does not occur. The parameter *th* = 5.

First, I focus on movement properties of the model. Figure 1 shows an example of an agent trajectory obtained from 1 trial. According to this figure, the agent seems to sometimes produce straight movements. In fact, the mean squared displacement (msd) between the start point and end points reveals that the agent demonstrates a super diffusive movement (Figure 2A). Here, each end point was obtained every 100 time steps and each msd obtained from 100 trials was plotted. In the random walk analysis, the relation between the mean squared displacement $<R^2>$ and the step is often calculated since this property presents the diffusive property of the walker. It is well known that his property follows the following relation (Viswanathan et al. 1999):

$$<R^2> \sim t^{2H}$$

Parameter H is determined depending on the model (H>1/2 for a Lévy walk (super-diffusion), H=1/2 for a Brownian walk (normal diffusion) and H<1/2 for sub-diffusive movements). The fit for parameter H according to Figure 2 was $H \sim 0.91$, indicating that super-diffusion was achieved (R-squared=0.99).

For the evaluation of the parameter effects, I replaced the parameter *th* from 5 with 50. Figure 2B represents the diffusive property in case of *th* = 50. Results suggest that super-diffusive movements can be maintained even after the parameter replacement (Figure 2B: threshold = 50, $H \sim 0.91$, R-squared = 0.99).

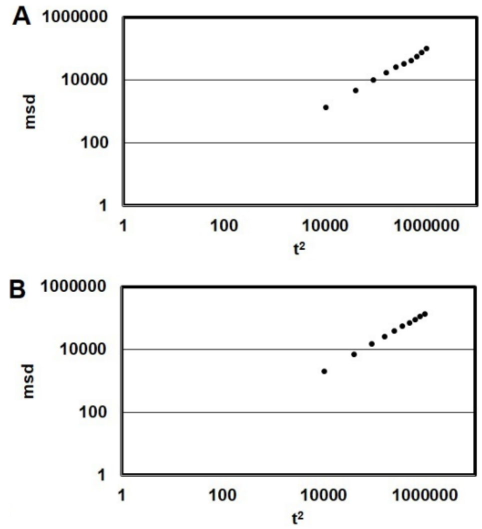

Figure 2: Log-scale plot of mean squared displacement (msd) and t^2 obtained from 100 trials for each threshold. A. *th* = 5. B. *th* = 50.

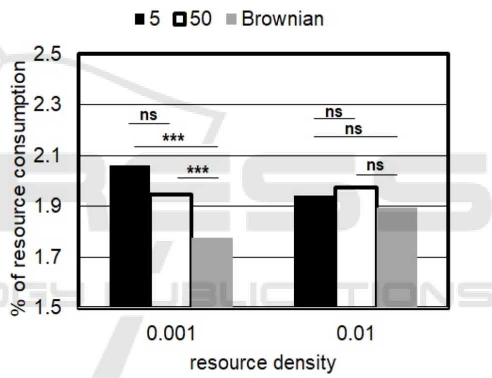

Figure 3: % of resource consumption in respect with resource density; 0.001 and 0.01 for each threshold value and for the Brownian walker under the condition where the resource depletion does not occur. *** indicates $p < 1.0E\text{-}03$, ns indicates non-significant.

In fact, the resource search ability of this model seems to be not dependent on the parameter threshold. According to Figure 3, which showed the fraction of the resource consumption, I found that there was no significant difference between *th* =5 and 50 (Figure 3: resource density = 0.001, *th* =5 (2.06) vs. *th* = 50 (1.95), Mann-Whitney U test, P = 0.58, NS). Furthermore, this tendency is not changed even after the resource density is replaced with 0.01(Figure 3: resource density = 0.01, *th* =5 (1.94) vs. *th* = 50 (1.97), Welch Two Sample t-test, t = -0.69, df = 195.88, P = 0.49, NS) Here, I counted the number of resources consumed by the agent on each trial and converted it to the percentage against the total number distributed on the field. Importantly, I found that the proposed model outperformed the Brownian walk model when resource density was low (Figure 3: resource density = 0.001, *th* =5 (2.06) vs. Brownian (1.78), Mann-Whitney U test, P < 1.0E-04, *th* =50 (1.95) vs. Brownian (1.78), Mann-Whitney U test, P < 1.0E-04, resource density = 0.01, *th* =5 (1.94) vs. Brownian (1.90), Welch Two Sample t-test, t = 0.57, d*f* = 134.35, P = 0.57, NS, *th* =50 (1.97) vs. Brownian (1.90), Welch Two Sample t-test, t = 0.96, d*f* = 141.83, P = 0.34, NS). These results suggest that the proposed model can search effectively in the low-density environment and the performance is not affected by the parameter threshold. In other words, the agent is not necessarily to remember a large number of "Exp".

To investigate the influence of the food depletion to the search ability, I also conducted the same analysis under the condition where resource items were depleted once the agent consumed items. Figure 4 indicates that the proposed model again outperforms the Brownian walker model. Interestingly, this tendency is found not only in the low density environment but also in the (relative) high density environment (Figure 4: resource density = 0.001, *th* =5 (0.17) vs. *th* = 50 (0.16), Mann-Whitney U test, P = 0.31, NS, resource density = 0.01, *th*=5 (0.17) vs. *th* = 50 (0.17), Mann-Whitney U test, P = 0.39, NS, resource density = 0.001, *th* =5 (0.17) vs. Brownian (0.03), Mann-Whitney U test, P < 1.0E-15, *th* =50 (0.16) vs. Brownian (0.03), Mann-Whitney U test, P < 1.0E-15, resource density = 0.01, *th* =5 (0.17) vs. Brownian (0.03), Mann-Whitney U test, P < 1.0E-15, *th* =50 (0.17) vs. Brownian (0.03), Mann-Whitney U test, P < 1.0E-15). This is perhaps because a Brownian walker presents normal-diffusive movements, which may result in the inefficient search of the food resources under the condition where resource items are depleted.

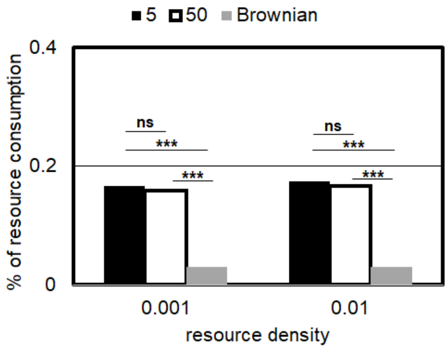

Figure 4: % of resource consumption in respect with resource density; 0.001 and 0.01 for each threshold value and for the Brownian walker under the condition where the resource depletion occurs. *** indicates p < 1.0E-03, ns indicates non-significant.

4 CONCLUSIONS

In the developed random walker algorithm, the agent modulates its directional rule and avoids a certain direction. However, it modifies its directional rule when the inconsistency of the recent series of the directional move beyond a threshold value. As a results, I found that the agent presented and maintained super-diffusive movements in some threshold values. Thanks to this, that model outperforms the Brownian walk model when the resource density is low or when resources are depleted once the agent consumes those items. Moreover, the performance of resource search ability was not influenced by the threshold replacement. These results suggest that the proposed model does not require the large number of "Exp" to achieve an effective search.

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