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Adaptive Switching Between Search and Exploitation in "Yuragi"-based Searching Behavior

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1. Introduction

Search is an essential function of mobile robot(s). A general aim is to maximize the chance of finding targets under certain criteria, such as total time elapsed or traveled distance. If the probability distribution of the targets is known, it is possible to calculate and employ certain optimal strategies [1][2]. However, if it is unknown, the problem can be seen as how to adapt and choose the best random search strategy based on recent findings, as different strategies may provide different chances to find the targets.

In realizing simple yet adaptive behavior, biological creatures are often considered as inspirational resources. In fact, in nature, ranging predators do random search as they have to make foraging, search for foods, decisions with little, if any, knowledge of present resource distribution and availability [3]. Amazingly, in studies of animal foraging, various kinds of creatures seem to show effective random search with proper statistical properties. In relation with this, in [4], a general question of what is the best statistical strategy to optimize a random search is addressed. It is shown that for sparse targets, the number of targets found versus the traveled distance, is maximized when the flight lengths, the moving length between subsequent change of direction, follow power law distribution with a heavy tail, a characteristic of Levy distribution. This specialized random walk with power law trajectory, called the Levy flight or to be more exact Levy walk, receives many attention in the literatures [3][4][5][6].

However, Brownian walk, another common random walk model where the distribution is not heavy tailed, is not a null model which should be improved. Instead, in [5] it is shown that while Levy walk is beneficial for a search with scarce, smaller and slower targets, Brownian walk can be more useful for certain opposite conditions. Furthermore, even Levy walk already alternates between extensive and intensive search, a simple switching rule from Levy to Brownian walk to exploit the current area once a target is find, is shown to be beneficial for one dimensional, patchy-like distribution [6].

Researches about random search do exist in mobile robot literatures [7][8]. However, none seems to really concentrate on how to realize a simple searching behavior, based on simple design, yet can properly adapt the statistical properties of the search to effectively cope with unknown, possibly complex, target distribution.

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The aim of the research is to realize such adaptive random searching behavior, taking inspiration from the nature. We are particularly interested in random power law trajectory found in bacteria, as the simplest creature. Our approach is to implement the phenomena based on "Yuragi", or biological fluctuation. We will show that based on this simple framework, the robot will be able to perform bacterial based power law random search, a Levy walk statistic. Furthermore, it will also be able to switch to Brownian walk based exploitation once a target is found. This adaptive switching between extensive search and exploitation is being conducted in a patchy target distribution setting.

The organization of the paper is as follow. First, we will explain about power law trajectory found in biological creatures. After that, we will explain "Yuragi" or biological fluctuation and how an adaptive power law searching behavior can be realized based on it. Simulation experiments are performed to confirm the effectiveness of our approach. Therefore, we will explain about the experiment setup and condition, before showing the result. At the end, we will discuss the conclusion and mention some future works.

2. Power Law Trajectory in Biological Creatures

2.1 Levy Walk: A Power Law Trajectory

The term Levy flight is used to describe a specialized random walk in which the move steps are drawn from a probability distribution with a power-law tail [3][4]:

$$p(l) \approx l^{-\mu} \tag{1}$$

with $1<\mu<3$, and l is the flight length. In other word, the random walk will have a random power law trajectory. Sums of those flight lengths converge to a Levy stable distribution. For $\mu\geq 3$, the sums converges to a Gaussian distribution due to the Central Limit Theorem, thus we recover Brownian walk. The case of $\mu\leq 1$ does not correspond to distributions that can be normalized.

The trajectory of a Levy flight comprises of walk clusters' of short flight lengths with longer reorientation jumps between them. This pattern is repeated across all scales, with the resultant scale-invariant clusters creating trajectories with fractal patterns. However, to be more exact, a more technically correct term is actually Levy walk: essentially means Levy flight with time cost that depends on the flight lengths [9].

In [9][10][11], it is shown that trajectory of ranging animals from marine predators, fruit flies and spider monkeys fits this Levy walk trajectory. More amazingly, creatures as simple as zooplankton switch from Brownian to Levy walk as the resource availability changes [12]. However, the simplest creature that ever shows a power law statistic in its moving forward movement is bacteria [13][14].

The underlying mechanism on how such trajectory is generated in biological creatures is also considered as interesting topic. For example, as will be explained more, in bacteria, a Gaussian, internal protein fluctuation is a possible cause [14]. In higher level animals such as spider monkey, memory about the target locations is a more relevant explanation [11].

Mathematically speaking, in order to create a trajectory with statistical property explained by (1), one can of course sample a Levy stable distribution. However, it is not the only way. For example, in [15], it is explained that fractional Brownian motion, a generalized form of Brownian motion, can also be used to create such trajectory. In [5], a transformation method is used to create the flight length random variables from uniform distribution.

In this paper, we simply use the term "Levy walk" to describe such observed heavy tailed power law trajectory, regardless of the underlying process that generates it.

2.2 Levy Walk in Bacteria

In bacteria, such as Escherichia coli, the motion can be characterized as a sequence of smooth-swimming runs, punctuated by intermittent tumbles that effectively randomize the direction of the next run [16]. These two motions can be called the "swimming" and the "tumbling" mode, as shown in Fig. 1 (top left). The probability that a smooth swimming E. coli cell will stop its run and tumble is dictated by measurement of attractant chemical gradient in the environment.

E. coli are only a few microns long so they are unable to measure the gradient by comparing head-to-tail concentration differences, but use a kind of memory to compare current and past concentration. When the bacterium perceives conditions to be worsening, the tendency to tumble is enhanced. Conversely, when it detects that the condition, i.e. the attractant chemical concentration, is improving, tumbling is suppressed and it keeps running. As a result, when the bacterium runs up a gradient of attractant, it will do chemotaxis, a biased random walk toward the source of the attractant. In the absence of this gradient attractant, the bacterium will simply do random walk. This behavior is shown in top right figure of Fig. 2.

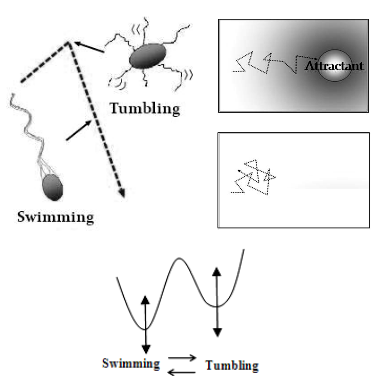

Fig.1 Description of bacterial movement.
Top left: swimming and tumbling mode;
Top right: when there is attractant, bacteria will do "chemotaxis" toward the source, when there is none, it will simple do random walk;
Bottom center: the probability to switch between the two modes depends on energy "barrier", whose level fluctuated by certain protein

Recently, unlike the conventional expectation that the swimming mode duration of E. coli follows Poisson-like distribution in absence of attractant, power law distribution is found [13]. Furthermore, in [14] a possible cause is explained. As illustrated in bottom center figure of Fig.1 (bottom center), it can be modeled that the switching probability between swimming and tumbling mode is affected by certain energy "barrier" whose level keeps changing due to fluctuation of certain protein inside the bacteria. If this protein fluctuates with long correlation time, such random power law trajectory in absence of attractant, a Levy walk, can be generated.

3. Yuragi-based Searching Behavior

3.1 The Principle

"Yuragi" is a Japanese word for biological fluctuation. It is used by Kashiwagi et al [17] to explain bacteria adaptation to environmental changes by altering their gene expression. This gene expression is controlled by a dynamical system with some attractors, and the model can be represented by Langevin equation as:

$$\tau_x \dot{\boldsymbol{x}} = -\frac{dU(\boldsymbol{x})}{d\boldsymbol{x}} \times A + \varepsilon \tag{2a}$$

$$= \boldsymbol{f}(\boldsymbol{x}) \times A + \varepsilon \tag{2b}$$

where x and $f(x)$ are the state and the dynamics of the attractor selection model, with $f(x)$ can be designed to have some attractors in $U(x)$. ε is the noise term. A is a variable called "activity" which indicates the fitness of the state to the environment. From the equation, $f(x) \times A$ becomes dominant when the activity is large, and the state transition approaches deterministic. When the activity is small, ε becomes dominant, and the state transition becomes more stochastic. The activity is therefore designed to be large when the state is suited to the environment and vice versa.

This framework introduces many design possibilities, but here we concentrate on realizing the following searching behavior.

3.2 The Realized Searching Behavior

In order to implement the "Yuragi" equation in (2) for realizing bacterial based Levy walk, the first step is to properly choose the state of the attractor selection model. To explain the bacterial movement, one can draw a probabilistic state machine shown in Fig. 2 (left). Here, "*P*" is the probability to keep on swimming. In other word, the probability to switch from swimming to tumbling mode is *1-P*. For simplification, the probability to switch from tumbling to swimming mode is simply set as 1. This means that after tumbling, the robot always switch to swimming mode at the next time step. The swimming mode defined as moving one unit forward, while tumbling means changing direction randomly.

Levy walk trajectory supposes to arise when the probability of switching between the two states fluctuates with long correlation time [14]. Therefore, a natural choice for the state of attractor selection model is *P* or *1-P*. Here, we choose *P* as the state.

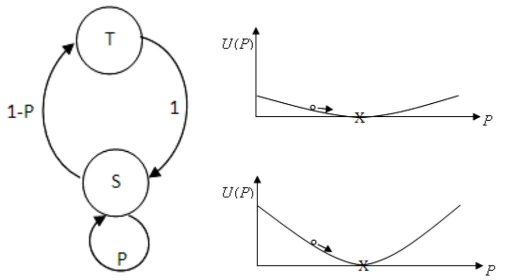

Fig.2 Description of the state used in the attractor selection model
Left: a probabilistic state machine between S=swimming
and T=tumbling mode to explain bacterial movement;
Right: conceptual potential design to fluctuate "P" with
(long/short) correlation time (top/bottom figure) around an attractor at "X"

To design the dynamic of P based on (2), we employ a unimodal potential function and define the dynamic of P as:

$$\tau_x \dot{P} = -k\frac{d(P-a)^2}{dP} \times A + \varepsilon \quad (3a)$$

$$= -2k(P-a) \times A + \varepsilon \quad (3b)$$

The first term represents slow adaptation toward a preferred value of a, which corresponds to the attractor. The noise term, ε, is zero mean Gaussian white noise, representing the stochastic driving force. τ_x is the time constant, and a gain k decides the time scale. A small value of k means a long time scale, or long correlation time, and vice-versa. The (top/bottom) figure of Fig.2 shows how the potential $U(P)$ should look like with a (small/large) value of k.

Based on this design, it is assumed that two kinds of searching behavior can be realized:

(1) Non-adaptive search type. In this design, the activity is simply kept constant, not a function of sensory input. The shape of the potential and therefore the time scale does not change. With a long time scale, supposedly Levy walk trajectory with certain power law exponent, "μ", will arise.

(2) Adaptive search type. In this design, the activity is a function of sensory input. When a target is not found, the shape of the potential should resemble Fig. 2 (top right). However, once a target is found, the activity should be high, the shape of the potential resembles Fig. 2 (bottom right), supposedly reduces the correlation between consecutive swimming modes. When this happens, the Levy walk supposes to switch to a usual, less correlated, random walk. Here, the activity function can be summarized in equation (4) and (5), with a minimum value of the activity is 1, and 0<C<1. Anytime a target is found, F will be triggered to a large value. By employing such function, the correlation time will be reduced once a target is found and gradually increases to the original value, if no more targets are found.

$$A(t) = \begin{cases} 1, & \text{if } \alpha(t) \le 1 \\ \alpha(t), & \text{if } \alpha(t) > 1 \end{cases} \quad (4)$$

$$\alpha(t) = C.\alpha(t-1) + F \quad (5)$$

4. Simulation Experiments

4.1 Experiment Setup and Conditions

In order to verify the effectiveness of the method, a simulation experiment was conducted. Fig.3 shows the examples of the resulting trajectory. The size of the area is 640x480 units. The starting position is from the center of the screen. Once the robot reaches the area boundary, it will do the tumbling mode. If a target is within a field of view of the robot, defined as two units, the robot will change orientation accordingly and move forward to obtain the target. Otherwise, it will have a probability of "swimming" or "tumbling" according to P. The turning angle is simply set to be uniformly distributed from 0 to 360 [deg].

The equation (3) is discretized with time sampling 0.5 [s]. The size of noise ε, defined by the standard deviation, is chosen as 0.1. In order to let P fluctuates with long correlation time, a small value of k=0.001 is chosen. For the non-adaptive search type, the activity is simple kept equals to 1. For the adaptive search type, the activity follows (4) and (5) with C simply chosen as 0.9, while a large value of F=100 is chosen to radically change the shape of the potential, and therefore the time scale, once a target is found.

First, we want to confirm that the robot will certainly do Levy walk. After that, we want to confirm whether it will certainly switch from Levy-based extensive search to Brownian walk based exploitation, and whether such behavior is useful. Therefore the experiment conditions are chosen as:

(1) With the value of k=0.001, we observe the logarithmic plot of the generated flight lengths to estimate value of μ. We also compare the searching efficiency in simple uniform distribution of a thousand targets with a "hardcoded" Levy walk, in which the flight lengths are generated by random number generator [18] with similar resulting value of μ.

(2) We let the robot to do a non-adaptive searching and adaptive searching type in patchy target distributions and compare the efficiency. We deploy ten circular shape patches, each contains five hundreds targets uniformly distributed. The radius of the patch is fifty units.

The search efficiency is defined as the number of targets found divided by total distance traveled, multiplied by a thousand. For both the conditions, we employ two scenarios for the target's condition after being found. The first case is the targets simply disappear, while for the second one, it will reappear in the original location after it is outside the field of view of the robot. We simply call these scenarios as "destructive" and "non-destructive" scenario, which has similarities with scenarios in several Levy walk literatures [3][4]. For all experiments, we performed ten trials and observe the average data.

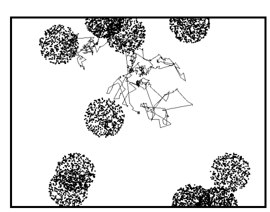
Fig.3Trajectory example of the simulation,
in a patchy target distribution

4.2 Experiment Results

Fig. 4 shows an example of log-log histogram of the flight's frequency $N(l)$ versus the lengths l obtained when the value of k=0.001. The frequency is normalized, while the lengths are put into bins with logarithmic binning. The negative value of the fitted line's gradient therefore indicates μ. From ten trials, the average value of μ is 2.22. As $1<\mu<3$, it shows that Levy walk emerges when k is small, as P has long term correlation. Fig. 5 shows the comparison of the trajectory and efficiency, between our approach and a "hardcoded" Levy walk, for a destructive search scenario. The bar shows the average, the line shows the standard deviation. They are shown to be similar.

Before we compare the search efficiency between the non-adaptive and adaptive search, we observe the estimated value of μ when a target has just been found, which means that $A(t)=F=100$. With the same procedure, it can be obtained that in 10 trials, μ averagely equals to 3.35. As $\mu \geq 3$, it means the robot performs a Brownian random walk. If the robot does not find more targets, it will gradually switch back to Levy walk, as the exponent μ gradually switches back to the "default" value range.

Fig. 6 shows the efficiency comparison of the non-adaptive and adaptive searching type for the two scenarios of target condition. The numbers below show the average of (targets found / traveled distance). It can be seen that switching to exploitation in possibly rich area, performed by the adaptive search type, has a clear effect in increasing the efficiency when the scenario is non-destructive, in other word, can be revisited.

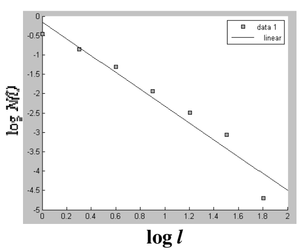

Fig.4 An example of log-log histogram of flight's frequency versus the lengths when P has long term correlation, with μ= 2.17

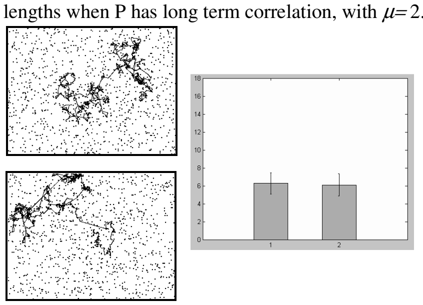

Fig.5 Comparison of the proposed approach and a "hardcoded" Levy walk. Left: the trajectory (top: the approach, bottom: "hardcoded" Levy walk). Right: the efficiency (left bar: the approach, right:"hardcoded" Levy walk)

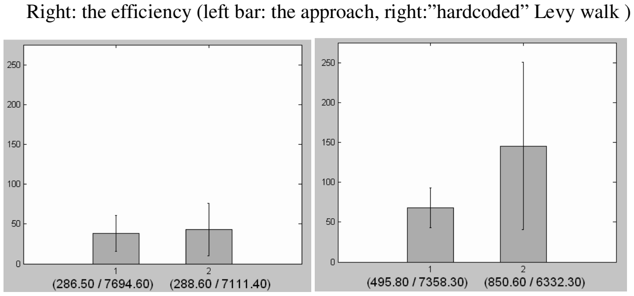

Fig.6 Comparison of the search efficiency between the non-adaptive search (left bar) and adaptive search type (right bar). Left: destructive scenario. Right: non-destructive

5. Conclusion and Future Works

In this paper, we propose a simple design that can realize an adaptive switching between search and exploitation by changing the statistical property of the search between Levy and Brownian random walk type. The design is based on biological fluctuation and bacterial movement. It has been shown that such behavior is useful. In principle, we show that based on this simple design, the robot can adapt to relatively complex environment.

Our future work is to try this simple design in a more complex environment. For example, the patches can have difference sizes, while the average distance among the targets within a patch can be different. We will see whether simple modification of the current design, such as moving the position of the attractor, or having more than one attractor could be useful for such situation.

6. References

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