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Attractor Selection-Based Biologically Inspired Navigation System

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Abstract

The paper describes a biologically inspired navigation system based on attractor selection mechanism. The robot can reach a particular signal source as a goal, with only a simple sensor and without a model of the environment. It is, therefore, robust to changes in the environment. The novelty of this approach is that it utilizes noise in the navigation system to keep the robot searching for the goal. Experiment results of simulation and real-robot experiments are shown and explained.

1. Introduction

Navigation is an important capability of a mobile robot. The common view of navigation is to use the robot's sensory inputs to update a single global representation of the environment, from which motor actions are derived by an elaborate inference procedure [1]. However, none of the systems built based on this view has yet reached the navigation flexibility of many kind of animals, and it attracts people to investigate biologically inspired techniques.

In a past decade, various biologically inspired navigation systems have been investigated. In [1, 2], a survey on various approaches in realizing biologically inspired navigation system is described. However, none of the approaches concentrates on utilizing noise in the navigation system.

In [3, 4], it is shown that *E. coli* bacterium actually utilizes noise in its navigation system when doing the chemotaxis behavior. However, the works concentrate more on modeling a motor control of the bacterium, which also include particular noise, and implementing it in a mobile robot, rather than how to properly utilize the noise.

Here, we would like to describe a biologically inspired navigation system based on attractor selection model. First, we would like to explain about the method, including the noise term, and how the navigation system was designed based on the method. Then, we will explain how we confirm that the system enables the robot to accomplish its task in reaching particular signal source as a goal. We will also explain the results of the experiments that include a clue on how to properly deal with the noise in the navigation system. The experiments are conducted in simulation and real robot. Conclusions and future works will also be explained.

2. Attractor Selection-Based Navigation System

The attractor selection model is inspired from the behavior of bacteria to adapt to environmental changes. The model is built based on biological fluctuation, and is called the attractor selection model [5]. It is described by the following Langevin equation:

$$\tau_x \dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x}) \times A + \boldsymbol{\varepsilon} \qquad (1)$$

Where $\boldsymbol{x}$ and $\boldsymbol{f}(\boldsymbol{x})$ are the state and the dynamics of the attractor selection model. τ_x and $\boldsymbol{\varepsilon}$ are the time constant and the noise, respectively. A is a variable called "activity" which indicates the fitness of the state to the environment. In order to apply this equation to the robot control, we interpret the state $\boldsymbol{x}$ as the position of the robot, thus $\dot{\boldsymbol{x}}$ as the motion of the robot. From the equation, $\boldsymbol{f}(\boldsymbol{x}) \times A$ becomes dominant when the activity is large, and the state transition approaches deterministic. When the activity is small, $\boldsymbol{\varepsilon}$ becomes dominant, and the state transition becomes probabilistic. The activity is designed to be large when the state is suited to the environment. Because $\boldsymbol{f}(\boldsymbol{x})$ is designed to have some attractors which correspond to particular motions, the state of the system is entrained into a particular attractor when the activity is large. This means that the robot tends to keep taking the same motion when the fitness is high.

The aim of the robot is to reach particular signal source as the goal. Therefore, to design the attractor system we use a following simple rule on how the robot should navigate. The activity is defined as the change of the amplitude of the signal in order to let the robot to approach the signal source as a goal. When the signal amplitude gets higher, the tendency of the robot to move straight forward should increase. When the amplitude gets lower or doesn't change, the tendency of the robot to move straight forward should decrease. Instead, the robot should tend more to move randomly forward until the signal amplitude gets higher again. The behavior is inspired from chemotaxis behavior of *E. coli* as explained in [2, 3, 6].

Fig.1 shows the designed attractor space to realize such behavior. The top left figure shows the vertical and horizontal axis that corresponds to the left and right wheel velocity of the robot respectively. We use two attractors, namely attractor 1 and 2. The coordinates of attractor 1 and

2 is (1,1) and (0.5,0.5) respectively. The (1,1) coordinates corresponds to (30,30) [cm/sec]. The diagonal line is the forward / backward border of the movement.

We define $\boldsymbol{f}_i(\boldsymbol{x})$ as the dynamics of the system caused by i[th] attractor described above, the designed dynamics of the system is shown in equation (2). The magnitude of $\boldsymbol{f}_i(\boldsymbol{x})$ is a function of distance between the current state to attractor *i*. If we define the vector coordinate of attractor *i* as $\boldsymbol{X}_i$, then $\boldsymbol{f}_i(\boldsymbol{x})$ is described in equation (3), while $g_i(\boldsymbol{x})$, that determines the magnitude of $\boldsymbol{f}_i(\boldsymbol{x})$ based on distance between current state to attractor *i*, is chosen as a sigmoid function in equation (4).

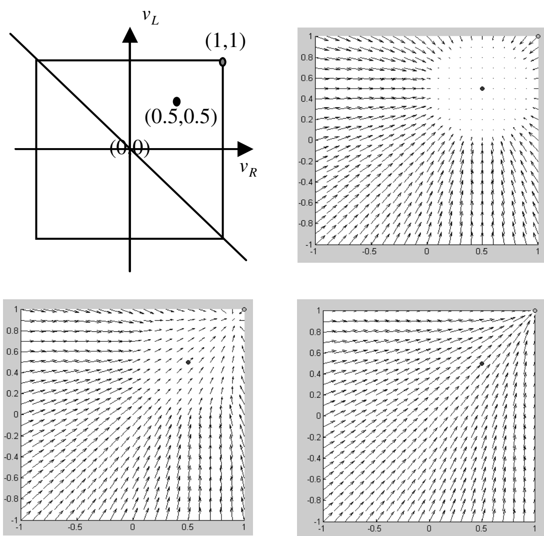

Fig. 1. Design of the Attractor System, clockwise from top left: Basic Design, Potential Field when The Activity=0, 1 and 0.5

We choose the value *k=1, a=15, b=0.5, n=2* for the attractor 1 and *k=1, a=50, b=0.1, n=1* for attractor 2. The resulting potential fields when the activity equal to 0, 0.5 and 1 are consecutively shown by the top-right, bottom-left and bottom-right figure in Fig.1.

$$\tau_x \dot{\boldsymbol{x}} = \boldsymbol{f}_1(\boldsymbol{x}) \times A + \boldsymbol{f}_2(\boldsymbol{x}) \times (1 - A) + \boldsymbol{\varepsilon} \qquad (2)$$

$$\boldsymbol{f}_i(\boldsymbol{x}) = \frac{(\boldsymbol{X}_i - \boldsymbol{x})}{\|\boldsymbol{X}_i - \boldsymbol{x}\|} g_i(\boldsymbol{x}) \qquad (3)$$

$$g_i(\boldsymbol{x}) = \frac{k}{1 + \exp\{-a(\|\boldsymbol{X}_i - \boldsymbol{x}\| - b)^n\}} \qquad (4)$$

The explanation of such arrangement is as follow. When the activity equals to 1, the state will be entrained to attractor 1, and therefore the robot will tend to move forward. When the activity equals to 0, the state will be entrained to attractor 2. Therefore, ideally the state will make a random walk inside the circle. In other words, the robot will tend to move randomly forward with moderate velocity. If the noise term is too big, there is of course possibility that it will move the state outside the circle, even outside the square. The vector field works to move the state back inside the circle.

The resulting linear and angular velocity of the robot is described by equation (5) and (6) consecutively, where *R* is the distance between the two wheels of the robot.

$$v = \frac{v_L + v_R}{2} \qquad (5)$$

$$\omega = \frac{v_R - v_L}{R} \qquad (6)$$

We choose to define the relationship between the activity and the change of the signal amplitude Δamp by a simple linear function in equation (7.a)-(7.c). It can be seen that by using this "activity rule", how fast the activity will change due to the change of signal amplitude is simply affected by constant *C*.

$$A = \begin{cases} 0, & \text{if } \Delta amp \le 0 & (7.a) \\ \dfrac{\Delta amp}{C}, & \text{if } 0 < \Delta amp \le C & (7.b) \\ 1, & \text{otherwise} & (7.c) \end{cases}$$

According to equation (2), when *A=0*, the dynamic of the system will not be affected by attractor 1, and when *A=1,* the dynamic of the system will not be affected by attractor 2.

For all the experiments in the paper, the initial state of $\boldsymbol{x}$ is (0,0), while the type of noise $\boldsymbol{\varepsilon}$ in equation (2) is zero-mean Gaussian and independent between vertical and horizontal component of the vector.

3. Simulation

3.1 Experiment Setup

In order to confirm that the proposed navigation system will enable the robot to reach the goal, we conducted both simulation and real-robot experiment, and chose sound as the signal source.

In building the simulation, first we obtained a sensory model from a real robot by attaching a microphone to the robot and collecting sound amplitude data versus the distance and the angle between the robot and a speaker. From the result, the sound amplitude on each distance is proportional to the inverse of the distance. It is theoretically correct. Because the energy of a sound wave from a source spread over a sphere and the area of this sphere is proportional to d^2 where *d* is the distance to the sound source, the energy of any wave decreases proportional to $1/d^2$. The energy is proportional to the square of amplitude of the wave, so the amplitude decrease should be proportional to *1/d*. At each distance, the sound amplitude is at maximum when the robot is facing toward the sound source and decreases when facing away. We model the relationship between the sound amplitude and robot orientation to the sound source on each distance by a

Gaussian function. Fig. 2 shows the data collection from real robot.

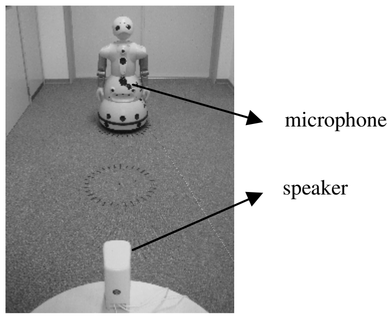

Fig. 2. Data collection from real robot

After that, we simulated the proposed attractor selection-based navigation system. The movement of the robot is modeled by using unicycle model. The linear velocity of the robot is limited to 30 [cm/sec], while the angular velocity is limited to 90 [deg/sec]. The simulated area is 6.4 x 3.7 [m], while the robot diameter is set as 25 [cm]. The simulated time length for the simulation is 100 [s]. Every simulated 0.02 [s], a new position and orientation is calculated and shown. However, the control system only output the next control output in every simulated 1 [s]. The goal is put at the center of the area. The initial position of the robot is 295 [cm] left from the goal, facing down.

Fig. 3 shows a screenshot of a simulation. The cross in the middle is the signal source, and it can be seen that the robot searches for the goal and moves towards it. The intensity of the trajectory indicates the activity. The graphs at the bottom of the screenshot show the changes of the activity, the robot linear and angular velocity, and the state in the attractor selection system.

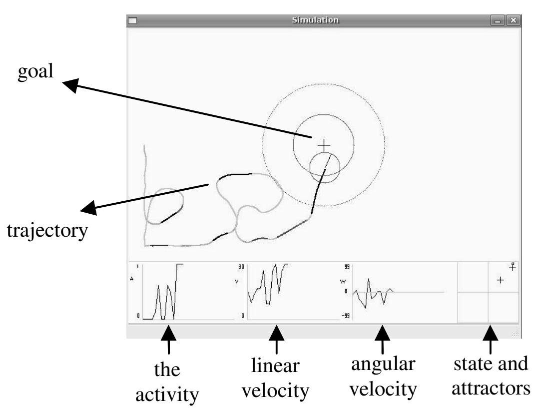

Fig. 3. Simulation screenshot

3.2 Experiment Result

After confirming that the robot can reach the goal, we collect data for analysis purpose. First, we analyze the effect of the noise term alone. This was conducted by setting $A=0$ in equation (2), and let the robot does random walk during the entire simulation. Top figures of Fig. 4 shows the trajectory examples for different noise, where σ indicates the noise standard deviation. It can be seen that as the noise is getting larger, the tendency of the robot to change behavior is increasing. It makes sense as when the noise size is higher, the states will spread faster inside the circle shown in Fig.1.

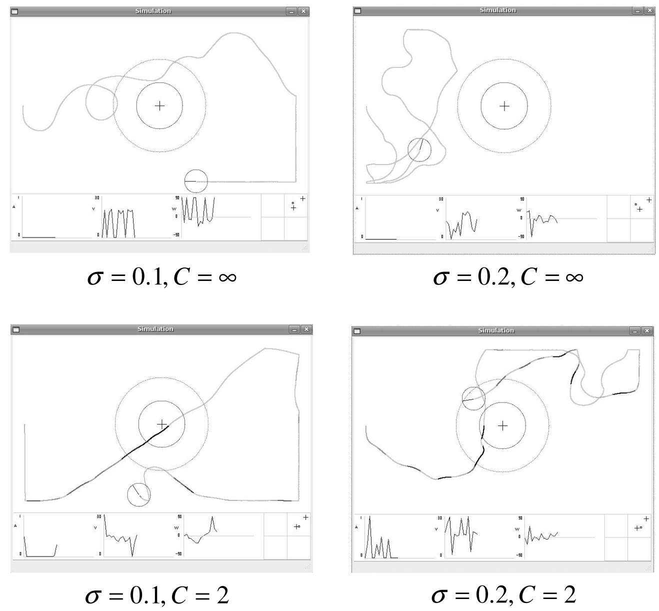

Fig. 4. Trajectory examples of random walk with different size of noise (top) and when the activity rule is used (bottom)

Then, we see whether the activity rule can increase the performance of the navigation system compares to random walk. It is conducted by setting the constant C in equation (7) to particular value *($C=2$)*. Three criteria are used to measure the performance, namely average distance from the goal, time to reach particular distance (100 [cm]) from the goal, and percentage of reaching that 100 [cm] distance in 50 trials within the 100 [s] simulated time. When the robot could not reach 100 [cm] within 100 [s] of simulated time, the time to reach 100 [cm] value is set as 101 [s]. It must also be noticed that random walk basically means setting $C=\infty$, that causes the activity never increases no matter how large the change of signal amplitude.

Bottom figures of Fig. 4 show the trajectory example when the system uses the activity rule *($C=2$)*, for different σ. The value of the activity can be seen from the intensity. It is ranged from light gray when the activity $A=0$ to black when $A=1$. It can be seen that by going straight forward when the change of amplitude adequately high, the robot has a better chance to reach the goal.

Fig. 5, which plots the activity and distance from the goal versus time for the examples shown in Fig. 4, confirms this behavior further. When using the activity rule, it can be seen that when the activity is high, the distance between the robot and the target is decreasing.

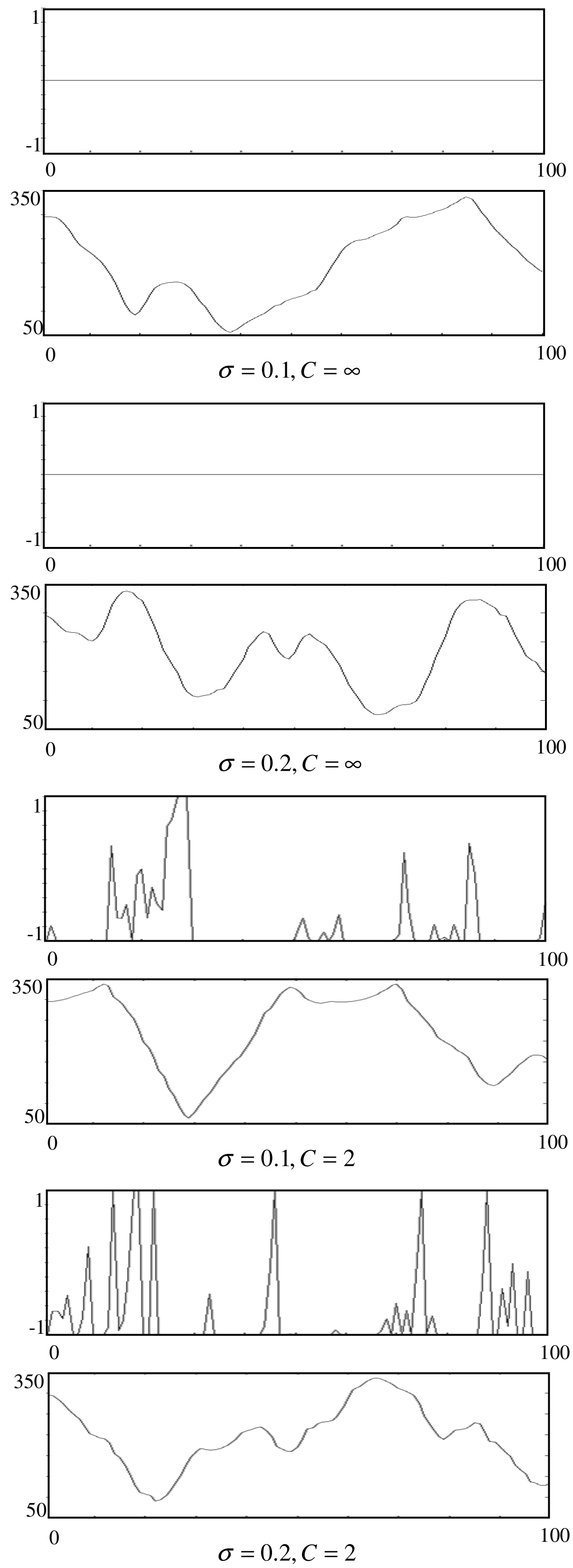

Fig. 5. The pairs of the activity vs time (top) and distance between robot and the goal vs time (bottom) graphics for the four trajectories shown in Fig. 4.

The average result of the 50 trials performance data for the explained four cases is shown in Table 1. It confirms that the activity rule can increase the performance of the navigation system compares to random walk.

Table 1 Performances comparison when C=2 and random walk

C	σ	Average distance [cm]	Time to reach 100 cm [s]	Reaching 100 cm [%]
2	0.1	210.41	60.10	66
∞	0.1	221.03	78.55	54
2	0.2	196.77	52.27	74
∞	0.2	220.94	73.98	60

Here, there are two parameters that can change the performance of the robot. The noise size, indicated by σ, and the constant C in the activity rule described in equation (7). While it is already shown that the use of the activity rule is able to increase the performance compares to random walk, it is interesting to investigate whether we can find the optimal values for these two parameters. In order to do this, we continue collecting 50 trials data, so that we can plot the three dimensional figures between the noise size, the constant C in the activity rule and the three performance criteria. The result is shown in Fig. 6.

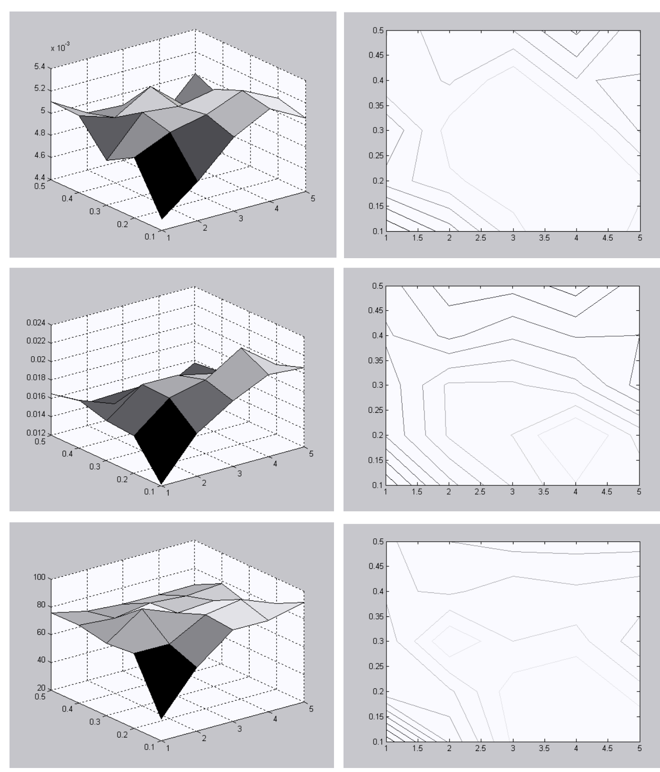

Fig. 6. The three dimensional figures (left) and contour (right) between noise size, constant in the activity rule and the three performance criteria: 1/average distance (top), 1/time to reach 100 cm (middle) and time to reach 100 cm (bottom)

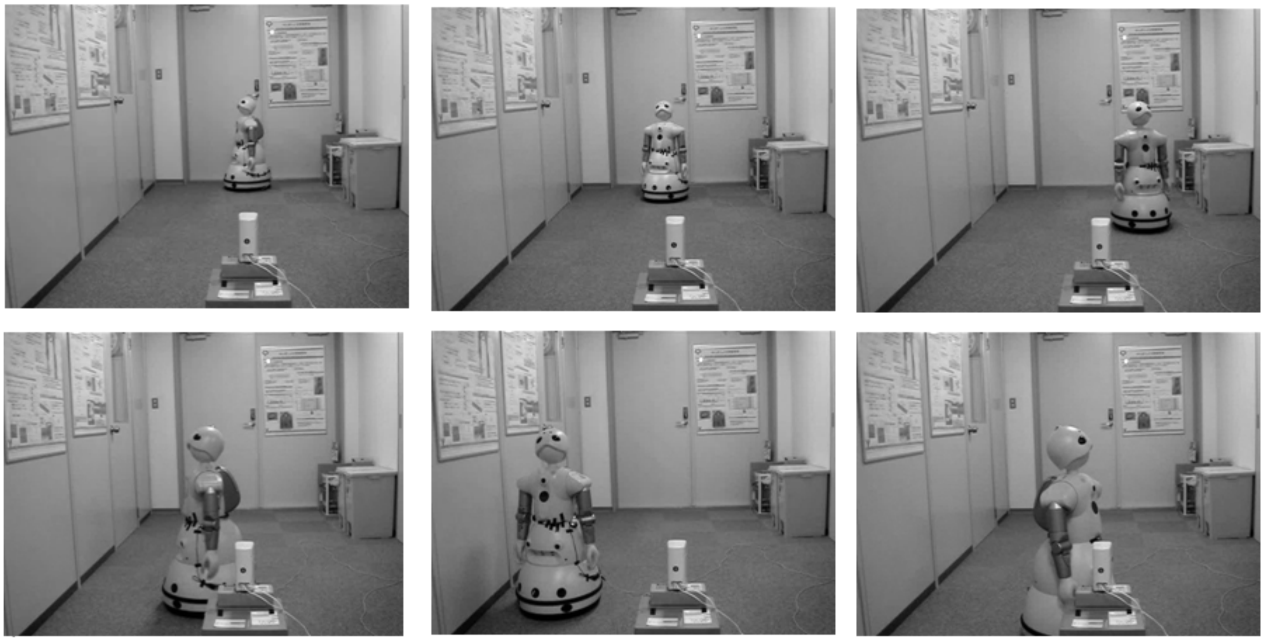

Fig. 7. Snapshot of real robot experiment

The values of σ is from 0.1 to 0.5, while the values of constant C in the activity rule is from 1 to 5. In order to see the maximum performance, we plot the 1/average distance from the goal, 1/time to reach 100 cm distance from goal, and time to reach this distance, versus those two parameters. The left figures show the three dimensional figures, and the right ones show the corresponding contour. As can be seen, the figures suggest that optimal values for the parameters that result in the best performance may exist.

It is interesting since, as observed, larger noise size means that the tendency of the robot to change behavior is increasing. On the other hand, smaller value for constant C in the activity rule means it is easier for the robot to keep executing the same behavior, even with a small positive change of sound amplitude. Therefore, there is a possibility that we can balance the tendency between randomly trying new behaviors and keep executing the same deterministic behavior, which results in the best performance.

4. Real Robot Experiment

4.1 Experiment Setup

To collect the sound amplitude data as explained in section 3.1, the microphone attached to the robot is connected to a remote PC as shown in Fig.2. Using the change of the sound amplitude as the input, the velocity must be executed by the robot using the attractor selection navigation system is then calculated, and sent remotely every one second. The robot cannot accept a new command faster than this, so the value of one second also chosen for the simulation as explained before. The initial distance of the robot is 3 [m] from the speaker, perpendicularly as in the simulation. The width of the corridor shown is about 2.1 [m].

4.2 Experiment Result

We run several trials in real robot and it is confirmed that the robot can reach the goal using attractor selection-based navigation system. One of the trials is shown in Fig.7. The time to reach the goal for the snapshot shown is 26.90 [s].

5. Conclusion

In this paper, we explained a biologically inspired navigation system based on attractor selection model. The novelty of the method is it utilizes noise in the navigation system to keep the robot searching for the goal. The method is simple, and does not need a model of the environment. It is therefore robust to changes in the environment. When the noise size is larger, it is observed that the tendency of the robot to change behavior is increasing. The use of the activity, defined by the activity rule, increases the performance of the navigation system compare to random walk. Different combination between noise size and the activity rule yields different performances. There is also a possibility that we can choose the optimal values that yield the best performance.

As a future work, we plan to analyze the results more, such as using mathematical tools like curvature value to express the trajectory by numerical value, confirming the situation when we can no longer control the noise, as well as having more experiments with the real robot. Another important future work is, of course, to try different attractor designs, including different activity rules, and compares the results.

6. Acknowledgement

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