Minimalistic Behavioral Rule for Reflecting Robot's Morphology

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Abstract: In a previos work, we proposed a very simple stochastic model, termed Minimalistic Behavioral Rule, in order to show how small bacteria such as *Escherichia coli* can robustly reach high concentrations of nutrient despite the noise in the sensory information. In particular, we showed that when this simple behavioral rule is employed, environmental or internally generated noise can be beneficial to the resultant behaviors of the living being, a phenomenon that can be explained by Stochastic Resonance. In this paper, we apply such behavioral rule to a real world complex robot, whose behavior is strongly influenced by its morphology and its surroning environment. Through the experiments, in particular, we show that the sensory information used for the task achievement greatly influences the resultant behavior.

Keywords: Minimalistic Behavioral Rule, Musculoskeletal robot arm, Adaptive behavior

1. INTRODUCTION

Living things can survive in complex and dynamical environments by taking full advantage of their body dynamics, sensing and interaction with the surrounding environments. Small bacteria such as *Escherichia coli* (E. coli) are no exception. In a previous work, we proposed a Minimalistic Behavioral Rule (MBR) in order to explain how E. coli can effectively reach high concentrations of nutrients and avoid high concentrations of repellent substance despite highly noisy sensory information[1]. Since MBR is extremely simple and makes very limited assumptions, it can be easily applied without knowing the robot's body structure or its actuators properties. Experiments showed that MBR can control simple mobile robots with no information on its actuators and sensors [2]. However, to date, MBR was not tested on complex, multi-DOFs robots.

The idea of applying a very simple control to highly complex robots is not new. So far, many researchers have developed biologically inspired robots [3] that can operate with simple control laws. Usually, the exploitation of the morphological computation[4], emergent from a well-designed robot's body, allows the achievement of a specific task with very simple control laws.

However, the identification of such simple control laws requires the developer's inspiration, knowledge and experience. In other words, even if the control laws are very simple, it is not easy to find them.

The ultimate goal of this research is to build a simple but general control law which can exploit the characteristics of the robot's morphology automatically. We propose MBR as a possible solution for controlling a robot when no previous knowledge on the robot's actuators and sensory data is available. If specific knowledge is available, clearly, task and robot specific controllers can be designed to improve the system efficiency. Actually, MBR can be used for collecting the data necessary to this development process.

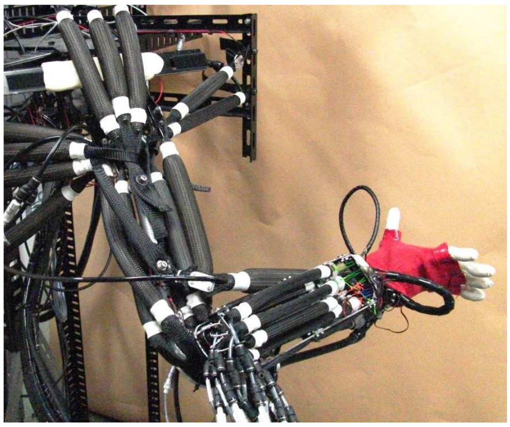

Fig. 1 The complex musculoskeletal robot arm used in the experiment.

In this paper, we show that MBR is applicable even when the robot has a very complex structure. In detail, MBR was used to control the pneumatic musculoskeletal robot arm shown in Fig. 1. This robot has a 7 DOFs driven by 17 McKibben pneumatic muscles. Each muscle is equipped with a pressure sensor, used for closed loop pressure control. In other terms, the robot is controlled by setting the variation of the pressure in each of the 17 pneumatic actuators. The task chosen consists in reaching three points in sequence. In the experiments, the sensory information available to the robot was changed in the experiments, to observe differences in the behavior.

2. MINIMALISTIC BEHAVIORAL RULE

In [2] we proposed the Minimalistic Behavioral Rule:

$$u^i_{t+1} = \begin{cases} u^i_t + \eta^i R & if\ \Delta A_t \geq 0 \\ random\ selection & otherwise \end{cases} . \quad (1)$$

Where the u^i_t indicates the i-th component of an m-dimensional motor command $u^i_t \in \mathbb{R}^>$ given at time t

and $R \sim \mathcal{N}(0,1)$ is a random variable and ΔA_t expresses how much the robot improved its conditions during time the t-th timestep. For instance, in a goal reaching task, ΔA_t could express how much a robot got closer to its target. The term $\eta^i R$ indicates internal noise, that could be generated intentionally [2] or not.

If no perturbations are introduced ($\eta^i = 0$), the binary evaluation ($\Delta A_t \geq 0$) can only correspond directly to "keeping" or "changing" the motor command. Conversely, if the perturbations are very strong, the motor command corresponds to a random walk in the motor command space. Intuitively, there is a specific noise intensity that maximizes the performances. This stochastic resonance phenomenonwas reported in [1], where we showed that an optimal level of noise is able to maximize the mutual information between the function that determines ΔA_t and the robot behavior.

MBR is very general, in fact only the sign of ΔA_t, and no precise "state value" is required. Furthermore, the behavior generated by the rule implicitly reflects the robot's characteristics. In fact, since the commands are chosen by random selection, commands that do not require a precise tuning, intuitively commands that are "simpler for the robot", are executed with high frequency.

3. EXPERIMENT AND RESULTS

We conducted an experiment in which the robot arm continuously and repeatedly reaches three targets in the robot reachable space. These targets are located at the robot's right, left and bottom part of the reachable space, and have coordinates, in m, $t_1 = (0.34, 0.21, 0.66)$, $t_2 = (0.24, 0.02, 0.62)$ and $t_3 = (0.46, -0.10, 0.46)$, respectively. In order to calculate ΔA_t, it is necessary to measure the position of the end-effector. We tested the following three ways to measure and express the end-effector position:

1. A four dimensional vector composed by the end-effector centroid in the images of the two cameras mounted on the head.
2. The three dimensional position of the end effector, obtained using stereo computation.
3. A three dimensional position of the end-effector observed by a motion capture system.

The task could be achieved with all the three types of the information. This result confirms the generality of MBR, that can be applied successfully with a variety of input information and without requiring a model of the robot's dynamics. In particular, the directions taken by the end effector when each muscle is contracted are unknown, and the mapping between the control signal u and the resulting ΔA_t is very complex, depending both on the robot structure and on the sensory information employed.

We analyzed the differences in the robot behavior when the sensory information varies. Fig.2 shows the reaching time for each of the three targets using each of the sensory information. For simplicity, the robot reaches the targets in the order $1, 2, 3, 1, 2, \ldots$. Analysis of the effect of the reaching order will be provided in future works. The figure reports the median values, with the 90% confidence intervals, and highlights the length distributions that are statistically different by the KruskalWallis analysis. We note that the task sensory information 1 and 3 lead better results than the sensory information 2. This is interesting, because the sensory information 2 and 3 are intuitively closer. In fact, for the three targets the normalized mutual information between the sensory information 1 and 3 is 0.73, 0.76 and 0.77, respectively, while the mutual information between the sensory information 2 and 3 is $0.81, 0.81, 0.83$ and 0.80.

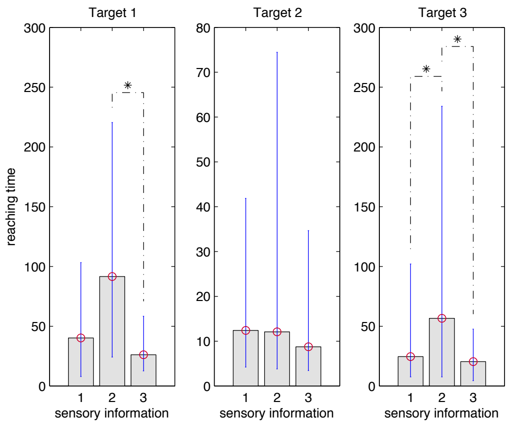

Fig. 2 The reaching time [sec] for each of the targets. The x axis indicates the sensory information type.

This result probably comes from the fact that the noise on the depth information has more influence on ΔA_t using the stereo computation than directly using the raw centroid information data. More detailed analysis will be presented in future works. Additionally, it is interesting to investigate whether the Stochastic Resonance effect, observed for simple 2D reaching, can be observed using complex robots like the one presented here.

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