Co-evolution of Sensors and Controllers

Komei Sugiura*
Takayuki Shiose*
Hiroshi Kawakami*
Osamu Katai*

Animal species have adapted their morphology (the placement of sensors and actuators, specific characteristics, etc.) to their ecological niche. However, so far very little is known about the relationship between the morphology of an evolutionary system such as self-organizing robot and its adaptive behavior in the environment. In this paper we investigate the evolutionary development of embodied agents that are allowed to evolve not only control mechanisms but also the sensitivity and temporal resolution of their sensors. The experimental results indicate that the sensors and controller co-evolve in an agents through interacting with the environments.

Keywords: sensor evolution, evolutionary robotics, embodiment, time resolution

1. Introduction

Artificial Intelligence (AI) has exhibited its ability to solve problems under very limited conditions such as playing chess. In these cases, human programmers have to design limited and digitized input information for the AI. Robots equipped with AI, however, are not capable of pick out meaningful inputs from the environment according to the problem to be solved. As a result of this situation, the Frame Problem [6, 16] arises.

How do animals cope with this Frame Problem? Uexküll insisted that animals have their own worlds (*Die Umwelten*) in which they are surrounded information that is meaningful to them [21]. Namely, animal species have evolved their sensory systems to pick out information that is meaningful only to them, so that each of them 'sees' the world differently.

Animals' behavior and their *Umwelten* are closely related. The sensitivity and resolution of insects' sensors depend on their feeding behavior, mating behavior, velocity and so on [7]. For instance, the human visual system has high spatial resolution and low temporal resolution, whereas the fly visual system has low spatial resolution and high temporal resolution. Critical Fusion Frequency (CFF) is an indicator of time resolution. Generally, insects that move at high speed have a high CFF, while insects that move slowly have a low CFF.

The sensitivity and resolution of sensors differ not only among animal species but also in a single species. For example, the fovea/periphery in the visual systems of both humans and mantes have high/low spatial resolution. In this case, the diversification of the ability of sensors is determined by the animals' physical characteristics.

Inspired by these biological facts, researchers have tried to artificially evolve the morphology and behavior of an agent in the field of Artificial Life and Evolutionary Robotics [18]. Sims and Lipson *et al.* realized a system that evolves the morphology and neural system of robots inside a computer [13, 19]. Other research efforts have been made on Sensor Evolution [1, 5, 12, 14, 15, 20]. Kortmann *et al.* studied the evolution spatial and temporal resolution in populations of simulated visuo-motor systems and showed that two factors are responsible for the trade-off between spatial and temporal resolution [9–11].

In this paper, we investigated the evolution of the sensors and controller of embodied agents. We developed simulated sensory-motor systems that can change the sensitivity and temporal resolution of their sensors. Then, we carried out two kinds of experiments in which populations of the sensory-motor systems perform tasks. Finally, we describe how the physical characteristics of agents affect the diversification of their sensors through interaction with the environment.

2. Sensory-Motor System and Task Environments

We constructed sensory-motor systems that can change sensitivity of the sensors, temporal resolution of sensors and connection weights in their neural network controllers. To investigate how embodied agents adapt their sensors and controllers to the task environment, we prepared two kinds of environments in which populations of sensory-motor systems perform different tasks. The individuals and environments were built using the robot simulator Webots[†]. Below we give the details of the sensory-motor system and the task environments.

2.1 Sensory-Motor System A top view of the sensory-motor system is shown in Fig. 1.

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* Graduate School of Informatics, Kyoto University
Yoshida-Honmachi, Sakyo-ku, Kyoto 606-8501, Japan
`sugiura@sys.i.kyoto-u.ac.jp`
`{shiose, kawakami, katai}@i.kyoto-u.ac.jp`

[†] `http://www.cyberbotics.com`

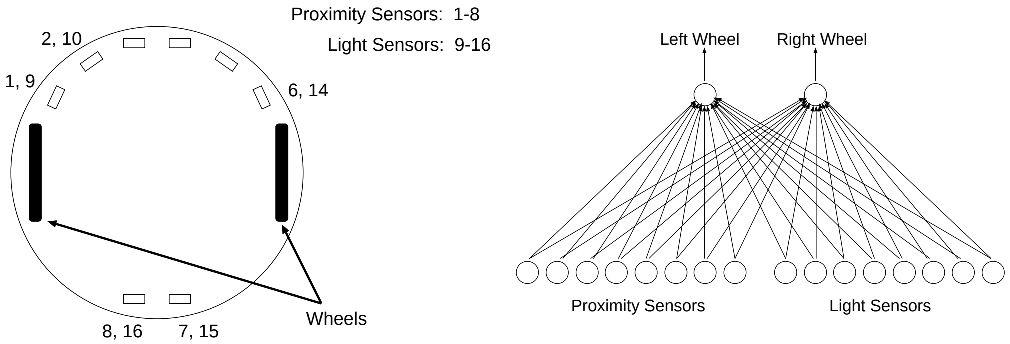

Fig. 1. Left: Top view of the structure of the simulated sensory-motor system (agent). The system is based on the Khepera robot; 28 mm in radius, and equipped with 8 infrared sensors used as both proximity sensors (1-8) and light sensors (9-16). Right: Schematic view of Braitenberg's Vehicle-like controller [2]. It has 16 input units, half of which receive information from the proximity sensors and the other half receive information from the light sensors, with two output units controlling the speed of the wheels.

Sensors

This Khepera-like agent has eight infrared sensors that are used as both proximity sensors and light sensors. The two kinds of sensors are physically one unified device, but the simulator models it as two different devices by applying different computing algorithms.

Each sensor has different sensitivity and resolution values. Here, the sensitivity s_i stands for a radix used to digitize the i^{th} sensor's input. The bigger s_i becomes, the more the sensor is able to detect slight changes.

The temporal resolution Δt_i stands for the interval that the i^{th} sensor's input is updated. Consequently, the sensor cannot detect changes occurring within Δt_i. Therefore, CFF is modeled by $1/\Delta t_i$.

We put a restriction on s_i and Δt_i in order to hold the amount of acquired information I constant. Here, I is defined as information that an agent can acquire from all of its sensor in a unit of time. s_i and Δt_i must fulfill the following equation.

$$\sum \frac{s_i}{\Delta t_i} = I \qquad (1)$$

Controller

The system is controlled by a simple neural network, which has only inputs, outputs, and multiplying connections. The right-hand side figure of Fig. 1 shows a schematic view of the controller. The rotation of each wheel is stimulated or inhibited in proportion to the normalized signal strength that each sensor senses. The connection weights are encoded in the individual's genotype, so they are fixed during one generation.

Actuators

Wheels are driven by two independent motors. The maximum angular speed ω_{max} and the maximum angular acceleration α_{max} can be varied. Agents with high ω_{max} and α_{max} simulates light insects that move at high speed.

2.2 Task Environments We carried out the following two kinds of experiments.

(I) Phototaxis

One individual is put in an arena (100 mm × 100 mm) and performs a phototaxis task. Individuals acquire fitness if they arrive at the circle in which a light source exists (see Fig. 2). At each generation, an individual is given one trial. The position and direction of each individual is initialized randomly at the start of each trial. A trial ends either when the individual arrives at the goal or when 300 time steps (approximately 20 seconds in real time) are performed.

(II) Predator-Prey Pursuit

Two species of agents (predator and prey) are used in this experiment. Several researchers have investigated predator-prey co-evolution in both simulated [3, 4] and real robotic experiments [8, 17]. Cliff and Miller also showed that task-dependent morphological parameters (view range) are evolved in co-evolving predator and prey agents [3, 4]. In this experiment, we investigated dependencies on the ecological niche and the sensitivity and resolution of agents' sensors.

The same arena as (I) is used, but there is no light source. Instead, each predator and prey agent is equipped with a light source on it. They are also provided with sensors having the same range.

At each generation, all couples of randomly chosen predator and prey agents perform tournaments. In each tournament, both the predator and the prey are put randomly in the arena. Once the tournament has started, it continues until the individuals collide or 300 time steps are performed. We examined several cases in which the prey has different maximum speed.

3. Evolution of Sensors and Controllers

Genetic algorithms (GAs) are used in order to make simulated embodied agents adapt both their sensor

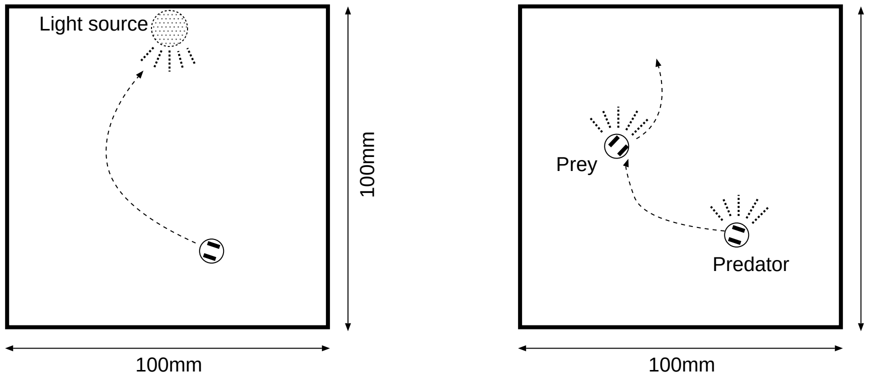

Fig. 2. Left: Schematic View of the arena used in (I). Agents are asked to perform phototactic behavior. Right: Prey evades from the predator in the arena. Sensors equipped on the two species have the same range. A light source is also put on each agent.

properties and behaviors to their morphologies and tasks. The GA is allowed to optimize four kinds of parameters of each sensor: sensitivity s_i, time resolution Δt_i, left wheel input multiplier l_i, and right wheel input multiplier r_i.

3.1 Genetic Representation The genotype of an individual has the following form:

$$G = (s'_1, t'_1, l_1, r_1, s'_2, t'_2, l_2, r_2, \ldots, s'_{16}, t'_{16}, l_{16}, r_{16}),$$

where s'_i and t'_i are the ratios of spatial and temporal resolution. Each of the parameters (s'_i, t'_i, l_i, r_i) is binary encoded by four bits in the genotype. An individual has 16 sensors altogether, therefore the length of a genome is 256 bits.

The weights (l_i, r_i) are decoded into real values ranging from -1 to 1. On the other hand, s_i and Δt_i are calculated as follows to fulfill the equation (1):

$$s_i = s'_i \sqrt{\frac{I}{\sum \frac{s'_j}{t'_j}}}$$

$$\Delta t_i = t'_i \sqrt{\frac{\sum \frac{s'_j}{t'_j}}{I}}$$

3.2 Genetic Algorithm Each genotype of an individual in the first generation is a random combination of 0 or 1. In each generation, the GA assesses the fitness of all individuals. Roulette selection is used to select individuals that participate in mating. The GA then generates new children from selected individuals to replace the 10% worst individuals of the population.

Each population consists of 100 individuals in (I). In (II), 100 predators and 100 preys compose independent populations. We made the cross-over rate 50% and the probability of mutation per bit 0.002%.

3.3 Fitness Function The fitness function Φ for individuals in (I) is calculated as follows:

$$\Phi = 1 - \frac{t}{T_{max}}$$

where t is the time to arrive at the goal and T_{max} is the maximum time steps performed in the experiment.

For (II), We adopted a fitness function similar to that of [8]. Namely, both Φ_{pr} for a predator and Φ_{py} for a prey are based on the *time to contact*:

$$\Phi_{pr} = 1 - \frac{t}{T_{max}}$$

$$\Phi_{py} = \frac{t}{T_{max}}$$

where t is the time the predator needs to contact the prey.

4. Results and Discussion

4.1 Performance We carried out experiments in five populations for both (I) and (II). We kept $I = 32$ and α_{max} fixed. The factor ω_{max} varied between the populations, but was kept fixed within a population in (I). In the experiments (II), we kept the predators' $\omega_{max} = 60$, but varied the preys' ω_{max} between the prey populations.

In Fig. 3, the average fitness of the individuals (left) and the predators (right) is plotted against the number of generations. All populations converged within 300 generations in (I), while the predators' fitness values stay unsteady in (II).

Fig. 3 shows that the fitness of the agents ($\omega_{max} = 100$) reaches lower values than that of the agents ($\omega_{max} = 20$). This result can be explained by the fact that the range of the sensors is not enough for the agents with high ω_{max} to avoid the wall.

4.2 Diversification of Sensors We also studied the variation of the degree of dependence on each sensor. Here, the degree of dependence on the i^{th} sensor is calculated as follows:

$$d_i = \frac{\frac{s_i}{\Delta t_i}}{I}$$

In Fig. 4, the average degree of dependence on each sensor is plotted against the number of generations. The

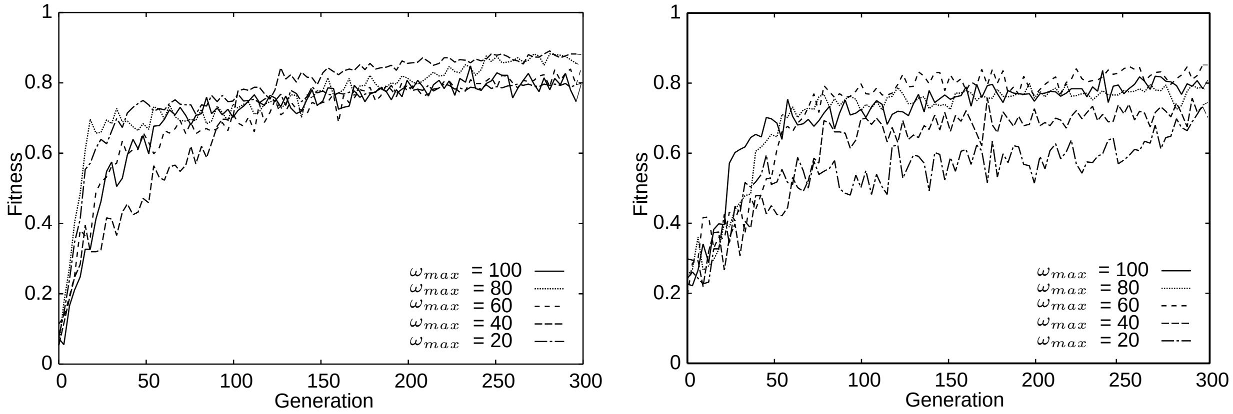

Fig. 3. Left: Each curve represents the average fitness of the five different populations between which ω_{max} is varied. Right: Experiment on predator-prey pursuit problem showing the average fitness of the predators' performance. Each curve represents the average fitness of the five different populations between which the preys' ω_{max} is varied.

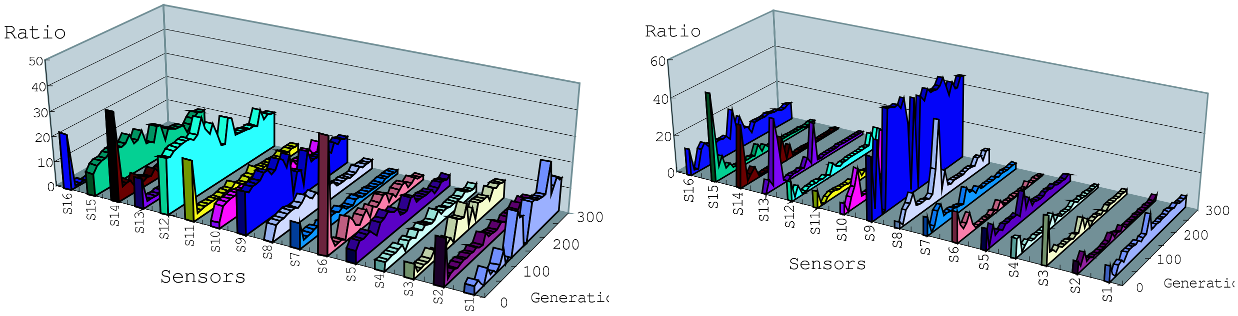

Fig. 4. The average degree of dependence on each sensor (S1-S16) in (I). Left: $\omega_{max} = 100$. Right: $\omega_{max} = 20$.

left-hand side figure shows that the agents ($\omega_{max} = 100$) after 300 generations acquire information from both proximity sensors and light sensors. On the other hand, the agents with low ω_{max} acquire almost all information from one light sensor (see the left-hand side figure). This result can be explained by the fact that agents with high ω_{max} need more information from the proximity sensors so as not to hit the wall.

In Fig. 5 and Fig. 6, average degree of dependence on each sensor is plotted against the number of generations (Left: predators, Right: preys).

Fig. 5 shows that the predators concentrate attention on two light sensors to catch the relatively quick preys (cf. Fig. 6). Fig. 3 and Fig. 5 show that the fitness of the predators drastically increases with the increase in the degree of dependence on the fifteenth sensor. This clearly indicate that both the sensor morphologies (sensitivity and resolution) and control mechanisms evolved in these sensory-motor systems.

5. Conclusions

In this paper, we investigated the dependencies on the behaviors and morphologies in populations of sensory-motor systems. Genetic algorithms (GAs) were used to make simulated embodied agents adapt both their sensor properties and behaviors to their morphologies and tasks. We carried out two kinds of experiments in which agents were asked to perform phototactic and pursuit/evading behaviors. The experimental results show that the physical characteristics of an agent and the task environment affect the sensitivities and the resolution of its sensors, and thus task-dependent morphologies are evolved. Future work will include the evolution of sensor morphology including placement, resolution, and sensitivity in agents performing tasks in noisy environments.

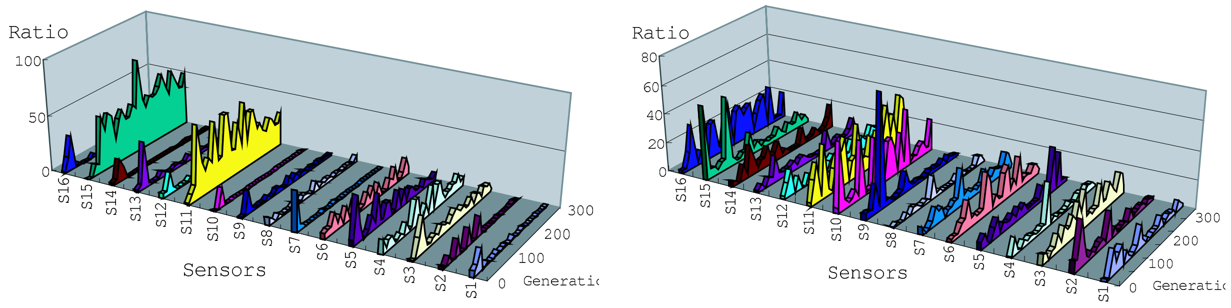

Fig. 5. The average degree of dependence on each sensor (S1-S16) in (II). The predators' $\omega_{max} = 60$, and the preys' $\omega_{max} = 100$. Left: In the predators. Right: In the preys.

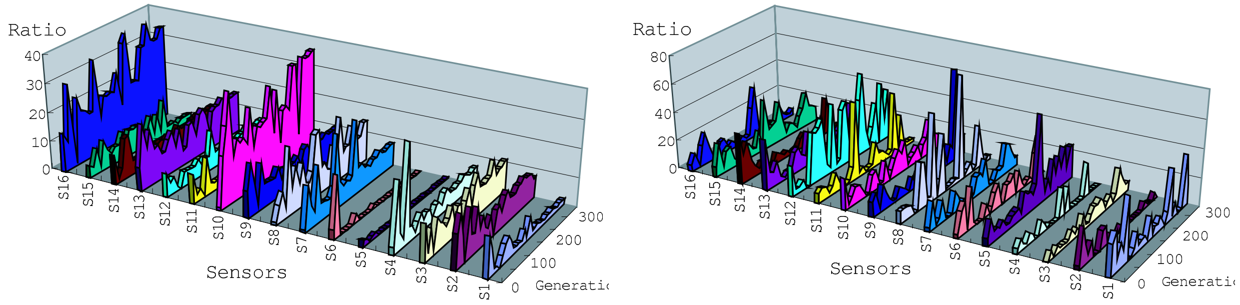

Fig. 6. The average degree of dependence on each sensor (S1-S16) in (II). The predators' $\omega_{max} = 60$, and the preys' $\omega_{max} = 20$. Left: In the population of predators. Right: In the population of preys.

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