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CPG-based Control of a Simulated Snake-like Robot Adaptable to Changing Ground Friction

Kousuke Inoue
Department of Intelligent Systems Engineering, Ibaraki University
Nakanarusawa-cho 4-12-1, Hitachi City, Ibaraki Prefecture, 316-8511, JAPAN
k.inoue@mx.ibaraki.ac.jp

Takaaki Sumi
Department of Intelligent Systems Engineering, Ibaraki University
Nakanarusawa-cho 4-12-1, Hitachi City, Ibaraki Prefecture, 316-8511, JAPAN
sumi@roboken.dse.ibaraki.ac.jp

Shugen Ma
The Organization for the Promotion of the COE Program, Ritsumeikan Univ.
Noji Higashi 1-chome, 1-1 Kusatsu, 525-8577 Shiga-ken, Japan
shugen@fc.ritsumei.ac.jp

***Abstract*— In this paper, development of a CPG-based controllers for meandering locomotion of a snake-like robot that can adapt to changing friction is presented. The controllers are composed of two kinds of CPG models and receives environmental information from friction force sensors attached on the bottom of the robot. Adaptive CPG parameters are obtained using genetic algorithm with environments with different friction conditions.**

***Index Terms*: CPG, Snake-Like Robots, GA**

I. Introduction

Snakes exhibit very unique locomotion ability by curving its long cord-shaped body and realize extremely high environmental adaptability. Because of their small cross-section area, they can crawl into very narrow spaces. And by distributing their weight belong their long body, they can move on soft or fragile materials. They can move in almost all natural environments, such as grass, rubble, tree branch, mud, marsh, or water.

Aiming at realizing robots with such high adaptability, many snake-like robots have been developed. These robots can be classified into two categories: crawler-based robots and meandering robots. Crawler-based snake-like robots are developed for practical applications such as “search & rescue” in disaster area (for example, [6]). Locomotion of these robots are based on driving force generated by crawlers and achieve comparatively high ability to move in unstructured environments. However, in these studies, mechanisms that give living snakes extremely high adaptability are not considered. Therefore, achievable mobility in future is limited.

On the other hand, meandering robots generate propulsion force by curving their body shape. In general, snake-like robots are equiped with passive wheels on the bottom that can not generate propulsion force by itself. Propulsion force is generated from joint torque in the same way as living snakes. Living snakes exhibit their locomotion in various environments based on such principle. Therefore, by establishing such body structure and control method, extremely high adaptability is expected in future.

In previous studies on snake-like robots, the control methods were based on phenomenalismic manner: Control signals are generated in order to imitate observed curvature of real snakes. One example of resultant control signal for joint angle is sinusoidal waveforms with specific phase-shift [7], [13]. In such methodology, it is quite difficult for the controllers to adapt to unknown or changing environments and embodiment.

Meanwhile, animals adopt decentralized manner to control their complicated body adapting to changing environments. Many of voluntary locomotion of animals are rhythmic and such rhythmic motion pattern is generated and controlled by CPGs (Central Pattern Generators) distributed in spinal cord. By feeding back information from peripheral sensors (such as pressure on skin or length of a muscle) to CPGs, robustness of locomotion to disturbance is realized [1].

Recently, studies using CPGs for locomotion control of animal-like robots are actively conducted. Ekeberg modeled CPG of lamprey whose characteristics are physiologically revealed by Grillner [5] and present realization of swimming locomotion in simulations in which neural network model and musculoskeletal model are combined [3]. Ijspeert presented swimming and walking locomotion of lamprey [8] and salamander [9] and realized adaptation to watar flow. Kimura et al. realized quadruped walking robot adaptable to outdoor environment using a controller with a CPG and reflex arcs [4], [11].

It is natural to consider that living snakes also have CPGs for locomotion. Recently, some groups including the authors [10] start studies to control meandering locomotion of snake-like robots with CPGs [2], [12]. However, previously proposed models are open-loop, i.e. the models did not have any sensory feedback information to CPGs, and therefore, environmental adaptability was not discussed.

Based on the above discussion, the purpose of this study is to realize environmental adaptability in meandering locomotion control of a snake-like robot by the use of sensory information from the environments. In low-level control of meandering locomotion, essential sensory information is reaction force from the environment acting on the bottom of the robot (in robots with passive wheels, friction force). We construct a CPG-based controller that can change locomotion according to changing friction condition using information from sensors that detect reaction force.

In section 2, we will explain the model of a snake-like robot we assume in this study. In section 3, construction

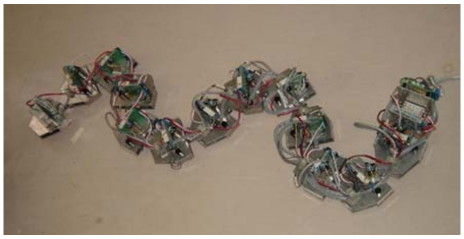


Fig. 1. Real snake-like robot

Fig. 2. Friction force sensors

TABLE I
PARAMETERS OF SNAKE-LIKE ROBOT

Number of links n	12
Total length of the robot $L = nl$	2.04 [m]
Total weight of the robot $M = nm$	19.44 [kg]
Rotational Inertia of a link I_i	0.03656 [kg m^2]

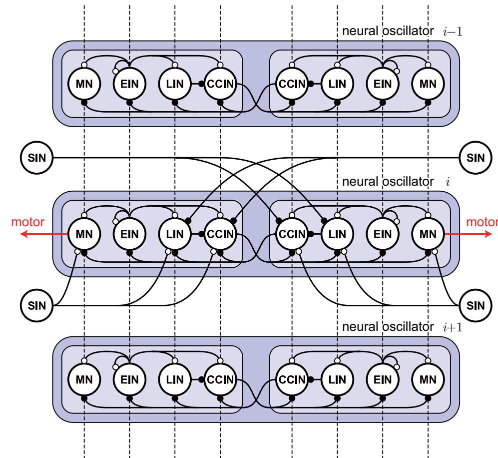


Fig. 3. Ekeberg's CPG model

of CPG-based controller for adaptive control of meandering locomotion is presented. In section 4, application of GA (genetic algorithm) for synthetic derivation of adaptive controller is explained. In Section 5, we will present simulation results derived by GA and discussion is made. Finally, in section 6, conclusion and future works are presented.

II. Mechanical Model of Snake-like Robot

As the first step, we consider a mechanical model of snake-like robot moving on two-dimensional horizontal plane in this paper. The robot model is composed of serially connected links. Between every two links, a one-dimensional joint rotating on vertical (yaw) axis is located. In the same way as living snakes, friction force between the robot body and the environment is supposed to be large in normal direction and small in tangential direction. Commonly this is realized using passive wheels in real robots. Based on the Newton-Euler equation, the dynamics of the robot can be summarized as follows (for details, see [13]):

$$\boldsymbol{D}\boldsymbol{\tau} = {}^{f}\boldsymbol{\tau} + {}^{0}\boldsymbol{\tau} + \boldsymbol{M}_0(\ddot{\boldsymbol{p}}_0 + \boldsymbol{g}) + \boldsymbol{M}\ddot{\boldsymbol{\phi}}, \tag{1}$$

where, $\boldsymbol{D}$ is coefficient matrix, $\boldsymbol{\tau}$ is torque, ${}^{f}\boldsymbol{\tau}$ is frinction force, ${}^{0}\boldsymbol{\tau}$ is centrifugal and Coriolis force, $\ddot{\boldsymbol{p}}_0$ is acceleration of the end of the robot, $\boldsymbol{g}$ is gravity, $\boldsymbol{M}$ is inertia matrix, $\boldsymbol{M}_0$ is inertia matrix expressing influence of $\ddot{\boldsymbol{p}}_0$ and $\boldsymbol{g}$, and $\ddot{\boldsymbol{\phi}}$ is angular acceleration of joints.

The mechanical arrangements of the robot are shown in Table I. The real robot we have developed is shown in Fig. 1. The model is based on this robot.

In order to realize environmental adaptability, we developed sensors to measure lateral firction force and normal reaction force from the ground. Sensors are located on the bottom of each link (with passive wheels) (Fig. 2). This sensor can detect lateral and vertical forces acting to the passive wheel. Lateral force is friction force, and vertical force is normal reaction force from the ground (in horizontal plane, this is basically equal to the weight of a link). In this paper, force information in lateral direction is used.

III. CPG Model

We adopt two kinds of CPG model as controllers for adaptive control of meandering locomotion. One is Ekeberg's model derived from physiological study on lamprey [3]. Although this model is biologically realistic, it is difficult to implement this model to real robots because of its structural complexity. And another model we use is a CPG model proposed by Matsuoka [14]. This model is numerically designed based on engineer's manner.

A. Ekeberg's Model

Ekeberg's CPG model is shown in Fig. 3. As shown in the figure, this model is composed of serially connected neural oscillators. Each oscillator is composed of four pairs of neurons located symmetrically. In the figure, MN is motoneuron, LIN is lateral inhibitory interneuron, EIN is excitatory interneuron and CCIN is contralateral inhibitory interneuron. Small white circles indicate excitatory connections and black ones are inhibitory connections. Dynamics of each neuron can be described by following non-linear simultaneous differential equation:

$$\dot{\xi}_+ = \frac{1}{\tau_D}(\Sigma u_i w_i - \xi_+) \tag{2}$$

$$\dot{\xi}_- = \frac{1}{\tau_D}(\Sigma u_i w_i - \xi_-) \tag{3}$$

$$\dot{\nu} = \frac{1}{\tau_A}(u - \nu) \tag{4}$$

$$u = \begin{cases} 1 - \exp\{(\Theta - \xi_+)\Gamma\} \\ -\xi_- - \mu\nu & \text{(if } u > 0\text{)} \\ 0 & \text{(otherwise)} \end{cases} \tag{5}$$

TABLE II

NEURAL CONNECTION IN EKEBERG'S CPG

From	To	Extent	From	To	Extent
EIN	EIN	(2,2)	CCIN	EIN	(1,10)
EIN	CCIN	(2,2)	CCIN	CCIN	(1,10)
EIN	LIN	(5,5)	CCIN	LIN	(1,10)
EIN	MN	(5,5)	CCIN	MN	(5,5)
LIN	CCIN	(1,5)			

TABLE III

CORRESPONDENCE BETWEEN CPG AND ROBOT IN EKEBERG'S CPG

Joint	1	2	…	i	…	11
Oscillator	10	18	…	$8i+2$	…	90
Sensor input	1,2	2,3	…	$i, i+1$	…	11,12

where ξ_+, ξ_-, ν are excitatory input, inhibitory input and fatigue, respectively. u is output of neuron whose range is $0 \leq u \leq 1$. $w, \tau_D, \tau_A, \Theta, \Gamma, \mu$ are synaptic weight, time constant for input, time constant to fatigue, threshold for excitatory input, gain and fatigue coefficient, respectively. For MN and LIN, μ is set to 0, i.e. fatigue is not considered. Each neuron excites by receiving tonic input from upper center.

Neurons in each neural oscillator have multiple connection to neurons in nearby oscillators. Table II describes detailed connection. In the table, "extent" indicate span of the connection: the first is afferent, the second is efferent. Based on this configuration, we construct a CPG model composed of 100 oscillators.

Difference of outputs of two motoneurons in a oscillator is used as control signal for corresponding motor of the snake-like robot. Because the robot has only 11 joints, outputs of only 11 oscillators are used. The correspondence is shown in Table III. In this research, as the first step of implementation, output of oscillators are used as the target values of joint angles. On the robot, joint motors follows to this target using PD control.

The robot has friction force sensors between joints (bottom of links). Measured values are input to SIN (sensory interneuron). SIN performs as (1) first-order lag element and (2) dead time component. (1) is to deal with noise of sensors and (2) is to add purposive phase-shift to sensory information. The dynamics of SIN is as follows:

$$\dot{p} = \frac{1}{\tau_D}(S_{t-\Delta t} - p) \quad (6)$$

$$u_L = \begin{cases} p & (\text{if } p > 0) \\ 0 & (\text{otherwise}) \end{cases} \quad (7)$$

$$u_R = \begin{cases} 0 & (\text{if } p > 0) \\ -p & (\text{otherwise}) \end{cases} \quad (8)$$

$$\Delta t = \gamma T_t \quad (0 < \gamma \leq 1) \quad (9)$$

Output of SIN is fed back to CPG as shown in Fig. 3.

B. Matsuoka's Model

CPG model proposed by is shown in Fig. 4. Similarly, our CPG is composed of serially connected neural oscillators.

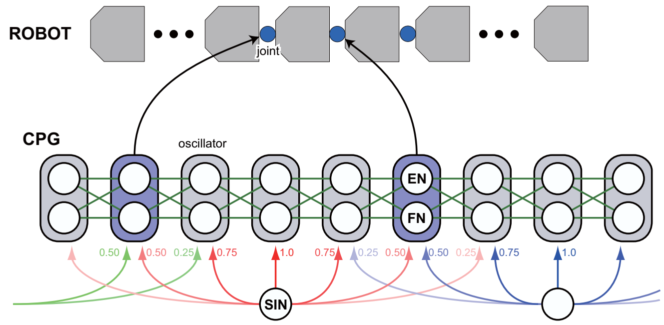


Fig. 4. Matsuoka's CPG model

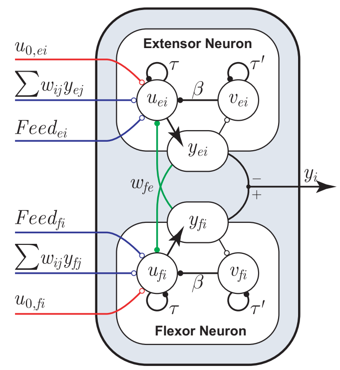


Fig. 5. Unit oscillator in Matsuoka's model

Unit oscillator in Matsuoka's model is shown in Fig. 5. An oscillator is composed of two neurons: extensor neuron (EN) and flexor neuron (FN). For many animals, they correspond to extensor and flexor muscles. Every adjacent two oscillators have complete connections: efferent-afferent and parallel-crossing connections. Dynamics of a oscillator can be described by following equations:

$$\begin{aligned} \tau \dot{u}_{\{e,f\}i} = & -u_{\{e,f\}i} + w_{\{fe,ef\}} y_{\{f,e\}} \\ & -\beta v_{\{e,f\}i} + u_{0,\{e,f\}i} + Feed_{\{e,f\}i} \\ & + w_{ep} y_{\{f,e\}(i-1)} + w_{ap} y_{\{f,e\}(i+1)} \\ & + w_{ec} y_{\{f,e\}(i-1)} + w_{ep} y_{\{f,e\}(i+1)} \end{aligned} \quad (10)$$

$$y_{\{e,f\}i} = \max(u_{\{e,f\}i}, 0) \quad (11)$$

$$\tau' \dot{v}_{\{e,f\}i} = -v_{\{e,f\}i} + y_{\{e,f\}i} \quad (12)$$

$$y_i = -y_{ei} + y_{fi} \quad (13)$$

where $u_{\{e,f\}i}$ is membrane potential of EN and FN, $v_{\{e,f\}i}$ is fatigue effect, $y_{\{e,f\}i}$ is output of a neuron, y_i is output of i-th oscillator. β is fatigue coefficient, w_{ef} is connection weight between two neurons. $Feed_{\{e,f\}i}$ is feedback signal from SIN (sensory interneuron). $w_{ep}, w_{ap}, w_{ec}, e_{ac}$ are connection weight between oscillators (in subscripts, e: efferent, a: afferent, p: parallel, c: crossing).

Similarly to the case of Ekeberg's model, output of 11 oscillators are used as motor control signals. Correspondence is shown in Table IV.

As the same as in Ekeberg's model, sensory information is input to SIN and the output of SIN is fed back to CPG.

TABLE IV

CORRESPONDENCE BETWEEN CPG AND ROBOT IN MATSUOKA'S CPG

Joint	1	2	...	i	...	11
Oscillator	4	8	...	j	...	44
Sensor input	1,2	2,3	...	$k, k+1$	...	11,12

TABLE V

OPTIMIZED PARAMETERS FOR EKEBERG'S MODEL

parameters for neurons	$x_1 \sim x_{20}$
connections in oscillators	$x_{21} \sim x_{29}$
connections between oscillators	$x_{30} \sim x_{38}$
parameters for sensory interneuron	$x_{39} \sim x_{44}$

TABLE VI

OPTIMIZED PARAMETERS FOR MATSOKA'S MODEL

Time constant τ	x_1
Time constant τ'	x_2
Fatirue constant β	x_3
Connection weight w_{fe}	x_4
Driving input u_0	x_5
Connection weight w_{ep}	x_6
Connection weight w_{ap}	x_7
Connection weight w_{ec}	x_8
Connection weight w_{ac}	x_9
Time constant tau_s	x_{10}
Delaty time Δt	x_{11}
Connection weight w_s	x_{12}

TABLE VII

GA OPERATIONS

selection	roulette selection, elite preservation
crossover	one-point crossover
mutation	random bit inversion

IV. EVOLUTION OF ADAPTIVE CPG PARAMETERS

In order to analytically configure appropriate CPG parameters (parameters for neurons and connection weights), we have to know what set of parameter yields purposive locomotion of the snake-like robot. However, considering the total system (combination of mechanical system and neural system), the total dynamics is too complicated to discuss analytically. In such case, synthetic approach is effective.

We use GA (genetic algorithm) to obtain CPG parameters that realize adaptive meandering locomotion of the snake-robot. In order to achieve adaptability, evaluation fuction (fitness function) is based on performance in different multiple environments with different friction coefficients.

A. Coding of Genom

In GA, candidates of solusion are coded as genoms. Here, we code genom as array of CPG parameters discretized to 16-bit digits. For Ekeberg's model, parameters to optimize are as shown in Table V. For Matsuoka's model, parameters are as shown in Table VI.

B. Genetic Operation

In GA, performances of all genoms in the population are evaluated and fitness values are assined to genoms. Based on these values, genetic operations, "selection," "crossover" and "mutation" are applied. GA operations we applied are shown in Table VII.

C. Fitness Evaluation

In order to evaluate performance of the robot using parameters coded in each genom, we use dynamics simulator of the snake-like robot. This simulator can simulate two dimensional locomotion of the robot. Friction force and consuming power at each time step can be obtained.

Friction force is caliculated based on Coulomb's model:

$$f_i^n = \begin{cases} -\frac{v_i^n}{V_n}\, \mu_{nS}\, f_{Ni} & (\text{if } |v_i^n| < V_n) \\ -sign(v_i^n)\, \mu_{nK} \;\; f_{Ni} & (\text{if } |v_i^n| \geq V_n) \end{cases} \tag{14}$$

$$f_i^t = \begin{cases} -\frac{v_i^t}{V_t}\, \mu_{tS}\, f_{Ni} & (\text{if } |v_i^t| < V_t) \\ -sign(v_i^t)\, \mu_{tK} \;\; f_{Ni} & (\text{if } |v_i^t| \geq V_t) \end{cases} \tag{15}$$

Details about this simulator can be seen in [13].

Here, in order to obtain CPG parameter set adaptable to changing ground friction condition, meandering locomotion is tested for three environments shown in Table VIII and performance is evaluated according to the following equation:

$$f = -\alpha \left(\frac{1}{v_A} + \frac{1}{v_B} + \frac{1}{v_C} \right) - \beta (p_A + p_B + p_C) \tag{16}$$

where, v_A, v_B, v_C are realized averaged speeds and p_A, p_B and p_C are averaged consumed powers for environment A, B and C. This performance index represents penalty for totally consumed time and power.

D. Constraint for motor limits

In a simulation, if angle, angular velocity or torque of a motor goes over the limits specific to the real motor, corresponding genom is destroyed and a new one is randomly added. Angle limit is ± 1.3 [rad], angular velocity limit is ± 1.5 [rad/s] and torque limit is ± 34 [Nm] (based on real robot).

E. Convergence criterion

In order to evaluate performance at steady state, convergence of CPG and robot is needed to be judged. At the first stage of the simulation, the robot is not drived and only CPG starts generating rhythm pattern. Pattern will be judged converged when ratio of output amplitude between successive two cycles are within $[0.99, 1.01]$.

After CPG converges, the outputs of CPG are input to the robot and locomotion starts. And locomotion is judged converged when displacement of velocity between 5 cycles are within 1% of the velocity.

If CPG or robot cannot converge within preset time limit, corresponding genom is destroyed.

F. Parameters for GA

GA parameters we used are shown in Table IX.

TABLE VIII

ENVIRONMENTS FOR FITNESS EVALUATION

	μ_n	μ_t
Env. A	0.1	0.03
Env. B	0.6	0.03
Env. C	1.0	0.03

TABLE IX

PARAMETERS FOR GA

population size	50
number of elite	1
number of childs in new generation	40
number of randomly generated genoms	9
mutation probability	0.01

TABLE X

SIMULATION RESULTS FOR EKEBERG'S MODEL

(a) Generation 89

Env.	A	B	C
v [m/s]	0.373	0.593	0.576
p [W]	6.963	16.115	30.766
f	-175.91		

(b) Generation 100

Env.	A	B	C
v [m/s]	0.472	0.710	0.707
p [W]	11.375	22.019	42.813
f	-175.07		

V. SIMULATION RESULTS

A. Results for Ekeberg's CPG Model

For Ekeberg's model, we set parameters in (16) as $\alpha = 20.0$, $\beta = 1.0$. Evolusion was made up to 100 generations.

Resultant performances at generation 89 and generation 100 are shown in Table X. Resultant locomotion of snake at generation 89 is shown in Fig. 6

At generation 89, as shown in the figure, adaptation of locomotion is observed. In environment A (slippy), the robot meanders with larger amplitude to gain friction force in forward direction. This is the same tendency with living snakes.

Fig. 7 shows adaptation to changing ground friction. First, the robot moves on a ground with high friction coefficient, and after robot moves to slippy area, robot autonomously changed body shape to cope with slippy condition.

Devrived adaptive CPG parameters are shown in Table XI.

However, from generation 90, new parameters are obtained with slightly higher fitness. With this parameter set, the robot consumes much higher power and body shape of the robot does not change much with different conditions.

B. Results for Matsuoka's CPG Model

For Matsuoka's CPG model, we set parameter in (16) as $\alpha = 10.0$, $\beta = 1.0$. GA was run up to 500 generations.

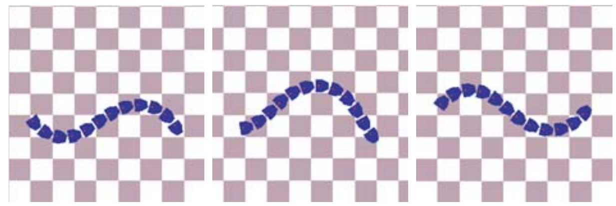
Resultant performances for Matsuoka's model are shown in Table XII and parameters are shown in Table XIII.

As for adaptability, amplitude of body shape becomes slightly bigger in slippy environment (environment A), but clear distinctness could not be seen.

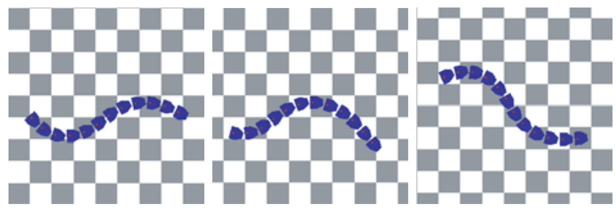
C. Discussion

For Ekeberg's CPG mode, adaptive parameter set is obtained temporally and using this parameter set, adaptive locomotion of a snake-like robot was realized as shown in Fig. 7.

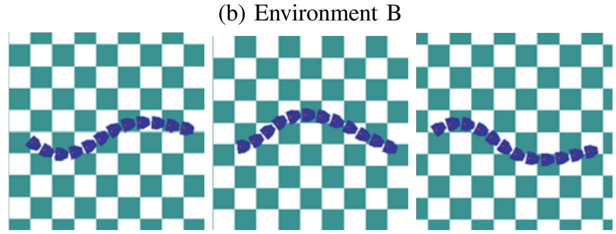
However, at generation 90, other parameters without adaptability replaced it. The cause of this is supposed to be inadequacy of fitness function. In (16), we put simply weighted sum of penalties and settings of parameters α and β has not sufficient ground. More deliberate design for these settings are needed.



(a) Environment A



(b) Environment B



(c) Environment C

Fig. 6. Resultant lonomotion for Ekeberg's model at generation 89

VI. CONCLUSION AND FUTURE WORKS

In this paper, CPG-based controller for meandering locomotion of a snake-like robot that is adaptive to changing ground friction is presented. Two CPG models, Ekeberg's model and Matsuoka's model are used as distributed controller. Environmental information is obtained by force sensors attached at passive wheels on the bottom of the robot. From parameter optimization by GA, one parameter set for Ekeberg's model realizing adaptation to changing friction condition is obtained.

However, for Ekeberg's model, fitness function is not completely adequate and final solution from GA was not adaptive. For Matsuoka's model, obvious adaptation cannot be observed.

As future works, we will investigate the cause of this problem. And we will realize adaptation on a real snake-like robot.

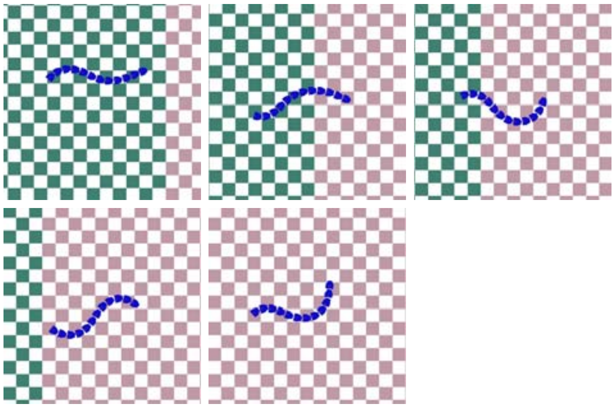


Fig. 7. Adaptaion of locomotion

TABLE XI

PARAMETERS FOR EKEBERG'S MODEL IN GENERATION 89

(a) Parameters for neuron

	τ_D	τ_A	Θ	Γ	μ	BS	γ
MN	1.195	-	0.940	0.162	-	4.711	-
EIN	0.893	5.090	-0.193	20954	0.354	1.839	-
LIN	2.001	-	5.594	0.465	-	6.958	-
CCIN	0.215	3.021	0.469	1.149	0.260	5.334	-
SIN	0.2263	-	-	-	-	-	0.016

(b) Synaptic weight in oscillator

	EIN	LIN	CCIN	SIN_r	SIN_c
MN	1.662	-	-2.447	0.0017	-0.0076
EIN	0.458	-	-2.244	-	-
LIN	13.609	-	-0.889	0.0124	-
CCIN	3.311	-1.090	-1.284	-0.0354	0.0021

(c) Synaptic weight between oscillators

	EIN	LIN	CCIN
MN	0.061	-	0.214
EIN	0.234	-	-0.117
LIN	0.232	-	-0.247
CCIN	-0.268	0.114	-0.604

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TABLE XII

PERFORMANCE FOR MATSUOKA'S MODEL

Env.	A	B	C
v[m/s]	0.350	0.601	0.821
p[W]	6.460	17.440	27.670
f	-108.96		

TABLE XIII

RESULTANT PARAMETERS FOR MATSUOKA'S MODEL

Time constant τ	31.288
Time constant τ'	0.229
Fatirue constant β	170.950
Connection weight w_{fe}	-13.440
Driving input u_0	30.241
Connection weight w_{ep}	30.289
Connection weight w_{ap}	-29.627
Connection weight w_{ec}	23.441
Connection weight w_{ac}	-41.406
Time constant tau_s	0.251
Delaty time Δt	0.853
Connection weight w_s	-0.055

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