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Simultaneous Generation of Morphology of Body and Neural System of Multi-Linked Locomotive Robot using Evolutionary Computation

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Abstract

This paper deals with the evolutionary design of the morphology of body and neural system of multi-linked locomotive robot that can adapt the changes in environment including unknown shape of ground. Morphology of the body and neural system has a close relation to control of the locomotion. So the model is constructed in which the morphology of the body and neural systems of the robot emerge simultaneously. The tasks are that the robots move on grounds including different height of hills from generation to generation in the two-dimensional lateral simulated world under the effect of gravity. The morphology of the body and neural system are generated simultaneously using a Genetic Programming. The robots are evaluated based both on a moving distance and efficiency in a certain period. As a result, various combinations of the morphology and neural system of the robot were generated simultaneously. In other word, the cooperation between the morphology and neural system was emerged. Moreover, the robot went over the hills that were not experienced.

1. Introduction

Many studies have been conducted on the moving mechanism and control of locomotive robots, in which the morphology of robots are decided at first. For example, the morphology of the robots was designed imitating those of creatures, and then, the way of controlling the robots are studied. Although the morphology of the robot and the control of its locomotion are deeply related to each other, they were studied separately.

Lately, artificial systems simulating the biological principals have been of interest by researchers in the field of artificial life. The emergence of morphology and locomotion using evolutionary method is studied. Sims [1] succeeded to generate a morphology and behavior of the virtual creatures toward the tasks such as walking, jumping and swimming using an evolutionary computation. He also generated virtual creatures which compete each other to obtain one resource [2]. Ventrella [3] also presented evolutionary emergence of morphology and locomotion behavior in animated characters. Kikuchi and Hara [4] studied a method of evolutionary design of robots having tree structure that change their morphology in order to adapt themselves to the environmental conditions [4]. However, all of them do not consider how to make practical robots.

On the other hand, evolutionary method is tried to apply to the practical hardware. Hagiwara [5] generated machines consist of parts as motors and blocks that are provided in advance. However, the machines move in unnatural way because dynamics is not considered •• Kitamura [6] used Genetic Programming, GP [7], to emerge the simple linked-locomotive robot in virtual space. Lipson [8] adopted the rapid prototyping to produce the creatures that were generated in three-dimensional virtual space. However emerged machines and creatures can generate only simple periodical movement in assumed environment because they cannot obtain any information from the environment. So they cannot adapt the change in the environment.

If the driving torque of each joint of robot is generated as a result of the dynamic interaction between its morphology and environment, the robot can change its locomotion pattern. If the robotic system is adaptive to the change in environment at the time when it is designed, the robot can move on an inexperienced environment. The interaction between morphology and locomotion must be considered simultaneously in order to adapt the change in environment.

In this study, a method for designing the morphology of body and neural system of multi-linked locomotive robot that can adapt the change in the environment is suggested. Both the morphology and neural system are represented as a simple large tree structure using GP. The robots move on the grounds including different height of hills from generation to generation in the two-dimensional lateral world under the effect of gravity. The problem for designing such robots is treated as a multi optimization problem, MOP. It is shown as a result that the generated robots have diverse morphology of the body and neural system and they have unique locomotive pattern and their movement is fast and efficient. The capability and adaptability of the locomotion are also shown by placing the robot on the changed environment.

2. Model of Robot

2.1 Body

Robots are composed of parts consist of t simple two-dimensional links that are easy to be produced in order for the real robots to be made in the future study. An example is shown in Fig. 1. Characteristics of links are set so as to produce the real robots easily. Each link has the parameters such as length of link, L, spring constant of joint, k, the first

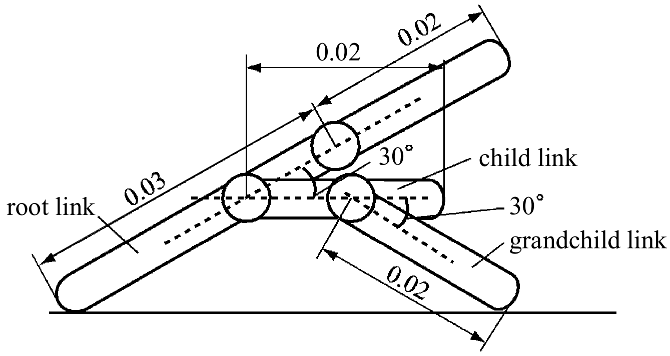


Fig. 1 Morphology of body of robot

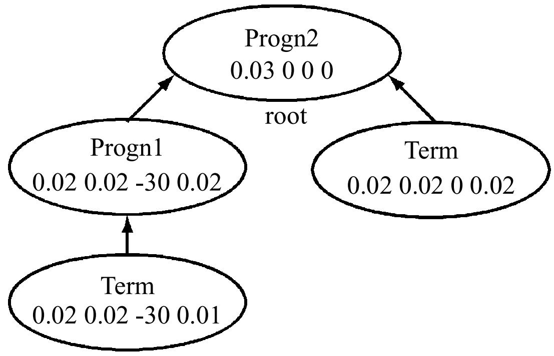


Fig. 2 Tree structure of morphology of body

angle of joint θ and the location of connecting point from the edge of the link, J. Value of these parameters are obtained in the evolutionary computation. When the values of these parameters are defined, the structure of robot is also defined.

Morphology of the robot is expressed as a tree structure using GP. First, a root link is defined. Then, several child links are connected to the root link at J. Other links can also be connected to the child links. Now, the robots that have bodies composed of links are simply expressed by tree structures including parameter L, θ and J. If zero, one and two links are connected to one link, structure of the links is expressed in the program as Progn1, Progn2, and Term, respectively. For example, if one link is connected to two links, it can be expressed as follows.

Progn2 [L θ J]

For other example, if one robot has morphology as shown in Fig. 1, it can be expressed as S expression of LISP language.

```
(Progn2 [0.03 0 0 0]
        (Progn1 [0.02 0.02 -30 0.02]
                Term [0.02 0.02 -30 0.01])
        Term [0.02 0.02 0 0.02]
)
```

Moreover, this robot can be expressed as a tree expression as shown in Fig. 2. One link can at most be connected to two links. The maximum depth of the tree is two. So the robot has at least two links and at most seven links.

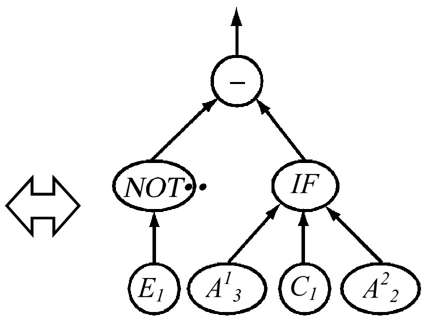
2.2 Neural System

The driving torque of the each joint of the links which decides the locomotion pattern is decided by the neural system that exists in each joint. The output of the neural system in each joint is a driving torque of each joint at the next time step simulation. Because of this, the emerged motion patterns are closely related to the contact conditions with ground and angle of joints. Contact condition of some links and angle condition of some joints are applied as inputs to the neural systems. The neural system is composed of program languages whose functions are defined in advance. The grammar of this program causes the neural system to construct tree structure. The maximum depth of this tree is five. Two kinds of simple neural systems are developed for comparing the capability of the change in environment caused by the difference in the quantity of information from the environment. One is a digital neural model in which the information of contact with ground and angle are expressed as a Boolean value. The other is an analog neural model in which the analog information is treated.

Table 1 Nodes used in a digital neural model

Function nodes	Number of argument
AND	2
NOT	1
IF	3
OR	2
=	2
Variable nodes	**Explanation**
C_i	Contact information of link i
A^k_i	Angle information of joint i
1	Constant
0	Constant
E_i	Output before one time step

(-
 ($NOT\ E_1$)
 ($IF\ A^1_3$
  C_2
  A^2_2)
)



(a) S expression (b) Tree structure

Fig. 3 S expression and tree structure of the digital neural model

(a) Digital Neural Model

Table 1 shows the function and variable nodes used in the digital neural model. It is necessary for all information from environment to be expressed as Boolean value. For example, if the link i is in contact with the ground, C_i is 1. Otherwise C_i is 0. The range of angle that link can rotate is divided into four parts and this information is decoded to two bits and each bit are contributed to A^1_i and A^2_i.

The function "-" is used as the root of the tree of digital neural model. This enables the digital neural model to provide three value, 0, 1, and –1 as outputs. The function "-" takes two arguments. First value of them is E_1 and second value is E_2 at the next time step. Finally, when the output value is -1, 0, and 1, driving torque of the joint where the neural system is located is -0.2, 0, and 0.2 Nm respectively.

An example of the digital neural model is shown in Fig. 3. In this way, these nodes compose S expression according to its grammar and expressed as tree structure as the same as the morphology.

(b) Analog Neural Model

Table 2 shows the function and variable nodes used in the analog neural model. The outputs of all nodes vary from $-\pi/2$ to $\pi/2$. The function *sig* is a sigmoid function represented by,

$$sig(r) = \frac{1}{e^{-r}+1} \tag{1}$$

where, r is the sum of the four arguments. The second argument of *sin* is the phase. *if* is the function that provides the second argument as an output if the first argument is positive, and provides the third argument if the first argument is negative. *not* multiply -1 to the argument.

If the total mass of the robot is M and external force to the link i is F, C_i is given by

$$C_i = \frac{F\pi}{Mg} - \frac{\pi}{2} \tag{2}$$

A_i means the information of the angle of joint i. So if the angle θ of joint i can rotate from $-\pi/3$ to $\pi/3$, A_i is defined by

$$A_i = \frac{3}{2}\theta \tag{3}$$

Thus the output P of the analog neural model also varies from $-\pi/2$ to $\pi/2$. Driving torque is defined by

$$\tau = 0.2P\frac{2}{\pi} \tag{4}$$

With this, the driving torque varies from -0.2 Nm to 0.2 Nm.

3. Method

3.1 Genetic Programming

Both the morphology of the body and neural system are represented by one large tree structure as shown in Fig. 4. The tree structures of neural systems are placed in each joint. One of the evolutionary computations, GP is the best method in order to deal with this tree structures including the information of both the morphology and neural system, because GP can handle the tree structures directly. Robots with low-fitness are eliminated by selection, and new robots are produced using crossover and mutation in this method,. Then their morphology and neural system are generated from generation to generation and finally converge to a reasonably optimal solution.

Crossover is the operation to exchange the sub trees of two parents selected due to their fitness. Crossover can exchange two sub trees of morphology including neural

Table 2 Nodes used in an analog neural model

Function nodes	Number of argument
sig	4
sin	2
tan	2
not	1
if	3
Variable nodes	**Explanation**
C_i	External force from ground
A_i	Angle of joint
N	Constant
E	Output before one time step

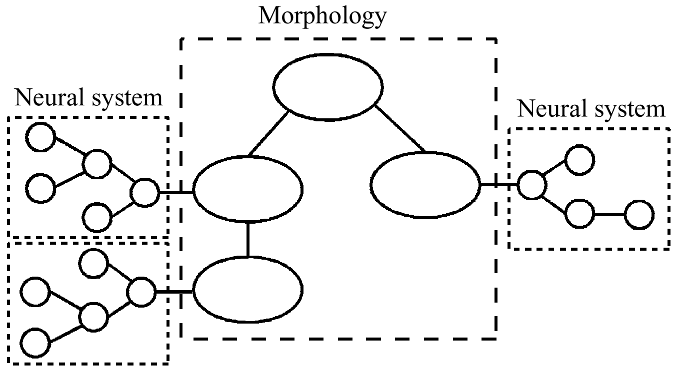


Fig. 4 Tree structure of a robot

system or two sub trees of neural system. In this way, the grammar of the tree structure is not broken. Mutation is the operation to reproduce the sub tree of one parent selected randomly. This operation also works without breaking the grammar.

3.2 Multi Optimal Problem

The design of the robot is taken as the multi optimal problem, MOP, in which various evaluate functions are considered.

Distance of movement is often used for emergence of the ability of moving robot. However this evaluation function largely depends on the size of the robot. The larger the robot is, the easier it can survive because the size of the robot is in proportion to the weight of the robot. So we define the fitness as,

$$fitness_1 = \frac{d}{M} \tag{5}$$

where, M is the mass of the robot and d is the moving distance during eight-second simulation.

The efficiency of movement is taken as a second evaluation. The larger the sum of driving torque of all joints of the robot is, the smaller the efficiency is. So as the second fitness,

$$fitness_2 = \frac{1}{\tau+1} \tag{6}$$

is defined, where, τ is the sum of driving torque of all joints per a unit time step. With this fitness, the larger this value is, the more efficient the movement is.

Moreover, we use the method that is combined with pareto preserving strategy, vector evaluated GA and sharing as well.

3.3 Method in detail

The environment on which the robots move includes the simple hill as shown in Fig. 5. Height of the hill, *h*, changes randomly from generation to generation. The range of *h* is form zero to 0.02 m. At first, the center of mass of root link is on the start point. Environment is just flat from the start point to the point apart for 0.5 m from the start point. Then, a simple hill appears. Flat ground continues after the hill. So the robots that can go through the flat-hill-flat environment faster and more efficiently can survive.

Dynamic simulation is conducted to calculate the movement of robots resulting from their interaction with the environment. Equations of motion of the robot are constructed using a Newton-Eular method. One time step is 5 ms. Contact response with ground of links is accomplished by a hybrid model using both spring and damper under the influence of friction and gravity.

GP parameters used for the calculation is as follows:

Population Size	200
Generation	300
Mutation Ratio	0.02

Note that the crossover ratio changes when the number of pareto optimal solutions changes from generation to generation.

4 Results

4.1 Digital neural model

Calculation using GP is conducted for the digital neural model. At first, all robots can move only a little bit and the value of $fitness_1$ is low. Gradually, the robots that can move efficiently are emerged and their moving distance increase. Finally, some robots reach and overcome the hill. As shown in Fig. 6(a), eleven pareto optimal solutions are emerged at generation 300. Moreover, six of them can overcome the hill of 0.02 m heights. As a preferred solution, the robot whose value of $fitness_1$ is the largest in the six solutions is selected.

The morphology of the preferred solution of the digital neural model is shown in Fig. 7. Joints are numbered as joint 1, 2, and 3 as shown in Fig. 7. This robot mainly moves using joint 1 and joint 3. The distance between the link 1, 2 and ground and the driving torque of joints 1and 2 are shown in Fig. 8. The negative and positive driving torque of joint 1 is generated when the root link is in contact and not in contact with the ground, respectively. Similar phenomena can be seen for the joint 3 and link2. Note that the locomotion pattern is generated not because each neural system can generate the rhythm but because the relationship between the neural systems and environment works cooperatively. Figure 9 shows the locomotion pattern of the robot and the angle of joints. The angle of each joint moves periodically when the robot move on the flat ground. The periodical locomotion pattern changes when the robot moves on the hill. When the robot returns to the flat ground, the locomotion pattern returns to the periodical one. The robot changes its length of step shorter to adapt the change in the environment. Calculation is also conducted when the environment is changed. Then the robot can also move on

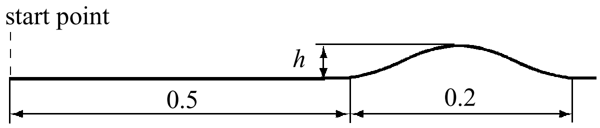


Fig 5 Environment for moving

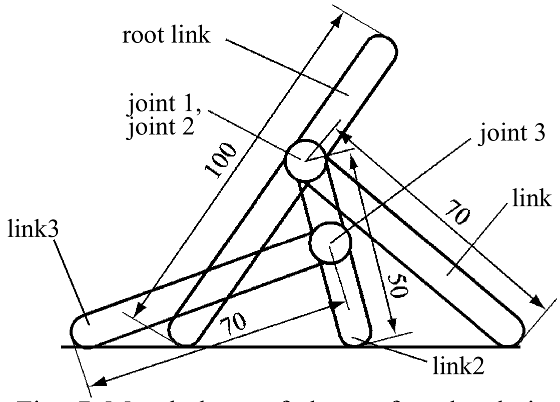
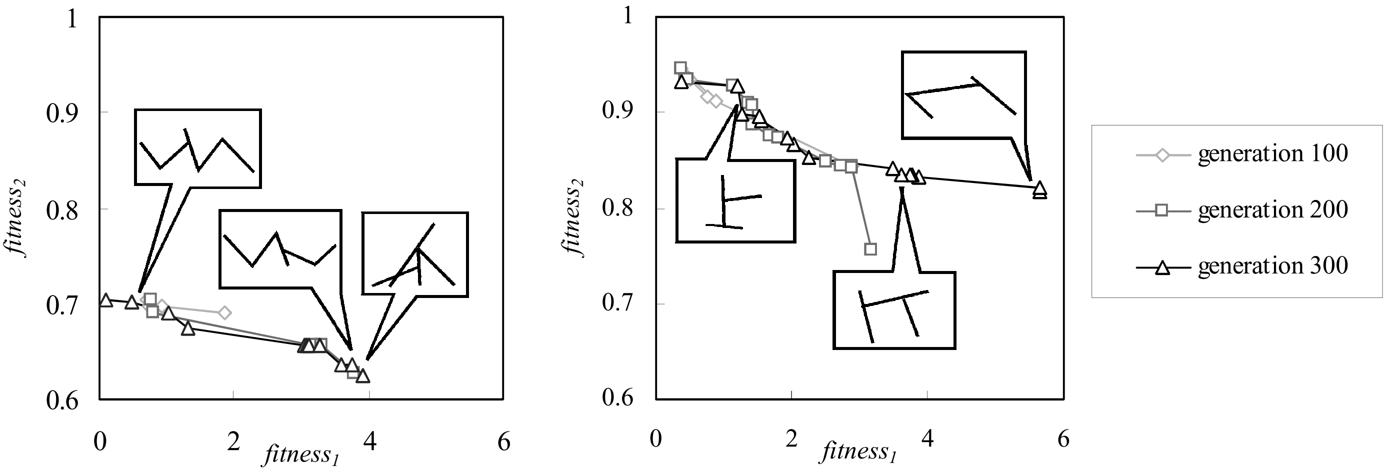


Fig. 7 Morphology of the preferred solution of the digital neural model



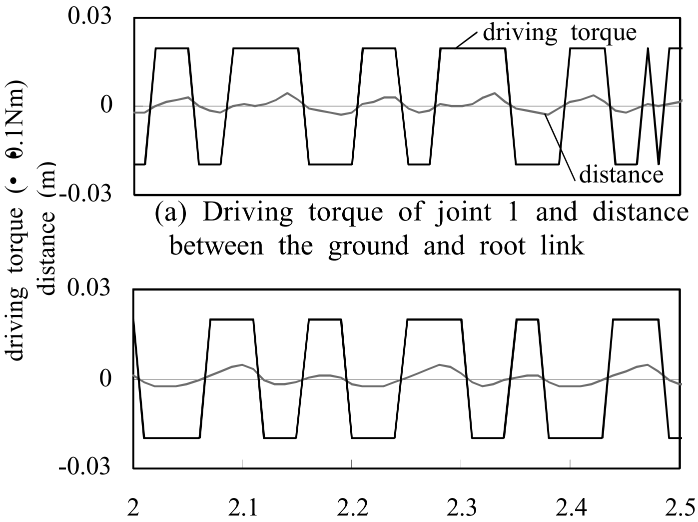
(a) Digital neural model
(b) Analog neural model

Fig. 6 Pareto optimal solutions of each generation the environment including several hills whose width is inexperienced. This means that both the morphology of body and neural system of the robot enable the robot to adapt the change in environment.

4.2 Analog neural model

As shown in Fig. 5(b), fifteen pareto optimal solution are emerged for the analog neural model at generation 300. The robots with analog neural model have much better fitness both on $fitness_1$ and $fitness_2$ than these of the digital neural model. It means that the analog neural model can be more adaptive toward the change in environment than the digital neural model. It is because the analog neural model can exchange much information with the environment than the digital model. Note that the obtained morphology of the body having large fitness, lift their certain link by other links as mammals lift their bodies by their limbs, whereas most results for the digital neural model were creeping motion without lifting their links as worms do. Results of this study correspond to the fact that higher animals have more complex neural systems.

Eight of the pareto optimal solutions can overcome the hill of 0.02 m heights. The robot whose value of $fitness_1$ is



(a) Driving torque of joint 1 and distance between the ground and root link

(b) Driving torque of joint 3 and distance between the ground and link 2

Fig. 8 Driving torque and distance between the ground and link

the largest in the eight solutions is selected as a preferred solution.

The morphology of the preferred solution of the analog neural model is shown in Fig. 10. Joints are numbered defined as shown in Fig. 10. This robot mainly moves using joint 2. The relationship between the driving torque of the joint 2 and external force of the link 2 from the ground is shown in Fig. 11. The driving torque is decided according to the strength of external force of link 2. Not only the information of contact or no contact with the ground, but the strength of the force from the ground which works at the contact point of the link is obtained by the analog neural model as an input. Similar to the digital neural model, this robot can move using information of environment as an input to the neural systems. Even through this robot has the simple morphology as shown in Fig. 10, it can overcome the hill of 0.02 m heights. Fig. 12 shows the locomotion pattern of this robot and the angle of joints. When the robot reaches the hill, larger external force works from the ground to the link 2 than that on the flat ground because the root link is lifted by the hill. Then larger driving torque is generated to the joint 2 to overcome the hill. However the robot does not change its periodical locomotion pattern so much as that of the digital neural model when it moves on the hill. Only the amplitude and period of the joint angle are changed. It is because the locomotion pattern of the robot is not a creeping motion but a walking motion similar to those of the higher animals. The robot can adapt the change in the environment by changing the strength of the driving torque of joint 2. In this way, the robot can overcome the hill. This robot also can move on the environment including several hills whose width is inexperienced as the same as the robot with the digital neural model can.

The obtained simple three link morphology of the body of the robot is similar to the robots by Doya [9] and Kawachino [10] by chance. Emerged locomotion pattern of these three studies are also similar. It means that the morphology of the robots by Doya and Kawachino are optimum. It also means that the validity of our method is confirmed because the generated morphology of the body and neural system and the locomotion pattern is adequate even if the way of expression of the robot is different.

5 Discussion

The purpose of this study is to suggest a method to

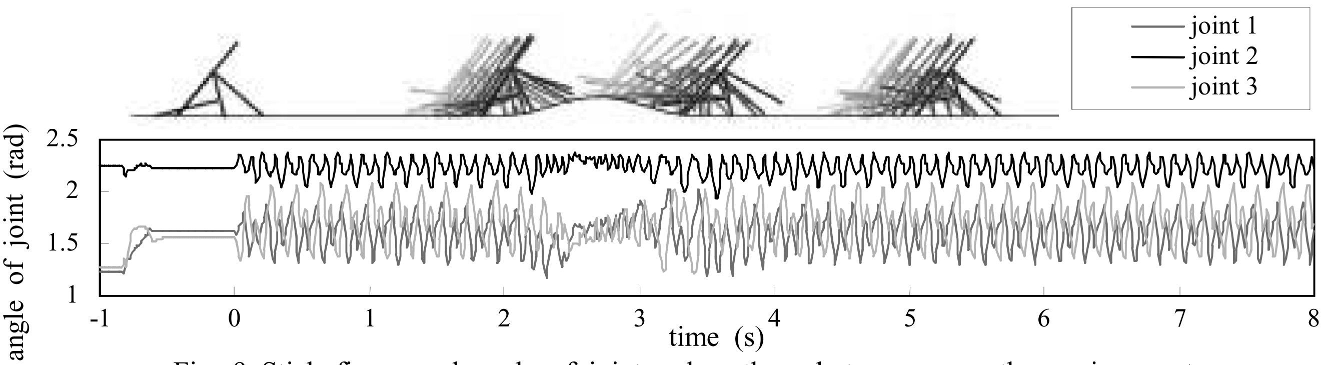


Fig. 9 Stick figure and angle of joints when the robot moves on the environment

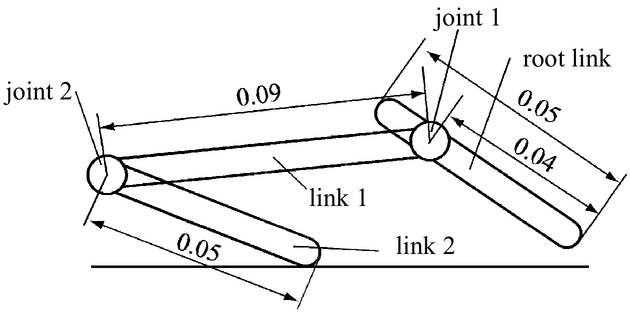


Fig. 10 Morphology of the preferred solution of the analog neural model

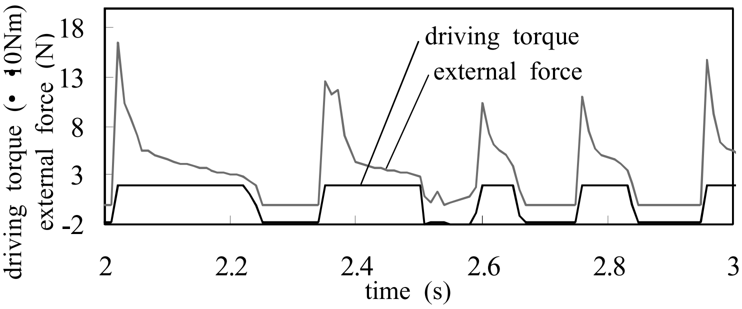


Fig. 11 Driving torque of joint 2 and external force of the link2

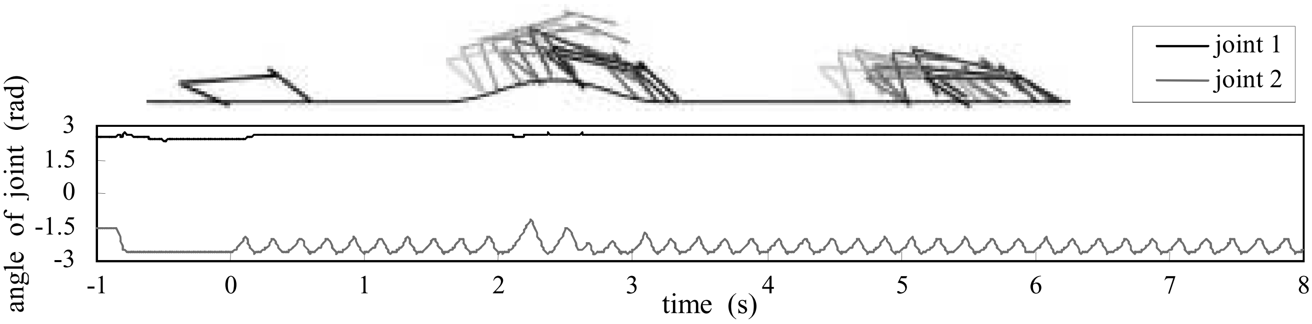


Fig. 12 Stick figure and angle of joints when the robot moves on the environment

design the morphology of the body and neural systems of the robot that can adapt the unknown environment. Various combination of the morphology of the body and neural system of the robot are emerged and they can move because the relation between the morphology and locomotion work cooperatively. This means that it is effective for the robot to generate the morphology of the body and the neural system simultaneously. Especially, it is confirmed that the analog neural model is more adaptive to the change in the environment than digital neural model. It is because the analog neural model can exchange much information from environment than the digital neural model. Simple link-type structure is only constructed and the characteristic of the real motors is ignored in this study to simplify the argument. If this is considered, the morphology and locomotion of the real robot can be emerged using this method. Moreover, an additional extension to this work would be to simulate in three-dimensional world. The three dimensional robots emerged using this method considering characteristics of motors will be produced actually to confirm the effectiveness of this method in the future study. The robots will be easily made and controlled because they are composed of the parts that are easy to be produced and controlled.

6 Conclusion

A method for designing the morphology of the body and the neural system of the robot which generates the unique morphology and locomotion is suggested. Various combinations of the morphology of the body and neural system that can move fast and efficiently are emerged. By comparing the digital and analog neural model, it is found that the analog neural model can generate much simple and adaptive morphology and locomotion like higher animals. It is also confirmed that the robots emerged in this method have adaptability to the inexperienced environment.

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